Describe the strategy and benchmark

Our project focuses on using momentum strategy and add filters to see if we can generate different results from class. we combined compustat and crsp data, and set up 4 criterias. We excluded the market cap in lower 30% to make sure penny stocks won't have impact to our results. Price/Book ratio shoulde be lower than 40, Price/Earnings ratio less than 30, and ROE ratio less than 40. In this way we eliminate outliers, and hope this method show us a clearer pattern for momentum strategy along with time.

Benchmark is imported from Fama_french research data, basically it is an interpretaion of Market returns (Market Excess Returns). We want to see if there exists advantage for the momentum strategy to outperform investment in market index funds.

We think our strategy should outperform the benchmark, because momentum method keeps focusing on portfoilo with top performances stocks. We think short-term profits generated by this strategy will eventually become long-term outperformance.

In [1]:
```
# Summarize the characteristics of stocks in the strategy

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

In [2]:
```
# Import the benchmark file.
# We consider Market Excess Return as our Benchmark.

ff = pd.read_csv(
    '..Code/Data/F-F_Research_Data_Factors.CSV',
    index_col=0,
    skiprows=3,
    nrows=12*(2020 - 1927 + 1) + 6 + 1
)
ff.index = pd.to_datetime(ff.index, format='%Y%m') + pd.offsets.MonthEnd(0)
ff /= 100
```

In [3]:
```
# Import CRSP data (monthly prices and returns)

df = pd.read_csv(
    '../Code/Data/crsp-2021-01-14.csv',
    parse_dates=['date'],
    na_values=['A', 'B', 'C'],
    usecols=['PERMNO', 'date', 'RET', 'PRC', 'SHROUT', 'SHRCD'])

df = df[df['SHRCD'].isin([10, 11])]
df.drop_duplicates(subset=['PERMNO','date'], inplace=True)
df.sort_values(['date', 'PERMNO'], inplace=True)
```

In [4]:
```
# Import compustat data (enables us to calculate different ratios)

compustat = pd.read_csv(
    '../Code/Data/compustat-2021-01-14.csv',
    parse_dates=['datadate']
)
compustat.sort_values(['datadate', 'LPERMNO'], inplace=True)
compustat.drop_duplicates(subset=['datadate','LPERMNO'], inplace=True, keep
```

In [5]:
```
# move the dates to the last day of the month

df['date'] += pd.offsets.MonthEnd(0)
compustat['datadate'] += pd.offsets.MonthEnd(0)
```

In [6]:
```
# merge crsp + computstat, to the NEW "crsp" DataFrame

crsp = pd.merge_asof(df, compustat,
                    left_on='date', right_on='datadate',
                    left_by='PERMNO', right_by='LPERMNO'
                   )
crsp.sort_values(['PERMNO', 'date'], inplace=True)

# Make sure crsp common equity is greater than ZERO.
crsp = crsp[crsp['ceq'] > 0]
```

Set up stock selection criterias

In [7]:
```
# Filter the data with market cap 70% top.
# We wouldn't want penny stock movements to affect our judgement.

crsp['MKTCPA'] = np.abs(crsp['PRC']) * crsp['SHROUT']
crsp['MKTCPA'].quantile(0.3)
```

Out[7]:
```
31733.649999999994
```

In [8]:
```
# Execute MC criteria.

crsp=crsp[crsp['MKTCPA']>31733.65]
```

In [9]:
```
### Setup 3 ratios.

# Filter the data with price/book ratio
crsp['p_b'] = (np.abs(crsp['PRC']) * crsp['SHROUT'] / 1000) / crsp['ceq']

# Filter the data with price/earnings ratio
crsp['p_e'] = crsp['csho'] * crsp['prcc_f'] / crsp['ni']

# Filter the data with ROE
crsp['roe'] = crsp['ni'] / crsp['ceq']
```

In [10]:

```
### Restrict3 ratio ranges.
### Any ratio changes/ideas can be modified in this and previous column.

crsp = crsp[(crsp['date'].dt.year >= 1926)].copy()


crsp = crsp.loc[     (crsp['p_b'] > 0) &
                     (crsp['p_b'] < 40) &
                     (crsp['p_e'] > 0   ) &
                     (crsp['p_e'] < 30  ) &
                     (crsp['roe'] > 0   ) &
                     (crsp['roe'] < 40  )
                      ]
crsp
```

Out[10]:

	PERMNO	date	SHRCD	PRC	RET	SHROUT	GVKEY	LPERMNO	LPERMCO	da
2947116	10001	2005-09-30	11.0	11.51	0.211579	2913.0	12994.0	10001.0	7953.0	2(
2976697	10001	2006-03-31	11.0	10.99	0.170394	2932.0	12994.0	10001.0	7953.0	2(
3001120	10001	2006-08-31	11.0	11.63	0.123574	2934.0	12994.0	10001.0	7953.0	2(
3005982	10001	2006-09-30	11.0	11.00	-0.054170	2947.0	12994.0	10001.0	7953.0	2(
3010840	10001	2006-10-31	11.0	11.08	0.007273	2947.0	12994.0	10001.0	7953.0	2(
...	...	...	...	...	...	...	...	...	...	
3267325	93435	2011-07-31	11.0	2.05	0.708333	23782.0	144356.0	93435.0	53452.0	2(
3271251	93435	2011-08-31	11.0	1.55	-0.243902	23782.0	144356.0	93435.0	53452.0	2(
3294598	93435	2012-02-29	11.0	1.50	0.181102	23864.0	144356.0	93435.0	53452.0	2(
3298453	93435	2012-03-31	11.0	2.69	0.793333	23864.0	144356.0	93435.0	53452.0	2(
3302303	93435	2012-04-30	11.0	1.76	-0.345725	23864.0	144356.0	93435.0	53452.0	2(

1223233 rows × 31 columns

In [11]:
```
# After criteria applies, sort/rearrange data once more to make sure everyt

crsp.sort_values(['PERMNO', 'date', 'RET'], inplace=True)
crsp.drop_duplicates(subset=['PERMNO', 'date'], inplace=True)

crsp
```

Out[11]:

	PERMNO	date	SHRCD	PRC	RET	SHROUT	GVKEY	LPERMNO	LPERMCO	da
2947116	10001	2005-09-30	11.0	11.51	0.211579	2913.0	12994.0	10001.0	7953.0	2(
2976697	10001	2006-03-31	11.0	10.99	0.170394	2932.0	12994.0	10001.0	7953.0	2(
3001120	10001	2006-08-31	11.0	11.63	0.123574	2934.0	12994.0	10001.0	7953.0	2(
3005982	10001	2006-09-30	11.0	11.00	-0.054170	2947.0	12994.0	10001.0	7953.0	2(
3010840	10001	2006-10-31	11.0	11.08	0.007273	2947.0	12994.0	10001.0	7953.0	2(
...	...	...	...	...	...	...	...	...	...	
3267325	93435	2011-07-31	11.0	2.05	0.708333	23782.0	144356.0	93435.0	53452.0	2(
3271251	93435	2011-08-31	11.0	1.55	-0.243902	23782.0	144356.0	93435.0	53452.0	2(
3294598	93435	2012-02-29	11.0	1.50	0.181102	23864.0	144356.0	93435.0	53452.0	2(
3298453	93435	2012-03-31	11.0	2.69	0.793333	23864.0	144356.0	93435.0	53452.0	2(
3302303	93435	2012-04-30	11.0	1.76	-0.345725	23864.0	144356.0	93435.0	53452.0	2(

1223233 rows × 31 columns

Apply momentum method

The method is zero investment: meaning to long the top 10% highest return stocks, and short the bottom 10% lowest return stocks.

We do have concerns about this strategy, because past returns never represent current price change or the future price movement. Stocks with abnormal high return will be considered "winner" stocks using momentum method, but this abnormal profit may disappear quickly, making our "winner" to "underperform".

In [12]:
```
# We focus on yearly(12 month) rerurn, and name the result into a new colum

crsp.loc[crsp.groupby('PERMNO').head(1).index, 'RET'] = np.nan
crsp['RET12'] = np.exp(np.log(1 + crsp['RET']).rolling(12).sum()) - 1
```

In [13]:
```
# Add the 2-month lagged yearly return into the crsp DataFrame.

temp = crsp[['PERMNO', 'date', 'RET12']].copy()

# Lag two months to make sure the stock is unaffected by short-term reversa
temp['date'] += pd.offsets.MonthEnd(2)

# Merge the previous 12-month returns to crsp with _lag2 suffix.
merged = pd.merge(
    left=crsp,
    right=temp.dropna(),
    how='inner',
    on=['PERMNO', 'date'],
    suffixes=['', '_lag2'])
```

In [14]:
```
# Add the 1-month lagged Market Cap to be precise, giving the beginning mon

temp = crsp[['PERMNO', 'date', 'MKTCPA']].copy()

temp['date'] += pd.offsets.MonthEnd(1)

merged = pd.merge(
    left=merged,
    right=temp.dropna(),
    how='inner',
    on=['PERMNO', 'date'],
    suffixes=['', '_lag1'])
merged
```

Out[14]:

	PERMNO	date	SHRCD	PRC	RET	SHROUT	GVKEY	LPERMNO	LPERMCO
0	10001	2007-08-31	11.0	-14.54	0.027562	2859.0	12994.0	10001.0	7953.0
1	10001	2007-09-30	11.0	13.91	-0.032325	2856.0	12994.0	10001.0	7953.0
2	10001	2007-10-31	11.0	13.35	-0.040259	2855.0	12994.0	10001.0	7953.0
3	10001	2007-11-30	11.0	14.25	0.079401	2858.0	12994.0	10001.0	7953.0
4	10001	2007-12-31	11.0	14.14	-0.003930	2875.0	12994.0	10001.0	7953.0
...	...	...	...	...	...	...	...	...	...
1035069	93429	2019-07-31	11.0	109.31	0.054810	111710.0	184500.0	93429.0	53447.0
1035070	93429	2019-08-31	11.0	119.16	0.093404	111682.0	184500.0	93429.0	53447.0
1035071	93429	2019-09-30	11.0	114.91	-0.035666	111682.0	184500.0	93429.0	53447.0
1035072	93429	2019-10-31	11.0	115.15	0.002089	111682.0	184500.0	93429.0	53447.0
1035073	93429	2019-11-30	11.0	118.90	0.035693	110861.0	184500.0	93429.0	53447.0

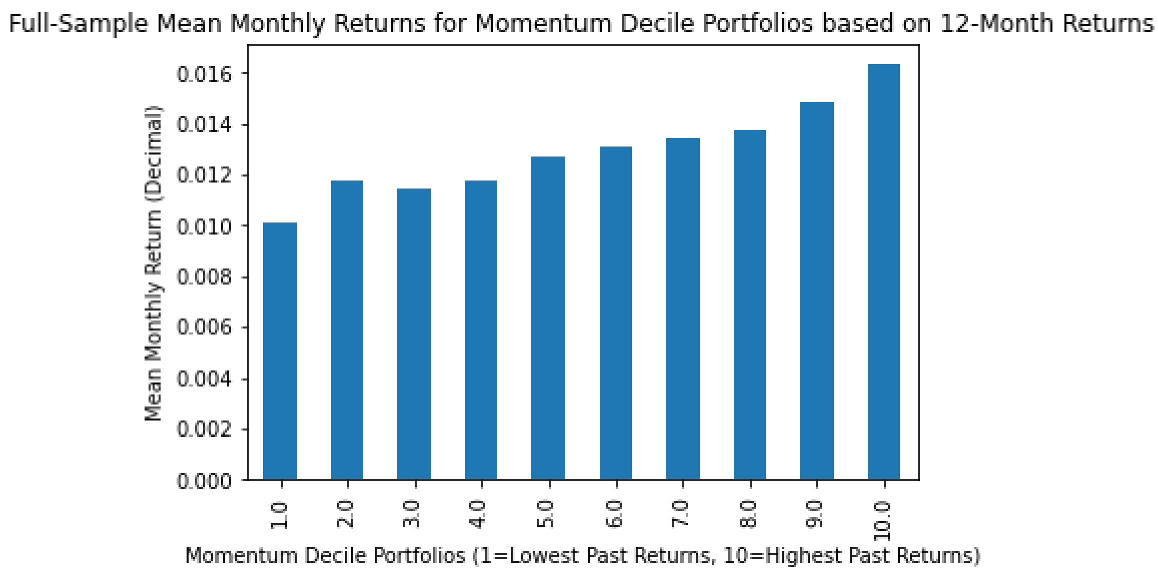
1035074 rows × 34 columns

In [15]:
```
# Bye bye outflows.

del temp
```

In [16]:
```
# Merge our Returns, 1 month lag returns, 2 month lag returns.

merged.dropna(subset=['RET', 'RET12_lag2', 'MKTCPA_lag1'], inplace=True)
```

In [17]:
```
# create ten momentum portfolios based on the 2-month lag of 12-month retur

merged['RET12_lag2_q10'] = merged.groupby('date')['RET12_lag2'].\
transform(lambda x: pd.qcut(x, 10, labels=False, duplicates = 'drop')) + 1
```

In [18]:
```
# Make sure the plot is more read-able.

merged.groupby('RET12_lag2_q10')['RET'].mean().plot(kind='bar')
plt.xlabel('Momentum Decile Portfolios (1=Lowest Past Returns, 10=Highest P
plt.ylabel('Mean Monthly Return (Decimal)')
plt.title('Full-Sample Mean Monthly Returns for Momentum Decile Portfolios
plt.show()
```



Theoretically, the graph shows us the profitability of longing winners and shorting losers. Theoretically, we can generate (0.016-0.010) percentage returns simply by buying top 10% and selling bottom 10%.

In [19]:
```
# Equally-weighted return for each portfolio each month

long = merged.groupby(['date', 'RET12_lag2_q10'])[['RET']].mean()
long.rename(columns={'RET': 'RET_EW'}, inplace=True)
```

In [20]:
```
# Create Value Weighted Portfolio DataFrame.

long['RET_VW'] = merged.groupby(['date', 'RET12_lag2_q10'])\
                .apply(lambda x: np.average(x['RET'], weights=x['MKTCPA_lag
```

In [21]:
```
long
```

Out[21]:

		RET_EW	RET_VW
date	**RET12_lag2_q10**		
1963-08-31	**1.0**	0.132530	0.132530
	4.0	0.154762	0.154762
	7.0	0.070175	0.070175
	10.0	0.076710	0.076710
1963-09-30	**1.0**	-0.111111	-0.111111
...	**...**	...	...
2019-12-31	**6.0**	0.025030	0.026870
	7.0	0.027089	0.046769
	8.0	0.021138	0.019328
	9.0	0.017158	0.033326
	10.0	-0.002961	0.025440

6757 rows × 2 columns

In [22]:
```
# make our portfolios to appear in the columns, not rows.

wide = long.unstack()
wide.columns = [col[0] + '_' + str(int(col[1])) for col in wide.columns.val
wide
```

Out[22]:

date	RET_EW_1	RET_EW_2	RET_EW_3	RET_EW_4	RET_EW_5	RET_EW_6	RET_EW_7	RET_EW_
1963-08-31	0.132530	NaN	NaN	0.154762	NaN	NaN	0.070175	Nal
1963-09-30	-0.111111	NaN	-0.046243	NaN	0.035161	NaN	NaN	-0.00518
1963-10-31	-0.035211	-0.072727	-0.075313	NaN	0.017877	0.052885	NaN	0.00348
1963-11-30	0.105720	0.002538	0.055794	-0.025114	-0.056738	-0.051111	0.011525	0.00296
1963-12-31	-0.025397	-0.012412	0.018750	0.009628	0.060843	0.018243	0.039604	0.09008
...	...	...	...	...	...	...	...	.
2019-08-31	-0.110318	-0.070465	-0.059376	-0.060415	-0.050140	-0.041782	-0.044633	-0.01596
2019-09-30	0.083873	0.056331	0.063814	0.058399	0.041459	0.052248	0.036381	0.03517
2019-10-31	-0.027360	0.030817	0.014528	0.040000	0.028358	0.023661	0.024721	0.00666
2019-11-30	0.025884	0.044275	0.023804	0.032333	0.032223	0.039994	0.033371	0.02561
2019-12-31	0.075465	0.040614	0.035063	0.031365	0.020034	0.025030	0.027089	0.02113

677 rows × 20 columns

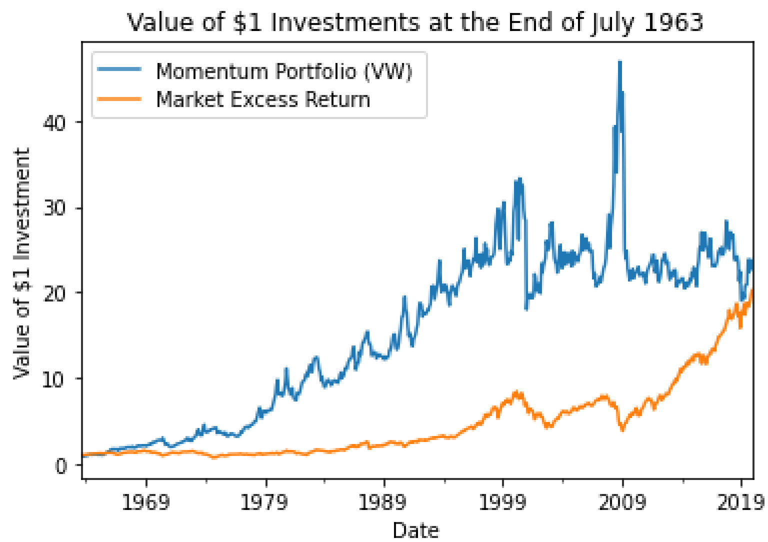
In [23]:
```
# long the Winners and Short the Losers.

wide['WML_EW'] = wide['RET_EW_10'] - wide['RET_EW_1']
wide['WML_VW'] = wide['RET_VW_10'] - wide['RET_VW_1']
```

In [24]:
```
# This is where we import the risk-free data and start to make comparison.

wide = wide.join(ff)
wide.rename(columns={'Mkt-RF': 'Mkt_RF'}, inplace=True)
```

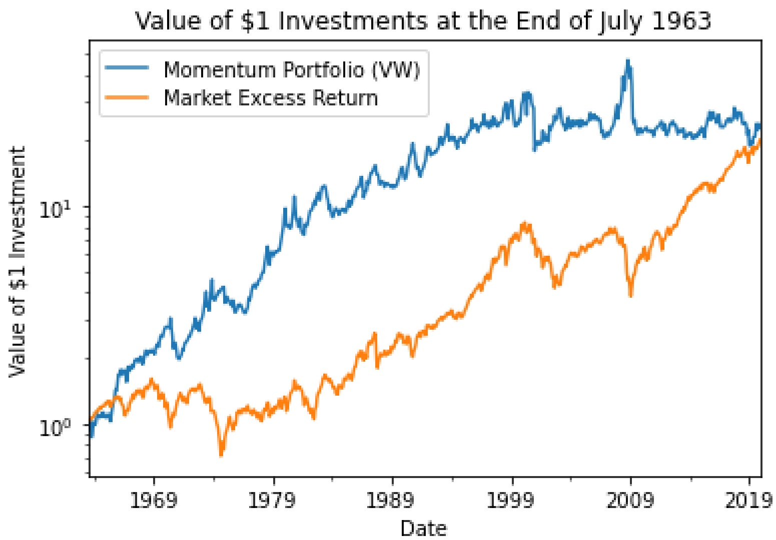
Compare strategy and benchmark, analyze the

performance

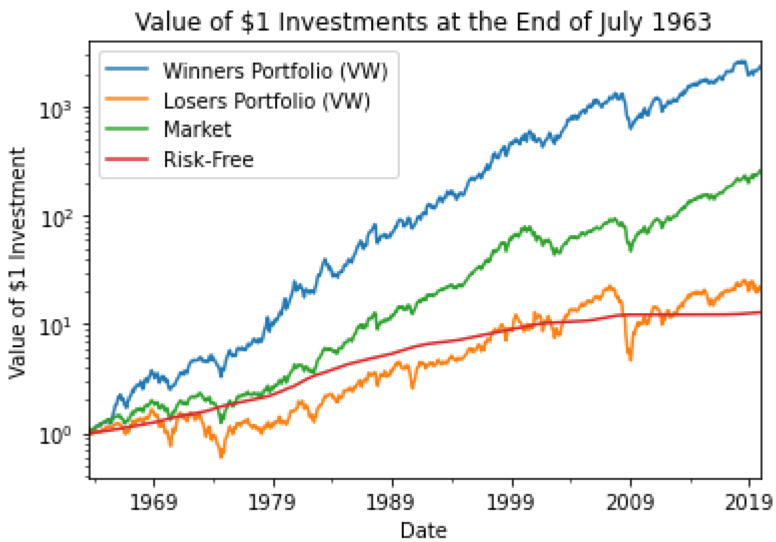
In [25]:
```
# Make comparison with market returns and our strategy.
# graph looks confusing.

wide[['WML_VW', 'Mkt_RF']].add(1).cumprod().plot()
plt.legend(['Momentum Portfolio (VW) ', 'Market Excess Return'])
plt.ylabel('Value of \$1 Investment')
plt.xlabel('Date')
plt.title('Value of \$1 Investments at the End of ' + (wide.index[0] - pd.o
plt.show()
```



In [26]:
```
# try to see the pattern in log scale
# Momentum strategy is getting less effective comparing to the 70s and 80s.

wide[['WML_VW', 'Mkt_RF']].add(1).cumprod().plot()
plt.legend(['Momentum Portfolio (VW)', 'Market Excess Return'])
plt.ylabel('Value of \$1 Investment')
plt.xlabel('Date')
plt.title('Value of \$1 Investments at the End of ' + (wide.index[0] - pd.o
plt.semilogy()
plt.show()
```



In [27]:
```
# Make a cross-comparison between winners/losers, market returns and rf.
# Trying to figure out what causes the momentum effect to generally become

wide['MktRet'] = wide['Mkt_RF'] + wide['RF']

wide[['RET_VW_10', 'RET_VW_1', 'MktRet', 'RF']].add(1).cumprod().plot()
plt.legend(['Winners Portfolio (VW)', 'Losers Portfolio (VW)', 'Market', 'R
plt.ylabel('Value of \$1 Investment')
plt.xlabel('Date')
plt.title('Value of \$1 Investments at the End of ' + (wide.index[0] - pd.o
plt.semilogy()
plt.show()
```



In [28]:
```
# Plot rolling portfolio volatilities over time for your strategy and bench

port=wide[['WML_VW','Mkt_RF','SMB','HML','RF']]
port
```

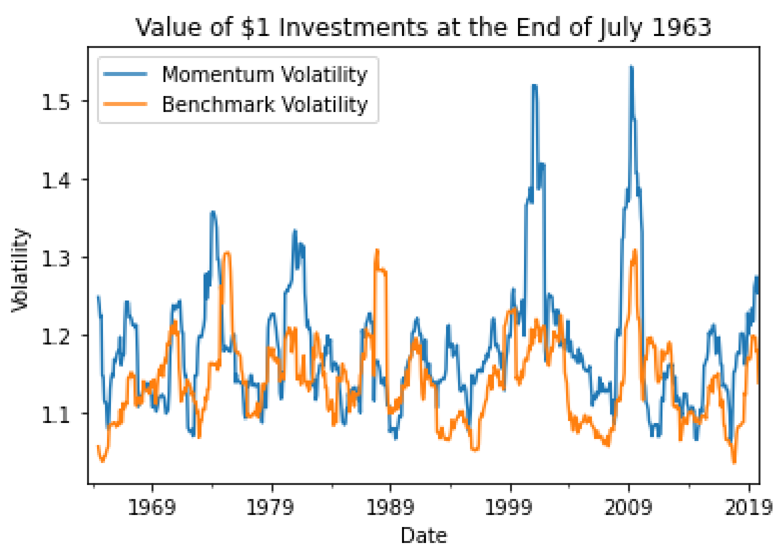
Out[28]:

	WML_VW	Mkt_RF	SMB	HML	RF
date					
1963-08-31	-0.055820	0.0507	-0.0102	0.0182	0.0025
1963-09-30	0.093625	-0.0157	-0.0031	0.0017	0.0027
1963-10-31	-0.010115	0.0253	-0.0057	-0.0004	0.0029
1963-11-30	-0.150516	-0.0085	-0.0115	0.0170	0.0027
1963-12-31	0.065776	0.0183	-0.0201	-0.0006	0.0029
...	...	...	...	...	...
2019-08-31	0.135716	-0.0258	-0.0240	-0.0485	0.0016
2019-09-30	-0.059497	0.0143	-0.0105	0.0677	0.0018
2019-10-31	0.063266	0.0206	0.0024	-0.0188	0.0015
2019-11-30	-0.002215	0.0387	0.0091	-0.0205	0.0012
2019-12-31	-0.043252	0.0277	0.0067	0.0191	0.0014

677 rows × 5 columns

In [29]:
```
# Volatility measure graphs
# momentum is more volatile than the overall Market.

port['WML_VW_std']=port['WML_VW'].rolling(12).std()*np.sqrt(12)
port['Mkt_std']=port['Mkt_RF'].rolling(12).std()*np.sqrt(12)
port[['WML_VW_std', 'Mkt_std']].add(1).plot()

plt.legend(['Momentum Volatility', 'Benchmark Volatility'])
plt.ylabel('Volatility')
plt.xlabel('Date')
plt.title('Value of \$1 Investments at the End of ' + (port.index[0] - pd.o
plt.show()
```

```
<ipython-input-29-0bb34db0f491>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  port['WML_VW_std']=port['WML_VW'].rolling(12).std()*np.sqrt(12)
<ipython-input-29-0bb34db0f491>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  port['Mkt_std']=port['Mkt_RF'].rolling(12).std()*np.sqrt(12)
```



In [ ]:

In [30]:
```python
#  Alpha and beta for strategy

# alpha is significantly positive, meaning it has a risk adjusted problem.
# counters efficient market hypothesis.
# shorted beta is higher than longed beta!!

import statsmodels.formula.api as smf
smf.ols(
    formula='WML_VW ~ Mkt_RF',
    data=wide
).fit().summary()
```

Out[30]:

OLS Regression Results

Dep. Variable:	WML_VW	**R-squared:**	0.012
Model:	OLS	**Adj. R-squared:**	0.010
Method:	Least Squares	**F-statistic:**	7.957
Date:	Wed, 28 Apr 2021	**Prob (F-statistic):**	0.00493
Time:	19:51:54	**Log-Likelihood:**	979.12
No. Observations:	677	**AIC:**	-1954.
Df Residuals:	675	**BIC:**	-1945.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0071	0.002	3.207	0.001	0.003	0.011
Mkt_RF	-0.1410	0.050	-2.821	0.005	-0.239	-0.043

Omnibus:	119.135	**Durbin-Watson:**	2.045
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	655.413
Skew:	-0.656	**Prob(JB):**	4.77e-143
Kurtosis:	7.638	**Cond. No.**	22.8

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

In [31]:
```
# We try to make the significant alpha disappear by adding HML and SMB as C
# Turns out the alpha still exists.

smf.ols(
    formula='WML_VW ~ Mkt_RF+SMB+HML',
    data=wide
).fit().summary()
```

Out[31]:

OLS Regression Results

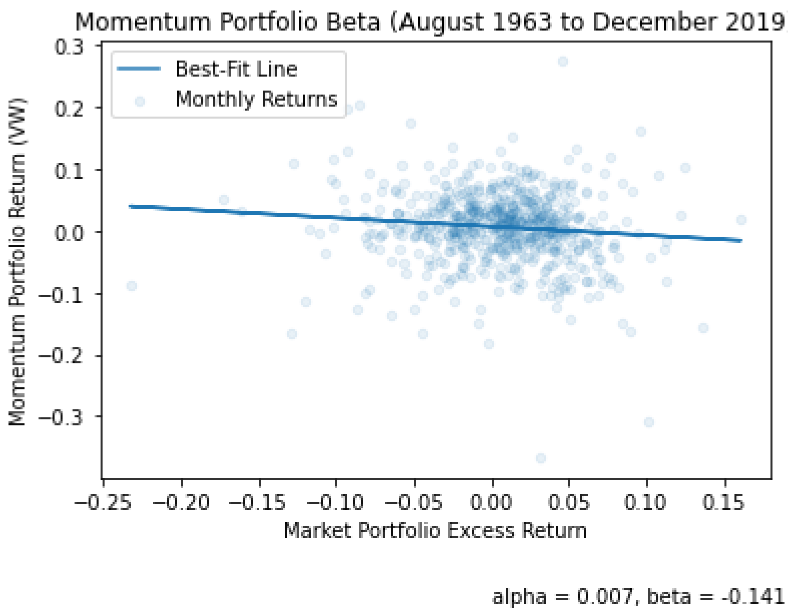
Dep. Variable:	WML_VW	**R-squared:**	0.064
Model:	OLS	**Adj. R-squared:**	0.060
Method:	Least Squares	**F-statistic:**	15.34
Date:	Wed, 28 Apr 2021	**Prob (F-statistic):**	1.15e-09
Time:	19:51:54	**Log-Likelihood:**	997.55
No. Observations:	677	**AIC:**	-1987.
Df Residuals:	673	**BIC:**	-1969.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0089	0.002	4.096	0.000	0.005	0.013
Mkt_RF	-0.2273	0.052	-4.360	0.000	-0.330	-0.125
SMB	0.0506	0.074	0.683	0.495	-0.095	0.196
HML	-0.4734	0.079	-5.960	0.000	-0.629	-0.317

Omnibus:	147.000	**Durbin-Watson:**	2.073
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	904.825
Skew:	-0.813	**Prob(JB):**	3.31e-197
Kurtosis:	8.425	**Cond. No.**	38.5

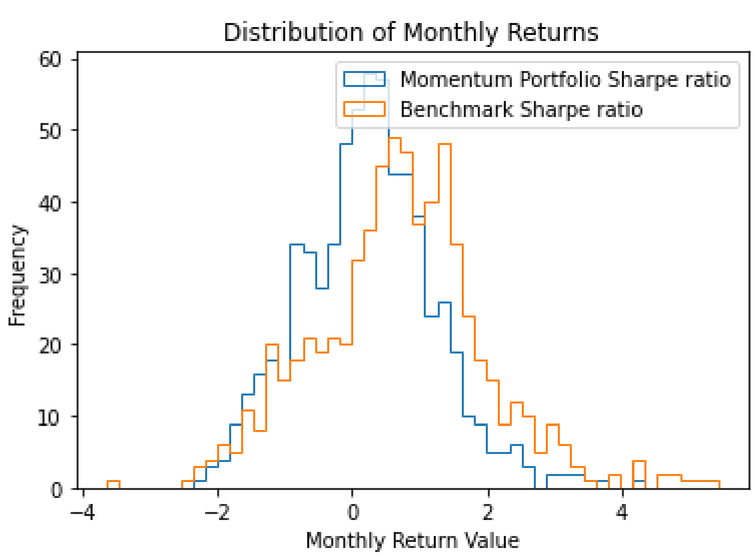
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [32]:
```
# Plot the regression graph.

temp = wide.copy()
temp_reg = np.polyfit(temp['Mkt_RF'], temp['WML_VW'], 1)

temp.plot(kind='scatter', x='Mkt_RF', y='WML_VW', alpha=0.1)
plt.plot(
    temp['Mkt_RF'],
    np.polyval(temp_reg, temp['Mkt_RF'])
)
plt.text(0, -0.6, 'alpha = {:.3f}, beta = {:.3f}'.format(temp_reg[1], temp_
plt.legend(['Best-Fit Line', 'Monthly Returns'])
plt.xlabel('Market Portfolio Excess Return')
plt.ylabel('Momentum Portfolio Return (VW)')
plt.title(
    'Momentum Portfolio Beta (' + temp.index.min().strftime(format='%B %Y')
)
plt.show()
```



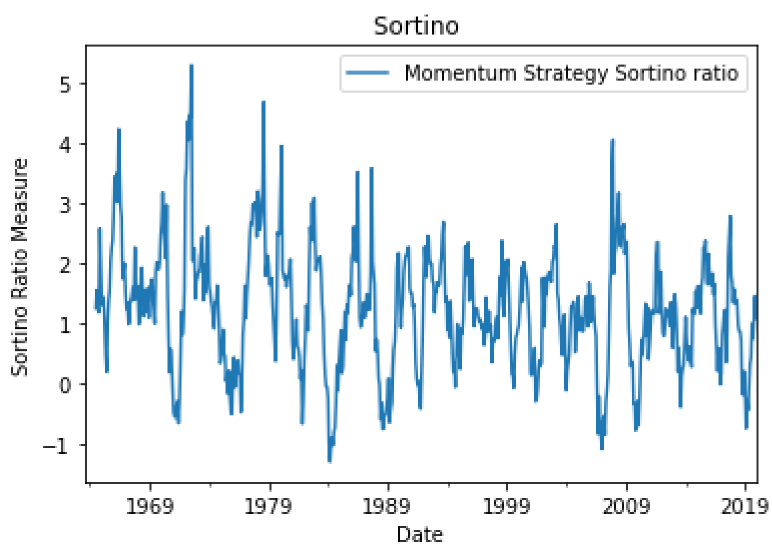
In [33]:
```
# Plot rolling Sharpe ratios over time for strategy and benchmark.
# momentum strategy forms a skewed distribution.
# omentum Portfolio has greater the value of the Sharpe ratio during the ar
# it indicates the more attractive the risk-adjusted return than the benchm

port['port_sharp']=(port['WML_VW']-port['RF']).rolling(window=12).mean()/(p
port['Mkt_sharp']=port['Mkt_RF'].rolling(window=12).mean()/port['Mkt_RF'].r
port[['port_sharp','Mkt_sharp']].plot(kind='hist', bins=50, histtype='step'
plt.legend(['Momentum Portfolio Sharpe ratio','Benchmark Sharpe ratio'])
plt.xlabel('Monthly Return Value')
plt.title('Distribution of Monthly Returns')
plt.show()
```

```
<ipython-input-33-9ba0deb14610>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  port['port_sharp']=(port['WML_VW']-port['RF']).rolling(window=12).mean
()/(port['WML_VW']-port['RF']).rolling(window=12).std()*np.sqrt(12)
<ipython-input-33-9ba0deb14610>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  port['Mkt_sharp']=port['Mkt_RF'].rolling(window=12).mean()/port['Mkt_R
F'].rolling(12).std()*np.sqrt(12)
```



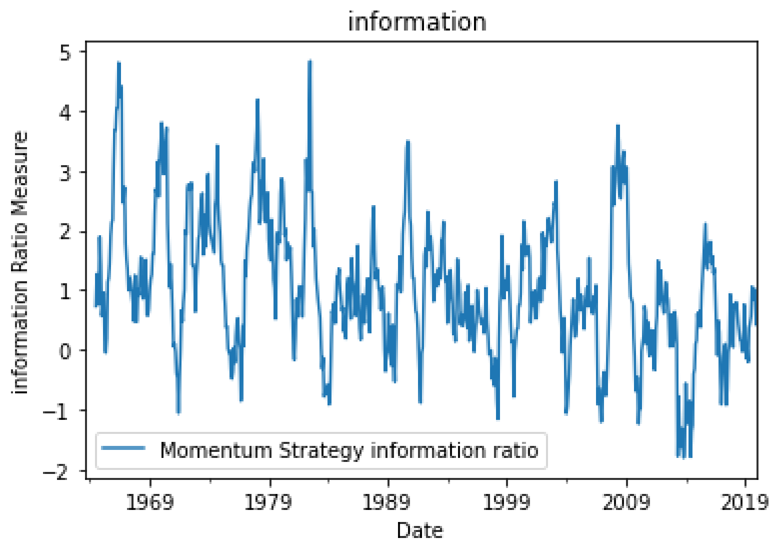
In [34]:
```
# Sortino Ratio Measure
#

port['Sortino']=(port['WML_VW']-port['RF']).rolling(12).mean()/(port['WML_V
port[['Sortino']].add(1).plot()
plt.legend(['Momentum Strategy Sortino ratio'])
plt.ylabel('Sortino Ratio Measure')
plt.xlabel('Date')
plt.title('Sortino ')
plt.show()
```

```
<ipython-input-34-1f752b5e4c65>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  port['Sortino']=(port['WML_VW']-port['RF']).rolling(12).mean()/(port['W
ML_VW']).rolling(12).std()*np.sqrt(12)
```



In [35]:
```
#  Information ratio

port['information']=(port['WML_VW']-port['Mkt_RF']).rolling(12).mean()/(por
port[['information']].add(1).plot()
plt.legend(['Momentum Strategy information ratio'])
plt.ylabel('information Ratio Measure')
plt.xlabel('Date')
plt.title('information ')
plt.show()
```

```
<ipython-input-35-b4031ece4f3d>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  port['information']=(port['WML_VW']-port['Mkt_RF']).rolling(12).mean()/
(port['WML_VW']-port['Mkt_RF']).rolling(12).std()*np.sqrt(12)
```



In [ ]:

limitations of the strategy & Conclusions

The strategy tends to outperforms the market during the whole period of the test. But the strategy is becoming less and less effective with time. The method seems to generate decent higher returns that positively relates to the market, the information ratio stays positive the most of the time. The portfolio tends to be sensitive towards market up & downs. Especially during the 1999 tech bubble and 2008 housing bubbles, the portfolio return peaks and falls down in a short period of time.

But after doing the regression models, we found out that the beta is actually slightly negatively correlated to the market, and we have a positive alpha, meaning there exists the risk-adjusted problems, and it counters the efficient market hypothesis. The possible reason is that in the top 10% winner portfolios, there exists abnormal ones that drags the outperformance up. While in fact, longing top 10% and shorting 10% may not generate higher returns, aside from those abnormal stocks. Momentum strategy should not be considered a consistent strategy.

After analyzing and visualizing different ratios, we wouldn't say that momentum is a good way to continuously invest in. We should not only look at returns, we need to dig deeper into the datas and find out true relationship with the strategy and the performance of the market.