

leveraged-etfs-returns-dispersion

March 16, 2026

0.1 Introduction

Over the past 15 years (or so), leveraged ETFs have become a frequently used vehicle for trading equity indices, sectors, and other asset classes for the investor that is seeking to use leverage to amplify their returns. The question remains, however, what happens to the returns of leveraged ETFs over extended time horizon? And is there an optimal leverage ratio for the long term buy-and-hold investor that allows them to take advantage of leverage to amplify the upside, while avoiding catastrophic losses on the down side? In this investigation, we will delve into these ideas and see what the data shows.

Python Imports

```
[1]: # Standard Library
import os
import sys
import warnings

from pathlib import Path

# Data Handling
import pandas as pd

# Suppress warnings
warnings.filterwarnings("ignore")
```

Add Directories To Path

```
[2]: # Add the source subdirectory to the system path to allow import config from
↳ settings.py
current_directory = Path(os.getcwd())
website_base_directory = current_directory.parent.parent.parent
src_directory = website_base_directory / "src"
sys.path.append(str(src_directory)) if str(src_directory) not in sys.path else
↳ None

# Import settings.py
from settings import config

# Add configured directories from config to path
```

```

SOURCE_DIR = config("SOURCE_DIR")
sys.path.append(str(Path(SOURCE_DIR))) if str(Path(SOURCE_DIR)) not in sys.path_
↳ else None

# Add other configured directories
BASE_DIR = config("BASE_DIR")
CONTENT_DIR = config("CONTENT_DIR")
POSTS_DIR = config("POSTS_DIR")
PAGES_DIR = config("PAGES_DIR")
PUBLIC_DIR = config("PUBLIC_DIR")
SOURCE_DIR = config("SOURCE_DIR")
DATA_DIR = config("DATA_DIR")
DATA_MANUAL_DIR = config("DATA_MANUAL_DIR")

```

0.2 Python Functions

Here are the functions needed for this project:

- `load_data`: Load data from a CSV, Excel, or Pickle file into a pandas DataFrame.
- `pandas_set_decimal_places`: Set the number of decimal places displayed for floating-point numbers in pandas.
- `plot_histogram`: Plot the histogram of a data set from a DataFrame.
- `plot_scatter`: Plot the data from a DataFrame for a specified date range and columns.
- `plot_timeseries`: Plot the timeseries data from a DataFrame for a specified date range and columns.
- `run_linear_regression`: Run a linear regression using statsmodels OLS and return the results.
- `summary_stats`: Generate summary statistics for a series of returns.
- `yf_pull_data`: Download daily price data from Yahoo Finance and export it.

```

[3]: from load_data import load_data
from pandas_set_decimal_places import pandas_set_decimal_places
from plot_histogram import plot_histogram
from plot_scatter import plot_scatter
from plot_timeseries import plot_timeseries
from run_linear_regression import run_linear_regression
from summary_stats import summary_stats
from yf_pull_data import yf_pull_data

```

0.3 Data Overview

For this exercise, we will investigate the long-term return relationships between the following:

- QQQ (Invesco QQQ Trust, Series 1) and TQQQ (ProShares UltraPro QQQ)
- SPY (SPDR S&P 500 ETF Trust) and UPRO (ProShares UltraPro S&P 500)

Just to clarify, any time we are referring to “close prices” in this analysis, we are referring to the partially-adjusted close prices that account for splits, but not dividends. Because we are dealing with leveraged ETFs, we want to focus on the pure returns due to change in price, but exclude the dividends, which are not leveraged in the same way as the price changes.

0.4 QQQ & TQQQ

0.4.1 Acquire & Plot Data (QQQ)

First, let's get the data for QQQ. If we already have the desired data, we can load it from a local file. Otherwise, we can download it from Yahoo Finance using the `yf_pull_data` function.

```
[4]: yf_pull_data(
    base_directory=DATA_DIR,
    ticker="QQQ",
    adjusted=False,
    source="Yahoo_Finance",
    asset_class="Exchange_Traded_Funds",
    excel_export=True,
    pickle_export=True,
    output_confirmation=False,
)

qqq = load_data(
    base_directory=DATA_DIR,
    ticker="QQQ",
    source="Yahoo_Finance",
    asset_class="Exchange_Traded_Funds",
    timeframe="Daily",
    file_format="pickle",
)

# Rename columns to "QQQ_Close", etc.
qqq = qqq.rename(columns={
    "Adj Close": "QQQ_Adj_Close",
    "Close": "QQQ_Close",
    "High": "QQQ_High",
    "Low": "QQQ_Low",
    "Open": "QQQ_Open",
    "Volume": "QQQ_Volume"
})

[*****100%*****] 1 of 1 completed
```

This gives us:

```
[5]: display(qqq)
```

Date	QQQ_Adj_Close	QQQ_Close	QQQ_High	QQQ_Low	QQQ_Open	\
1999-03-10	43.128670	51.062500	51.156250	50.281250	51.125000	
1999-03-11	43.339809	51.312500	51.734375	50.312500	51.437500	
1999-03-12	42.284039	50.062500	51.156250	49.656250	51.125000	
1999-03-15	43.498177	51.500000	51.562500	49.906250	50.437500	

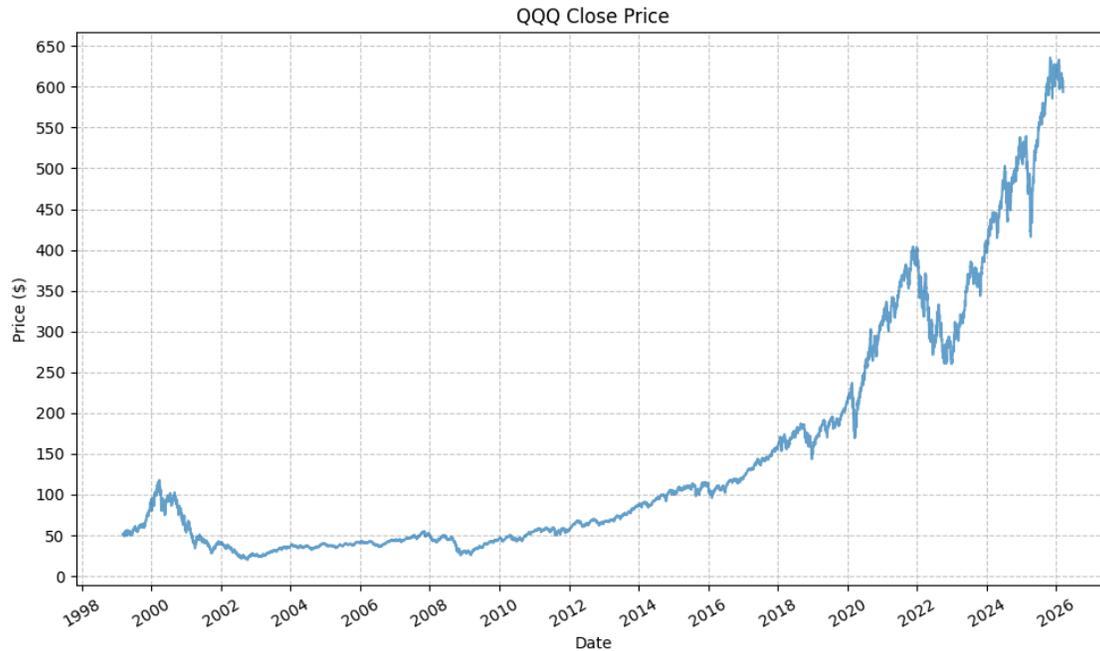
1999-03-16	43.867699	51.937500	52.156250	51.156250	51.718750
...
2026-03-09	607.760010	607.760010	609.270020	591.330017	594.229980
2026-03-10	607.770020	607.770020	613.289978	605.419983	607.780029
2026-03-11	607.690002	607.690002	612.429993	605.030029	608.950012
2026-03-12	597.260010	597.260010	604.140015	597.049988	602.760010
2026-03-13	593.719971	593.719971	603.599976	592.570007	599.729980

Date	QQQ_Volume
1999-03-10	5232000
1999-03-11	9688600
1999-03-12	8743600
1999-03-15	6369000
1999-03-16	4905800
...	...
2026-03-09	93068200
2026-03-10	64078900
2026-03-11	60114800
2026-03-12	71836600
2026-03-13	62986500

[6795 rows x 6 columns]

And the plot of the timeseries of adjusted close prices:

```
[6]: plot_timeseries(
    df=qqq,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["QQQ_Close"],
    title="QQQ Close Price",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=2,
    x_tick_rotation=30,
    y_label="Price ($)",
    y_format="Decimal",
    y_format_decimal_places=0,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    grid=True,
    legend=False,
    export_plot=False,
    plot_file_name=None,
)
```



0.4.2 Acquire & Plot Data (TQQQ)

Next, TQQQ:

```
[7]: yf_pull_data(
    base_directory=DATA_DIR,
    ticker="TQQQ",
    adjusted=False,
    source="Yahoo_Finance",
    asset_class="Exchange_Traded_Funds",
    excel_export=True,
    pickle_export=True,
    output_confirmation=False,
)

tqqq = load_data(
    base_directory=DATA_DIR,
    ticker="TQQQ",
    source="Yahoo_Finance",
    asset_class="Exchange_Traded_Funds",
    timeframe="Daily",
    file_format="pickle",
)

# Rename columns to "TQQQ_Close", etc.
tqqq = tqqq.rename(columns={
```

```
"Adj Close": "TQQQ_Adj_Close",
"Close": "TQQQ_Close",
"High": "TQQQ_High",
"Low": "TQQQ_Low",
"Open": "TQQQ_Open",
"Volume": "TQQQ_Volume"
})
```

[*****100%*****] 1 of 1 completed

This gives us:

```
[8]: display(tqqq)
```

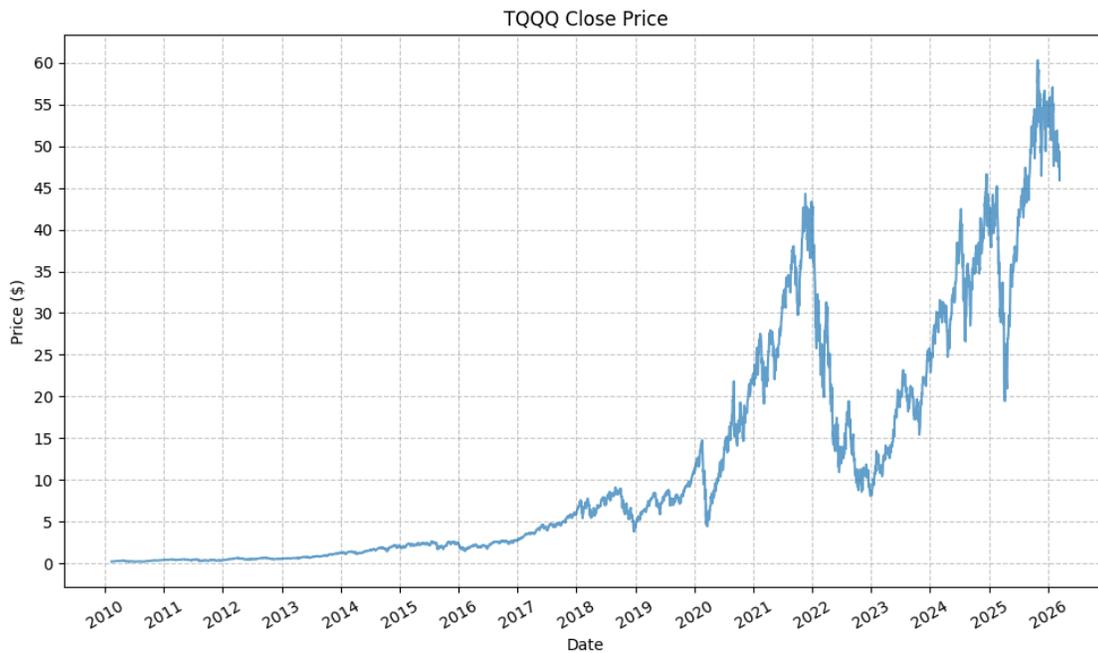
Date	TQQQ_Adj_Close	TQQQ_Close	TQQQ_High	TQQQ_Low	TQQQ_Open \
2010-02-11	0.206396	0.216276	0.217448	0.202786	0.203438
2010-02-12	0.207241	0.217161	0.219036	0.209167	0.210391
2010-02-16	0.215268	0.225573	0.226094	0.218776	0.222266
2010-02-17	0.218921	0.229401	0.229453	0.225156	0.228594
2010-02-18	0.223072	0.233750	0.235130	0.227786	0.229167
...
2026-03-09	49.389999	49.389999	49.770000	45.500000	46.189999
2026-03-10	49.400002	49.400002	50.740002	48.830002	49.410000
2026-03-11	49.349998	49.349998	50.520000	48.730000	49.680000
2026-03-12	46.830002	46.830002	48.490002	46.750000	48.150002
2026-03-13	45.930000	45.930000	48.250000	45.669998	47.349998

Date	TQQQ_Volume
2010-02-11	6912000
2010-02-12	17203200
2010-02-16	19238400
2010-02-17	38361600
2010-02-18	77721600
...	...
2026-03-09	159005500
2026-03-10	115057200
2026-03-11	91104300
2026-03-12	130823900
2026-03-13	141444100

[4046 rows x 6 columns]

And the plot of the timseries of ajdusted close prices:

```
[9]: plot_timeseries(
    df=tqqq,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["TQQQ_Close"],
    title="TQQQ Close Price",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=1,
    x_tick_rotation=30,
    y_label="Price ($)",
    y_format="Decimal",
    y_format_decimal_places=0,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    grid=True,
    legend=False,
    export_plot=False,
    plot_file_name=None,
)
```



Looking at the close prices doesn't give us a true picture of the magnitude of the difference in returns due to the leverage. In order to see that, we need to look at the cumulative returns and the drawdowns.

Calculate & Plot Cumulative Returns, Rolling Returns, and Drawdowns (QQQ & TQQQ)

Next, we will calculate the cumulative returns, rolling returns, and drawdowns. This involves aligning the data to start with the inception of TQQQ. For this exercise, we will not extrapolate the data for QQQ back to 1999, but rather just align the data from the inception of TQQQ in 2010.

```
[10]: etfs = ["QQQ", "TQQQ"]

# Merge dataframes and drop rows with missing values
qqq_tqqq_aligned = tqqq.merge(qqq, left_index=True, right_index=True,
    ↪how='left')
qqq_tqqq_aligned = qqq_tqqq_aligned.dropna()

# Calculate cumulative returns
for etf in etfs:
    qqq_tqqq_aligned[f"{etf}_Return"] = qqq_tqqq_aligned[f"{etf}_Close"].
    ↪pct_change()
    qqq_tqqq_aligned[f"{etf}_Cumulative_Return"] = (1 +
    ↪qqq_tqqq_aligned[f"{etf}_Return"]).cumprod() - 1
    qqq_tqqq_aligned[f"{etf}_Cumulative_Return_Plus_One"] = 1 +
    ↪qqq_tqqq_aligned[f"{etf}_Cumulative_Return"]
    qqq_tqqq_aligned[f"{etf}_Rolling_Max"] =
    ↪qqq_tqqq_aligned[f"{etf}_Cumulative_Return_Plus_One"].cummax()
    qqq_tqqq_aligned[f"{etf}_Drawdown"] =
    ↪qqq_tqqq_aligned[f"{etf}_Cumulative_Return_Plus_One"] /
    ↪qqq_tqqq_aligned[f"{etf}_Rolling_Max"] - 1
    qqq_tqqq_aligned.drop(columns=[f"{etf}_Cumulative_Return_Plus_One",
    ↪f"{etf}_Rolling_Max"], inplace=True)

# Define rolling windows in trading days
rolling_windows = {
    '1d': 1,      # 1 day
    '1w': 5,      # 1 week (5 trading days)
    '1m': 21,     # 1 month (~21 trading days)
    '3m': 63,     # 3 months (~63 trading days)
    '6m': 126,    # 6 months (~126 trading days)
    '1y': 252,    # 1 year (~252 trading days)
    '2y': 504,    # 2 years (~504 trading days)
    '3y': 756,    # 3 years (~756 trading days)
    '4y': 1008,   # 4 years (~1008 trading days)
    '5y': 1260,   # 5 years (~1260 trading days)
}

# Calculate rolling returns for each ETF and each window
for etf in etfs:
    for period_name, window in rolling_windows.items():
        qqq_tqqq_aligned[f"{etf}_Rolling_Return_{period_name}"] = (
            qqq_tqqq_aligned[f"{etf}_Close"].pct_change(periods=window)
```

)

```
[11]: display(qqq_tqqq_aligned)
```

Date	TQQQ_Adj_Close	TQQQ_Close	TQQQ_High	TQQQ_Low	TQQQ_Open \
2010-02-11	0.206396	0.216276	0.217448	0.202786	0.203438
2010-02-12	0.207241	0.217161	0.219036	0.209167	0.210391
2010-02-16	0.215268	0.225573	0.226094	0.218776	0.222266
2010-02-17	0.218921	0.229401	0.229453	0.225156	0.228594
2010-02-18	0.223072	0.233750	0.235130	0.227786	0.229167
...
2026-03-09	49.389999	49.389999	49.770000	45.500000	46.189999
2026-03-10	49.400002	49.400002	50.740002	48.830002	49.410000
2026-03-11	49.349998	49.349998	50.520000	48.730000	49.680000
2026-03-12	46.830002	46.830002	48.490002	46.750000	48.150002
2026-03-13	45.930000	45.930000	48.250000	45.669998	47.349998

Date	TQQQ_Volume	QQQ_Adj_Close	QQQ_Close	QQQ_High	QQQ_Low \
2010-02-11	6912000	37.951683	43.669998	43.790001	42.759998
2010-02-12	17203200	38.029903	43.759998	43.880001	43.160000
2010-02-16	19238400	38.516556	44.320000	44.349998	43.849998
2010-02-17	38361600	38.733829	44.570000	44.570000	44.259998
2010-02-18	77721600	38.977173	44.849998	44.930000	44.450001
...
2026-03-09	159005500	607.760010	607.760010	609.270020	591.330017
2026-03-10	115057200	607.770020	607.770020	613.289978	605.419983
2026-03-11	91104300	607.690002	607.690002	612.429993	605.030029
2026-03-12	130823900	597.260010	597.260010	604.140015	597.049988
2026-03-13	141444100	593.719971	593.719971	603.599976	592.570007

Date	...	TQQQ_Rolling_Return_1d	TQQQ_Rolling_Return_1w \
2010-02-11	...	NaN	NaN
2010-02-12	...	0.004092	NaN
2010-02-16	...	0.038736	NaN
2010-02-17	...	0.016970	NaN
2010-02-18	...	0.018958	NaN
...
2026-03-09	...	0.038915	-0.006237
2026-03-10	...	0.000203	0.027027
2026-03-11	...	-0.001012	-0.018106
2026-03-12	...	-0.051064	-0.059639
2026-03-13	...	-0.019218	-0.033866

Date	TQQQ_Rolling_Return_1m	TQQQ_Rolling_Return_3m \
------	------------------------	--------------------------

2010-02-11	NaN	NaN
2010-02-12	NaN	NaN
2010-02-16	NaN	NaN
2010-02-17	NaN	NaN
2010-02-18	NaN	NaN
...
2026-03-09	0.036734	-0.110250
2026-03-10	-0.023522	-0.120214
2026-03-11	-0.046193	-0.115591
2026-03-12	-0.082125	-0.163899
2026-03-13	-0.106420	-0.189232

Date	TQQQ_Rolling_Return_6m	TQQQ_Rolling_Return_1y \
2010-02-11	NaN	NaN
2010-02-12	NaN	NaN
2010-02-16	NaN	NaN
2010-02-17	NaN	NaN
2010-02-18	NaN	NaN
...
2026-03-09	0.075800	0.495760
2026-03-10	0.060883	0.465658
2026-03-11	0.051230	0.650226
2026-03-12	-0.003511	0.584504
2026-03-13	-0.038820	0.502699

Date	TQQQ_Rolling_Return_2y	TQQQ_Rolling_Return_3y \
2010-02-11	NaN	NaN
2010-02-12	NaN	NaN
2010-02-16	NaN	NaN
2010-02-17	NaN	NaN
2010-02-18	NaN	NaN
...
2026-03-09	0.583520	3.467662
2026-03-10	0.673442	3.211424
2026-03-11	0.641443	3.189304
2026-03-12	0.491164	3.129630
2026-03-13	0.529471	2.995650

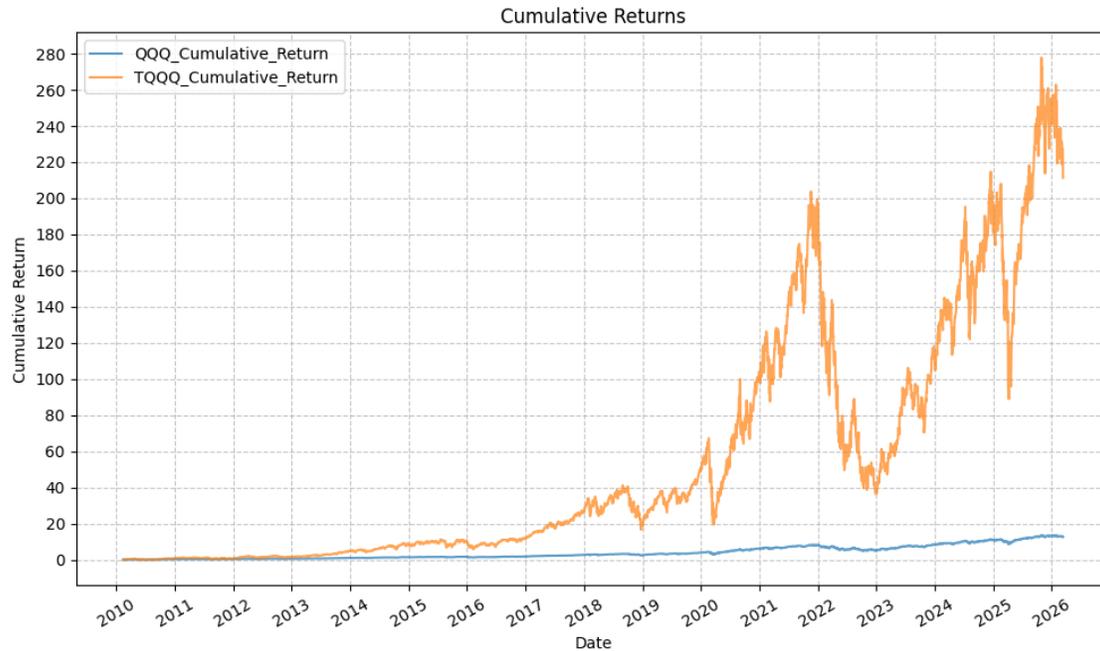
Date	TQQQ_Rolling_Return_4y	TQQQ_Rolling_Return_5y
2010-02-11	NaN	NaN
2010-02-12	NaN	NaN
2010-02-16	NaN	NaN
2010-02-17	NaN	NaN
2010-02-18	NaN	NaN
...

2026-03-09	0.974021	1.139253
2026-03-10	0.884417	1.342898
2026-03-11	0.964570	1.462268
2026-03-12	0.947598	1.236390
2026-03-13	1.150281	1.398433

[4046 rows x 38 columns]

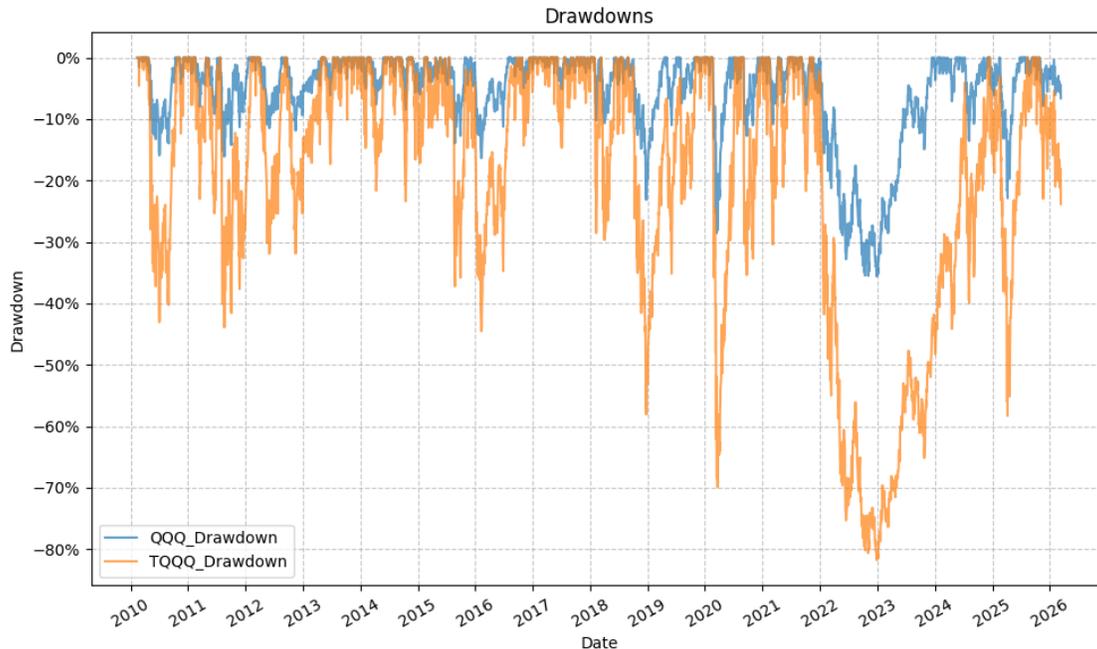
And now the plot for the cumulative returns:

```
[12]: plot_timeseries(  
    df=qqq_tqqq_aligned,  
    plot_start_date=None,  
    plot_end_date=None,  
    plot_columns=["QQQ_Cumulative_Return", "TQQQ_Cumulative_Return"],  
    title="Cumulative Returns",  
    x_label="Date",  
    x_format="Year",  
    x_tick_spacing=1,  
    x_tick_rotation=30,  
    y_label="Cumulative Return",  
    y_format="Decimal",  
    y_format_decimal_places=0,  
    y_tick_spacing="Auto",  
    y_tick_rotation=0,  
    grid=True,  
    legend=True,  
    export_plot=False,  
    plot_file_name=None,  
)
```



And the drawdown plot:

```
[13]: plot_timeseries(
    df=qqq_tqqq_aligned,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["QQQ_Drawdown", "TQQQ_Drawdown"],
    title="Drawdowns",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=1,
    x_tick_rotation=30,
    y_label="Drawdown",
    y_format="Percentage",
    y_format_decimal_places=0,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    grid=True,
    legend=True,
    export_plot=False,
    plot_file_name=None,
)
```



Here is where we truly see the volatility of TQQQ relative to QQQ. In the past 5 years, TQQQ has had drawdowns of 50%, 60%, 70%, and 80%. While it has recovered to make new highs (with the exception of the current ~10% drawdown), very few investors can endure those drawdowns and continue to hold their position. At the same time, we can see from the plot that a ~35% drawdown in QQQ equated to a ~80% drawdown in TQQQ, which is not in fact, 3x. So this tells us that there is dispersion in the long term returns relative to the short term returns between the non-leveraged QQQ and 3x leveraged TQQQ. This idea is well documented in the financial literature as “volatility decay” or “volatility drag”. But, and this is the question we are trying to answer, how significant is this effect over various time horizons?

0.4.3 Summary Statistics (QQQ & TQQQ)

Looking at the summary statistics further confirms our intuitions about the volatility and drawdowns.

```
[14]: qqz_sum_stats = summary_stats(
    fund_list=["QQQ"],
    df=qqz_tqqz_aligned[["QQQ_Return"]],
    period="Daily",
    use_calendar_days=False,
    excel_export=False,
    pickle_export=False,
    output_confirmation=False,
)

tqqz_sum_stats = summary_stats(
```

```

fund_list=["TQQQ"],
df=qqq_tqqq_aligned[["TQQQ_Return"]],
period="Daily",
use_calendar_days=False,
excel_export=False,
pickle_export=False,
output_confirmation=False,
)

sum_stats = pd.concat([qqq_sum_stats, tqqq_sum_stats])

display(sum_stats)

```

	Annual Mean Return (Arithmetic)	Annualized Volatility	\	
QQQ_Return	0.183897	0.206040		
TQQQ_Return	0.521888	0.609705		

	Annualized Sharpe Ratio	CAGR (Geometric)	Daily Max Return	\
QQQ_Return	0.892532	0.176501	0.120031	
TQQQ_Return	0.855969	0.396175	0.352442	

	Daily Max Return (Date)	Daily Min Return	Daily Min Return (Date)	\
QQQ_Return	2025-04-09	-0.119788	2020-03-16	
TQQQ_Return	2025-04-09	-0.344652	2020-03-16	

	Max Drawdown	Peak	Trough	Recovery Date	\
QQQ_Return	-0.356172	2021-11-19	2022-12-28	2023-12-15	
TQQQ_Return	-0.817545	2021-11-19	2022-12-28	2024-12-11	

	Days to Recovery	MAR Ratio
QQQ_Return	352	0.49555
TQQQ_Return	714	0.48459

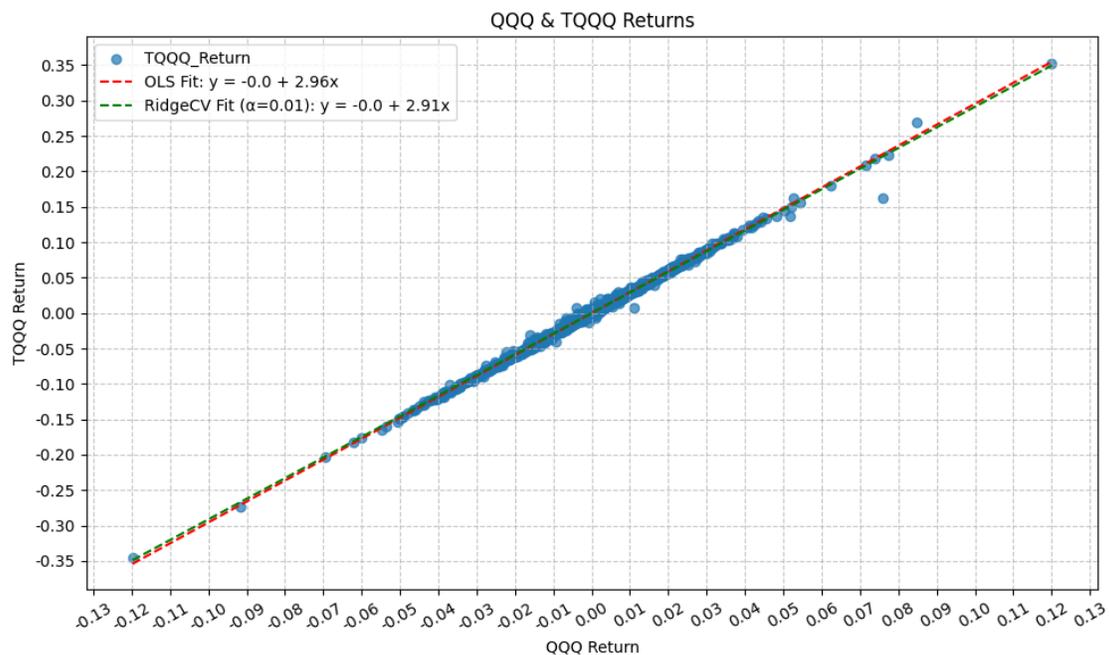
Note that these statistics are being run on the partially-adjusted close prices, which are not the true returns, but they do give us a good picture of the relative volatility and drawdowns of the two ETFs. The mean return for TQQQ is much higher than that of QQQ, but the standard deviation is also much higher, which is consistent with the idea of leverage amplifying both the upside and the downside. The maximum drawdown for TQQQ is also much higher than that of QQQ, which again confirms our observations from the drawdown plot.

Also note that the daily maximum return for both funds occurred during “Liberation Day” and the daily minimum return for both funds occurred early on during COVID.

0.4.4 Plot Returns & Verify Beta (QQQ & TQQQ)

Before we look at the rolling returns, let us first verify that the daily returns for TQQQ are in fact ~3x those of QQQ.

```
[15]: plot_scatter(
    df=qqq_tqqq_aligned,
    x_plot_column="QQQ_Return",
    y_plot_columns=["TQQQ_Return"],
    title="QQQ & TQQQ Returns",
    x_label="QQQ Return",
    x_format="Decimal",
    x_format_decimal_places=2,
    x_tick_spacing="Auto",
    x_tick_rotation=30,
    y_label="TQQQ Return",
    y_format="Decimal",
    y_format_decimal_places=2,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    plot_OLS_regression_line=True,
    OLS_column="TQQQ_Return",
    plot_Ridge_regression_line=False,
    Ridge_column=None,
    plot_RidgeCV_regression_line=True,
    RidgeCV_column="TQQQ_Return",
    regression_constant=True,
    grid=True,
    legend=True,
    export_plot=False,
    plot_file_name=None,
)
```



```
[16]: model = run_linear_regression(
    df=qqq_tqqq_aligned,
    x_plot_column="QQQ_Return",
    y_plot_column="TQQQ_Return",
    regression_model="OLS-statsmodels",
    regression_constant=True,
)

print(model.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  TQQQ_Return    R-squared:                  0.997
Model:                          OLS        Adj. R-squared:            0.997
Method:                        Least Squares    F-statistic:                1.492e+06
Date:                          Mon, 16 Mar 2026    Prob (F-statistic):        0.00
Time:                          14:26:00        Log-Likelihood:            19405.
No. Observations:              4045        AIC:                      -3.881e+04
Df Residuals:                  4043        BIC:                      -3.879e+04
Df Model:                      1
Covariance Type:              nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-8.554e-05	3.15e-05	-2.720	0.007	-0.000	-2.39e-05
QQQ_Return	2.9552	0.002	1221.329	0.000	2.950	2.960

```

=====
Omnibus:                      5272.508    Durbin-Watson:            2.566
Prob(Omnibus):                 0.000    Jarque-Bera (JB):        9175082.049
Skew:                          -6.344    Prob(JB):                0.00
Kurtosis:                     235.974    Cond. No.:               77.1
=====

```

Notes:

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

Visually, this plot makes sense and we can see that there is a strong clustering of points, but we double check with the regression, regressing the TQQQ daily return (y) on the QQQ daily return (X).

Given the above result, with a coefficient of 2.96 and an R^2 of 0.997, we can say that TQQQ does in fact return $\sim 3x$ QQQ. We would also intuitively expect the coefficient to be 0, which it is nearly.

Interestingly, the coefficient varies between OLS and Ridge cross-validation, and both are less than 3.

0.4.5 Extrapolate Data (QQQ & TQQQ)

We will now extrapolate the returns of QQQ to backfill the data from the inception of QQQ in 1999 to the inception of TQQQ in 2010. For this, we'll use the coefficient of 2.96 that we found in the regression results above.

```
[17]: # Set leverage multiplier based on regression coefficient
LEVERAGE_MULTIPLIER = model.params[1]

# Merge dataframes and extrapolate return values for QQQ back to 1999 using the
↳ leverage multiplier
qqq_tqqq_extrap = qqq[["QQQ_Close"]].merge(tqqq[["TQQQ_Close"]],
↳ left_index=True, right_index=True, how='left')

etfs = ["QQQ", "TQQQ"]

# Calculate cumulative returns
for etf in etfs:
    qqq_tqqq_extrap[f"{etf}_Return"] = qqq_tqqq_extrap[f"{etf}_Close"].
↳ pct_change()

# Extrapolate TQQQ returns for missing values
qqq_tqqq_extrap["TQQQ_Return"] = qqq_tqqq_extrap["TQQQ_Return"].
↳ fillna(LEVERAGE_MULTIPLIER * qqq_tqqq_extrap["QQQ_Return"])

# Find the first valid TQQQ_Close index and value
first_valid_idx = qqq_tqqq_extrap['TQQQ_Close'].first_valid_index()
print(first_valid_idx)
first_valid_price = qqq_tqqq_extrap.loc[first_valid_idx, 'TQQQ_Close']
print(first_valid_price)
```

```
2010-02-11 00:00:00
0.21627600491046906
```

Before we extrapolate, let's first look at the data we have for QQQ and TQQQ around the inception of TQQQ in 2010:

```
[18]: # Check values around the first valid index
print(qqq_tqqq_extrap.loc["2010-02-08":"2010-02-13"])
```

	QQQ_Close	TQQQ_Close	QQQ_Return	TQQQ_Return
Date				
2010-02-08	42.669998	NaN	-0.007213	-0.021315
2010-02-09	43.110001	NaN	0.010312	0.030473
2010-02-10	43.020000	NaN	-0.002088	-0.006169
2010-02-11	43.669998	0.216276	0.015109	0.044650
2010-02-12	43.759998	0.217161	0.002061	0.004092

Now, backfill the data for the TQQQ close price:

```
[19]: # Iterate through the dataframe backwards
for i in range(qqq_tqqq_extrap.index.get_loc(first_valid_idx) - 1, -1, -1):

    # The return that led to the price the next day
    current_return = qqq_tqqq_extrap.iloc[i + 1]['TQQQ_Return']

    # Get the next day's price
    next_price = qqq_tqqq_extrap.iloc[i + 1]['TQQQ_Close']

    # Price_{t} = Price_{t+1} / (1 + Return_{t})
    qqq_tqqq_extrap.loc[qqq_tqqq_extrap.index[i], 'TQQQ_Close'] = next_price / (1 + current_return)
```

Finally, confirm the values are correct:

```
[20]: # Confirm values around the first valid index after extrapolation
print(qqq_tqqq_extrap.loc["2010-02-08":"2010-02-13"])
```

Date	QQQ_Close	TQQQ_Close	QQQ_Return	TQQQ_Return
2010-02-08	42.669998	0.202157	-0.007213	-0.021315
2010-02-09	43.110001	0.208317	0.010312	0.030473
2010-02-10	43.020000	0.207032	-0.002088	-0.006169
2010-02-11	43.669998	0.216276	0.015109	0.044650
2010-02-12	43.759998	0.217161	0.002061	0.004092

And the complete DataFrame with the extrapolated values:

```
[21]: display(qqq_tqqq_extrap)
```

Date	QQQ_Close	TQQQ_Close	QQQ_Return	TQQQ_Return
1999-03-10	51.062500	13.813139	NaN	NaN
1999-03-11	51.312500	14.012991	0.004896	0.014468
1999-03-12	50.062500	13.004208	-0.024361	-0.071989
1999-03-15	51.500000	14.107675	0.028714	0.084855
1999-03-16	51.937500	14.461841	0.008495	0.025104
...
2026-03-09	607.760010	49.389999	0.013356	0.038915
2026-03-10	607.770020	49.400002	0.000016	0.000203
2026-03-11	607.690002	49.349998	-0.000132	-0.001012
2026-03-12	597.260010	46.830002	-0.017163	-0.051064
2026-03-13	593.719971	45.930000	-0.005927	-0.019218

[6795 rows x 4 columns]

After the extrapolation, we now have the following plots for the prices, cumulative returns, and drawdowns:

```

[22]: etfs = ["QQQ", "TQQQ"]

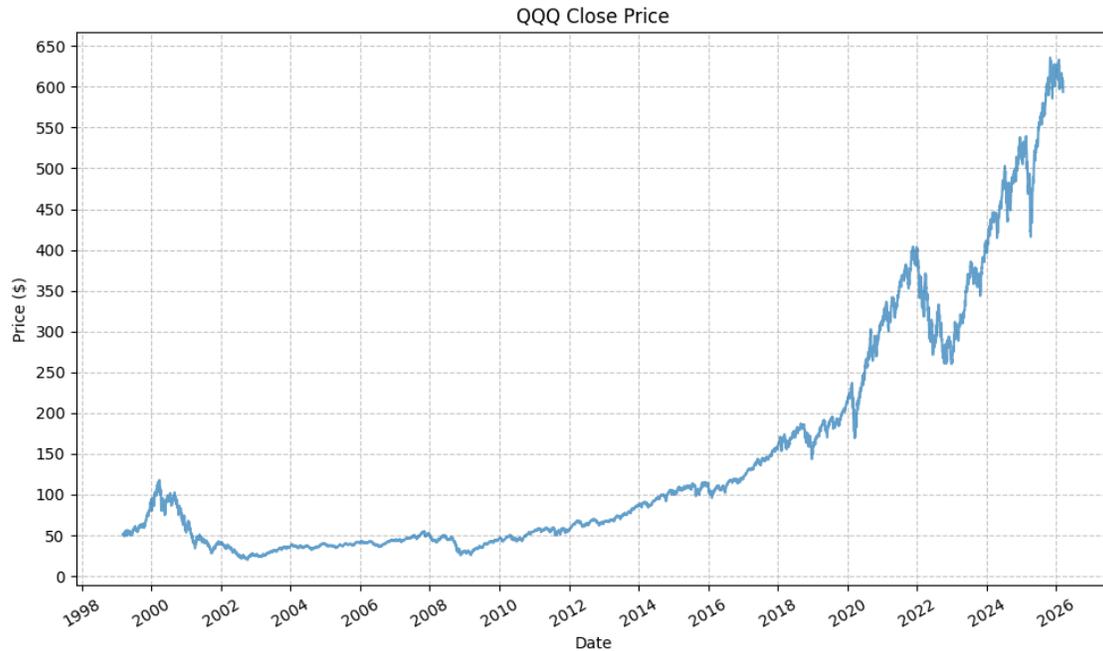
# Calculate cumulative returns
for etf in etfs:
    qqq_tqqq_extrap[f"{etf}_Return"] = qqq_tqqq_extrap[f"{etf}_Close"].
    ↪ pct_change()
    qqq_tqqq_extrap[f"{etf}_Cumulative_Return"] = (1 +
    ↪ qqq_tqqq_extrap[f"{etf}_Return"]).cumprod() - 1
    qqq_tqqq_extrap[f"{etf}_Cumulative_Return_Plus_One"] = 1 +
    ↪ qqq_tqqq_extrap[f"{etf}_Cumulative_Return"]
    qqq_tqqq_extrap[f"{etf}_Rolling_Max"] =
    ↪ qqq_tqqq_extrap[f"{etf}_Cumulative_Return_Plus_One"].cummax()
    qqq_tqqq_extrap[f"{etf}_Drawdown"] =
    ↪ qqq_tqqq_extrap[f"{etf}_Cumulative_Return_Plus_One"] /
    ↪ qqq_tqqq_extrap[f"{etf}_Rolling_Max"] - 1
    qqq_tqqq_extrap.drop(columns=[f"{etf}_Cumulative_Return_Plus_One",
    ↪ f"{etf}_Rolling_Max"], inplace=True)

```

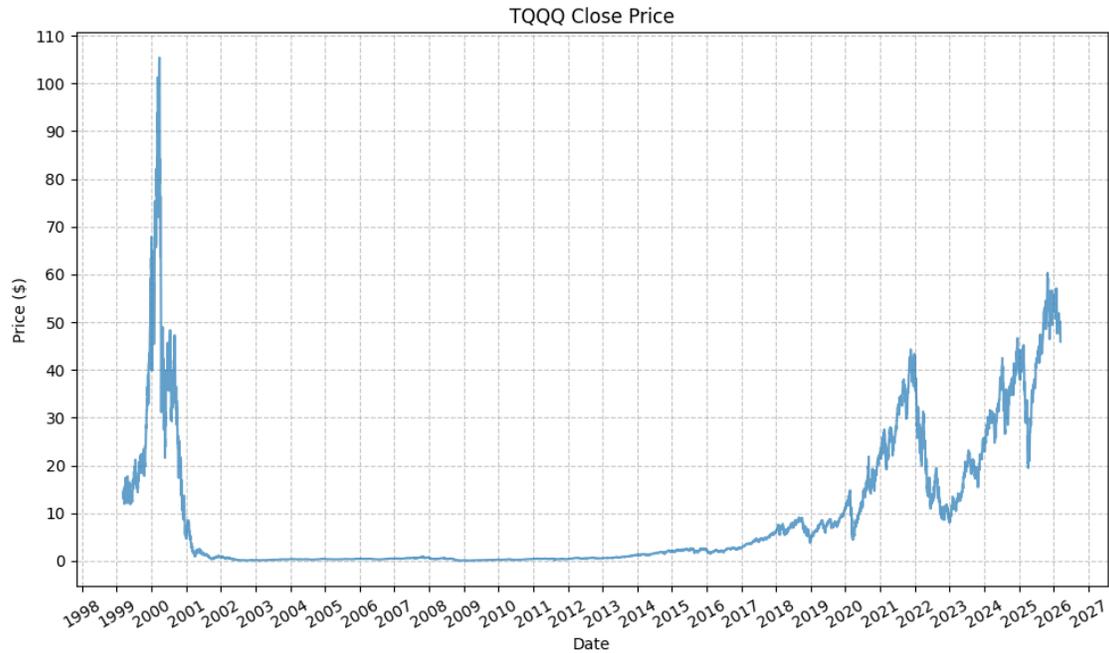
```

[23]: plot_timeseries(
    df=qqq_tqqq_extrap,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["QQQ_Close"],
    title="QQQ Close Price",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=2,
    x_tick_rotation=30,
    y_label="Price ($)",
    y_format="Decimal",
    y_format_decimal_places=0,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    grid=True,
    legend=False,
    export_plot=False,
    plot_file_name=None,
)

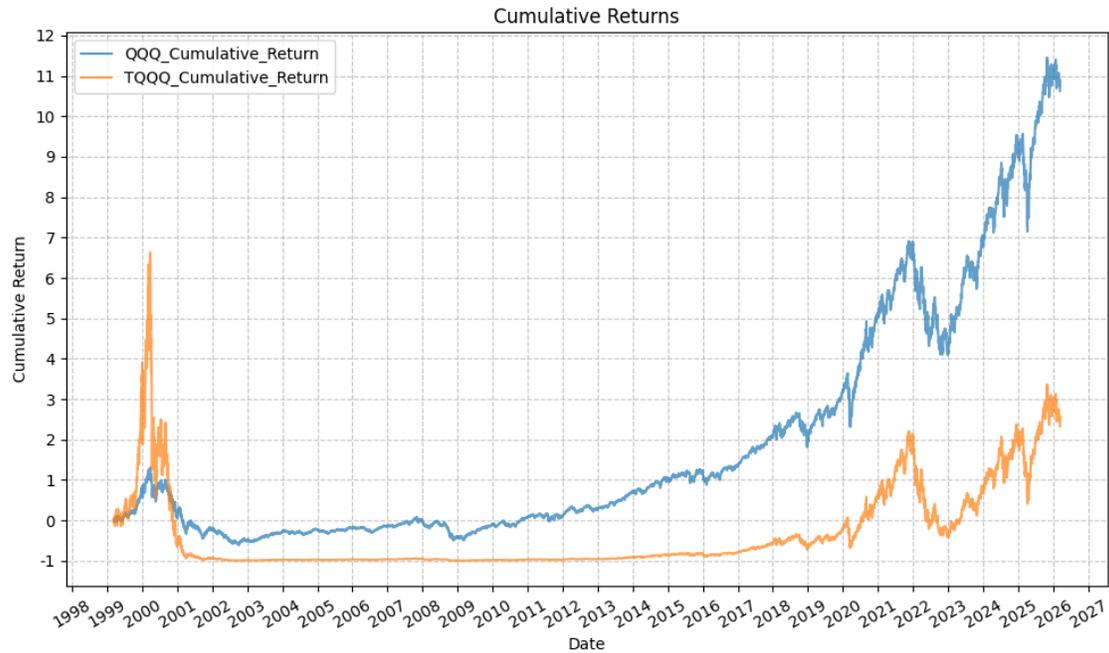
```



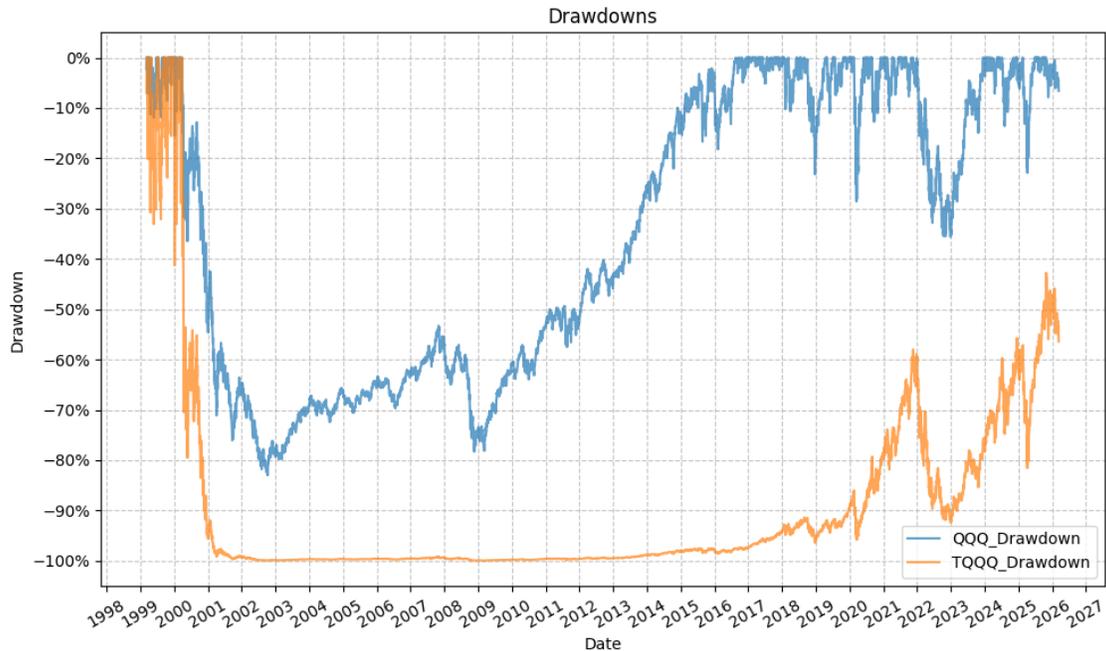
```
[24]: plot_timeseries(  
    df=tqqq_tqqq_extrap,  
    plot_start_date=None,  
    plot_end_date=None,  
    plot_columns=["TQQQ_Close"],  
    title="TQQQ Close Price",  
    x_label="Date",  
    x_format="Year",  
    x_tick_spacing=1,  
    x_tick_rotation=30,  
    y_label="Price ($)",  
    y_format="Decimal",  
    y_format_decimal_places=0,  
    y_tick_spacing="Auto",  
    y_tick_rotation=0,  
    grid=True,  
    legend=False,  
    export_plot=False,  
    plot_file_name=None,  
)
```



```
[25]: plot_timeseries(
    df=qqq_tqqq_extrap,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["QQQ_Cumulative_Return", "TQQQ_Cumulative_Return"],
    title="Cumulative Returns",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=1,
    x_tick_rotation=30,
    y_label="Cumulative Return",
    y_format="Decimal",
    y_format_decimal_places=0,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    grid=True,
    legend=True,
    export_plot=False,
    plot_file_name=None,
)
```



```
[26]: plot_timeseries(
    df=qqq_tqqq_extrap,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["QQQ_Drawdown", "TQQQ_Drawdown"],
    title="Drawdowns",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=1,
    x_tick_rotation=30,
    y_label="Drawdown",
    y_format="Percentage",
    y_format_decimal_places=0,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    grid=True,
    legend=True,
    export_plot=False,
    plot_file_name=None,
)
```



Some quick comments before we look at rolling returns. The drawdown is nearly 100%... which represents nearly a total loss of capital for any allocation to the extrap-TQQQ. Furthermore, as we walk forward through time (2002, 2003, ... etc.), there is really no reason to believe that the returns would ever recover (even partially). So, while we can look at the rolling returns and see how they compare to the 3x return of QQQ, we should keep in mind that the drawdown is so severe that it would be very difficult for any investor to hold through it.

0.4.6 Plot Rolling Returns (QQQ & TQQQ)

Next, we will consider the following:

- Histogram and scatter plots of the rolling returns of QQQ and TQQQ
- Regressions to establish a “leverage factor” for the rolling returns
- The deviation from a 3x return for each time period

For this set of regressions, we will also allow the constant. First, we need the rolling returns for various time periods:

```
[27]: # Define rolling windows in trading days
rolling_windows = {
    '1d': 1,      # 1 day
    '1w': 5,      # 1 week (5 trading days)
    '1m': 21,     # 1 month (~21 trading days)
    '3m': 63,     # 3 months (~63 trading days)
    '6m': 126,   # 6 months (~126 trading days)
    '1y': 252,   # 1 year (~252 trading days)
    '2y': 504,   # 2 years (~504 trading days)
```

```

'3y': 756,      # 3 years (~756 trading days)
'4y': 1008,    # 4 years (~1008 trading days)
'5y': 1260,    # 5 years (~1260 trading days)
}

# Calculate rolling returns for each ETF and each window
for etf in etfs:
    for period_name, window in rolling_windows.items():
        qqq_tqqq_extrap[f"{etf}_Rolling_Return_{period_name}"] = (
            qqq_tqqq_extrap[f"{etf}_Close"].pct_change( periods=window)
        )

```

This gives us the following series of histograms, scatter plots, and regression model results:

```

[28]: # Create a dataframe to hold rolling returns stats
rolling_returns_stats = pd.DataFrame()

for period_name, window in rolling_windows.items():
    plot_histogram(
        df=qqq_tqqq_extrap,
        plot_columns=[f"QQQ_Rolling_Return_{period_name}",
            f"TQQQ_Rolling_Return_{period_name}"],
        title=f"QQQ & TQQQ {period_name} Rolling Returns",
        x_label="Rolling Return",
        x_tick_spacing="Auto",
        x_tick_rotation=30,
        y_label="# Of Datapoints",
        y_tick_spacing="Auto",
        y_tick_rotation=0,
        grid=True,
        legend=True,
        export_plot=False,
        plot_file_name=None,
    )

    plot_scatter(
        df=qqq_tqqq_extrap,
        x_plot_column=f"QQQ_Rolling_Return_{period_name}",
        y_plot_columns=[f"TQQQ_Rolling_Return_{period_name}"],
        title=f"QQQ & TQQQ {period_name} Rolling Returns",
        x_label="QQQ Rolling Return",
        x_format="Decimal",
        x_format_decimal_places=2,
        x_tick_spacing="Auto",
        x_tick_rotation=30,
        y_label="TQQQ Rolling Return",
        y_format="Decimal",
    )

```

```

    y_format_decimal_places=2,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    plot_OLS_regression_line=True,
    OLS_column=f"TQQQ_Rolling_Return_{period_name}",
    plot_Ridge_regression_line=False,
    Ridge_column=None,
    plot_RidgeCV_regression_line=True,
    RidgeCV_column=f"TQQQ_Rolling_Return_{period_name}",
    regression_constant=True,
    grid=True,
    legend=True,
    export_plot=False,
    plot_file_name=None,
)

# Run OLS regression with statsmodels
model = run_linear_regression(
    df=qqq_tqqq_extrap,
    x_plot_column=f"QQQ_Rolling_Return_{period_name}",
    y_plot_column=f"TQQQ_Rolling_Return_{period_name}",
    regression_model="OLS-statsmodels",
    regression_constant=True,
)
print(model.summary())

# Add the regression results to the rolling returns stats dataframe
intercept = model.params[0]
intercept_pvalue = model.pvalues[0] # p-value for Intercept
slope = model.params[1]
slope_pvalue = model.pvalues[1] # p-value for QQQ_Return
r_squared = model.rsquared

# Calc skew
return_ratio = qqq_tqqq_extrap[f'TQQQ_Rolling_Return_{period_name}'] /
↳qqq_tqqq_extrap[f'QQQ_Rolling_Return_{period_name}']
skew = return_ratio.skew()

# Calc conditional symmetry
up_markets =
↳qqq_tqqq_extrap[qqq_tqqq_extrap[f'QQQ_Rolling_Return_{period_name}'] > 0]
down_markets =
↳qqq_tqqq_extrap[qqq_tqqq_extrap[f'QQQ_Rolling_Return_{period_name}'] <= 0]

avg_beta_up = (up_markets[f'TQQQ_Rolling_Return_{period_name}'] /
↳up_markets[f'QQQ_Rolling_Return_{period_name}']).mean()

```

```

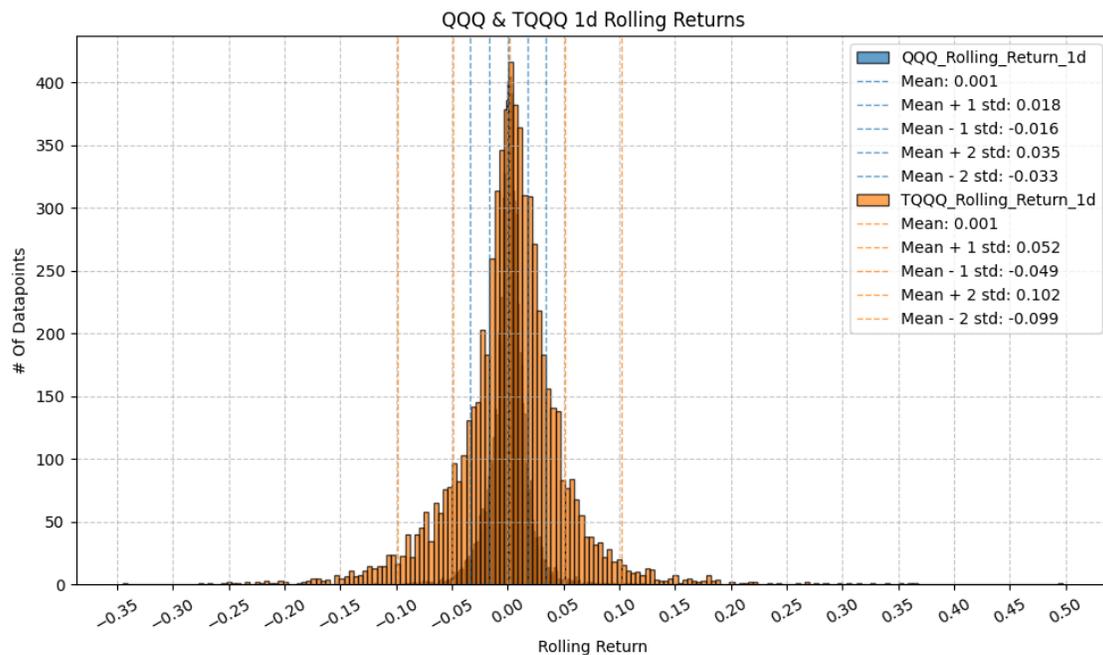
avg_beta_down = (down_markets[f'TQQQ_Rolling_Return_{period_name}'] /
↳down_markets[f'QQQ_Rolling_Return_{period_name}']).mean()

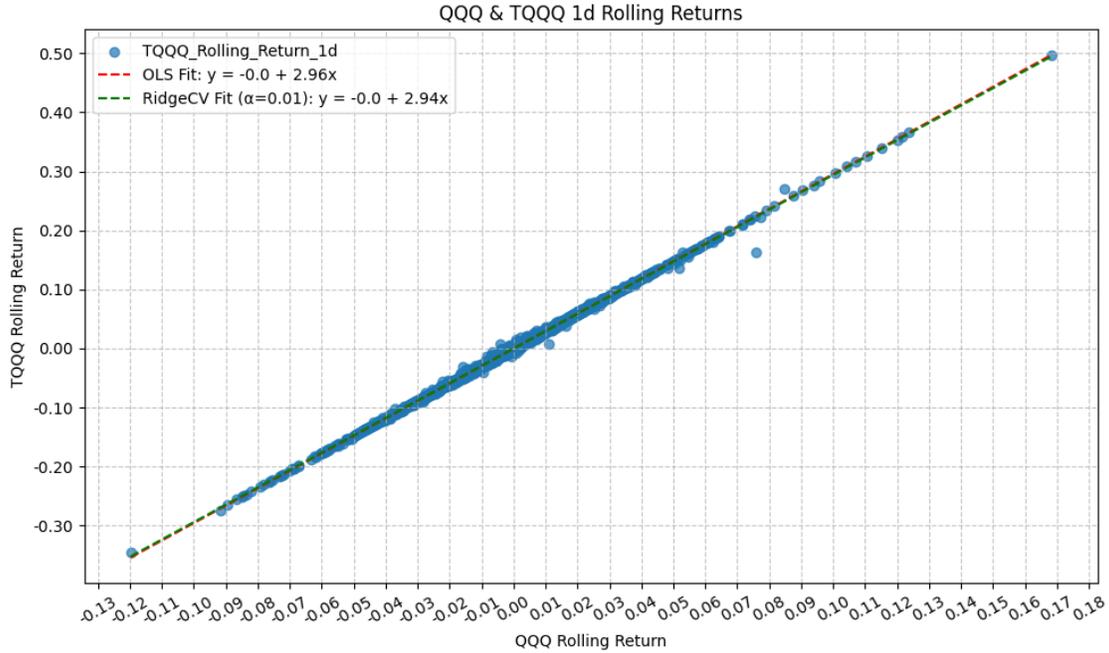
asymmetry = avg_beta_up - avg_beta_down

rolling_returns_slope_int = pd.DataFrame({
    "Period": period_name,
    "Intercept": [intercept],
    # "Intercept_PValue": [intercept_pvalue],
    "Slope": [slope],
    # "Slope_PValue": [slope_pvalue],
    "R_Squared": [r_squared],
    "Skew": [skew],
    "Average Upside Beta": [avg_beta_up],
    "Average Downside Beta": [avg_beta_down],
    "Asymmetry": [asymmetry]
})

rolling_returns_stats = pd.concat([rolling_returns_stats,
↳rolling_returns_slope_int])

```





OLS Regression Results

=====

```

Dep. Variable:      TQQQ_Rolling_Return_1d    R-squared:
0.999
Model:              OLS                      Adj. R-squared:
0.999
Method:             Least Squares           F-statistic:
7.215e+06
Date:               Mon, 16 Mar 2026         Prob (F-statistic):
0.00
Time:               14:26:03                 Log-Likelihood:
34352.
No. Observations:  6794                     AIC:
-6.870e+04
Df Residuals:      6792                     BIC:
-6.869e+04
Df Model:           1
Covariance Type:   nonrobust

```

=====

```

                                coef      std err          t      P>|t|      [0.025
0.975]
-----

```

```

const                -5.091e-05    1.87e-05    -2.721    0.007    -8.76e-05

```

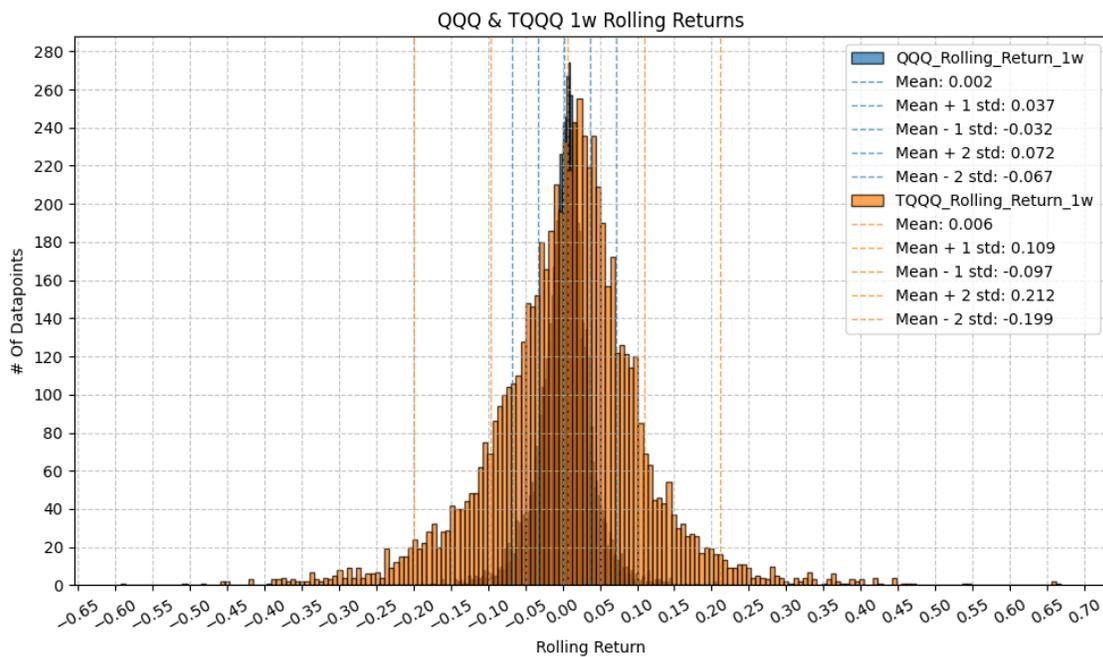
-1.42e-05

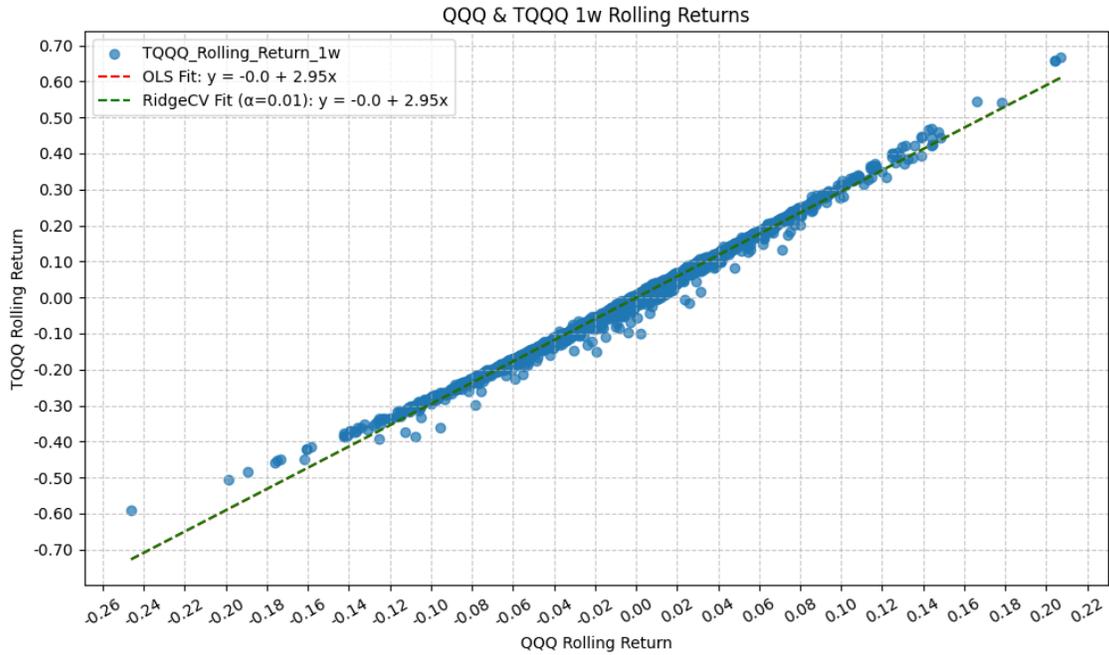
QQQ_Rolling_Return_1d 2.9551 0.001 2686.049 0.000 2.953
2.957

```
=====
Omnibus:                    10188.882      Durbin-Watson:                    2.565
Prob(Omnibus):              0.000      Jarque-Bera (JB):                43894224.936
Skew:                        -8.279      Prob(JB):                        0.00
Kurtosis:                    396.425      Cond. No.                        58.8
=====
```

Notes:

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





OLS Regression Results

=====

==

```

Dep. Variable:      TQQQ_Rolling_Return_1w      R-squared:
0.994
Model:              OLS                        Adj. R-squared:
0.994
Method:             Least Squares              F-statistic:
1.116e+06
Date:               Mon, 16 Mar 2026           Prob (F-statistic):
0.00
Time:               14:26:04                   Log-Likelihood:
23152.
No. Observations:  6790                       AIC:
-4.630e+04
Df Residuals:      6788                       BIC:
-4.629e+04
Df Model:          1
Covariance Type:   nonrobust

```

=====

```

=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----

```

```

const                -0.0008      9.73e-05      -8.330      0.000      -0.001

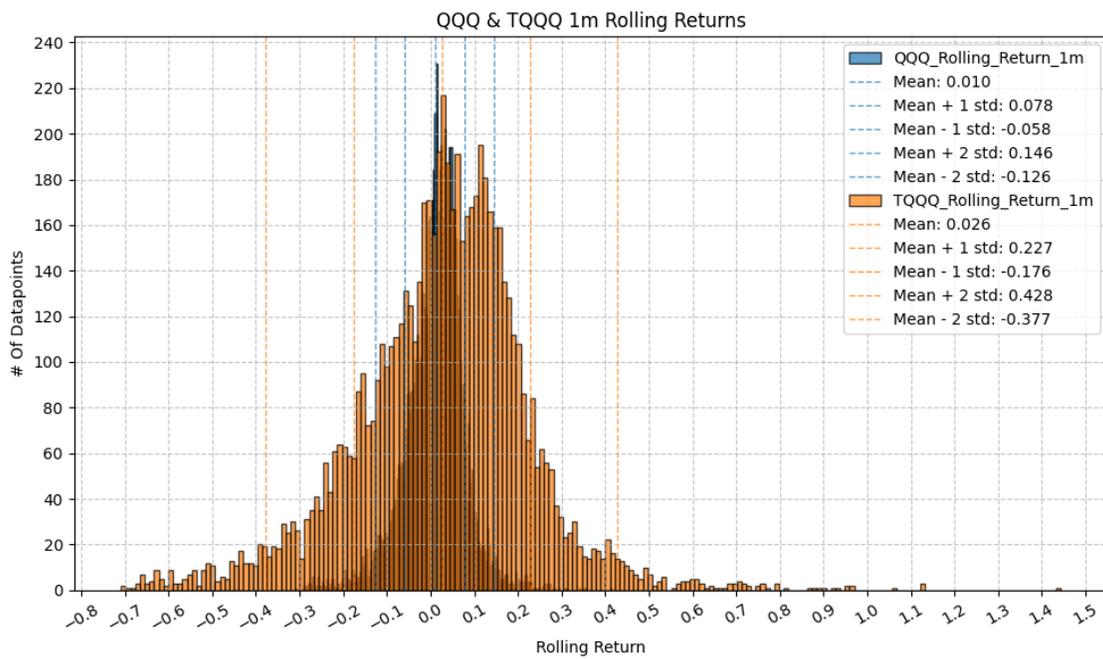
```

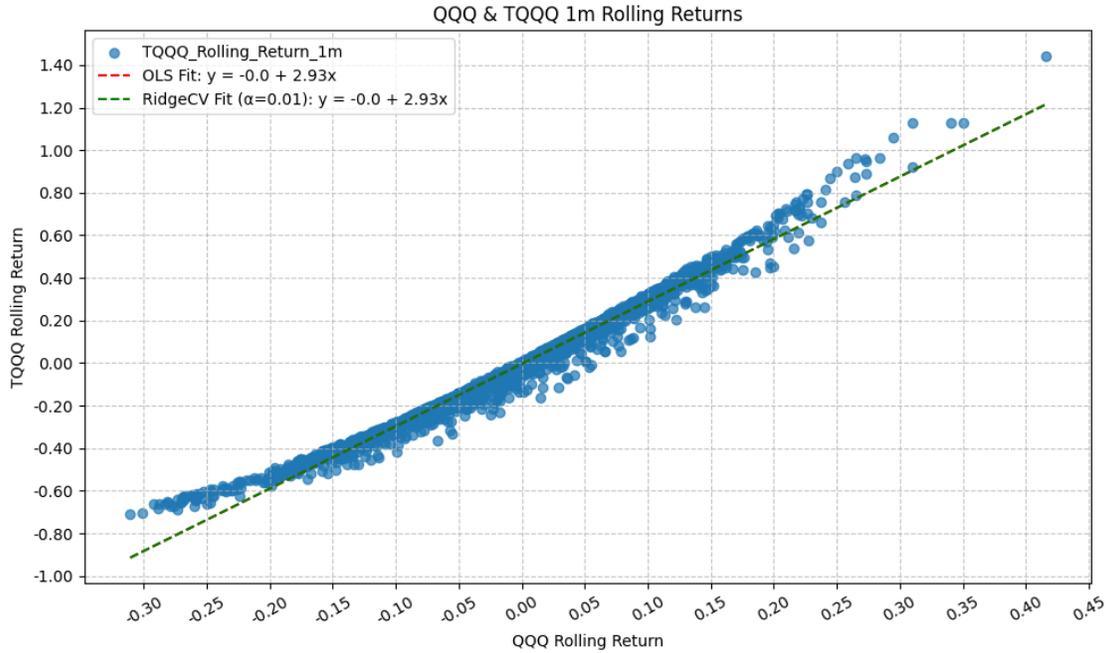
-0.001
 QQQ_Rolling_Return_1w 2.9524 0.003 1056.353 0.000 2.947
 2.958

```
=====
Omnibus:                    2839.003      Durbin-Watson:                    0.932
Prob(Omnibus):              0.000      Jarque-Bera (JB):                563907.961
Skew:                        -0.863      Prob(JB):                         0.00
Kurtosis:                    47.612      Cond. No.                         28.8
=====
```

Notes:

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





OLS Regression Results

=====

==

```

Dep. Variable:      TQQQ_Rolling_Return_1m    R-squared:
0.982
Model:              OLS                      Adj. R-squared:
0.982
Method:             Least Squares           F-statistic:
3.695e+05
Date:               Mon, 16 Mar 2026        Prob (F-statistic):
0.00
Time:               14:26:05                Log-Likelihood:
14852.
No. Observations:  6774                    AIC:
-2.970e+04
Df Residuals:      6772                    BIC:
-2.969e+04
Df Model:           1
Covariance Type:   nonrobust

```

=====

```

=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----

```

```

-----
const                -0.0037      0.000      -11.064      0.000      -0.004

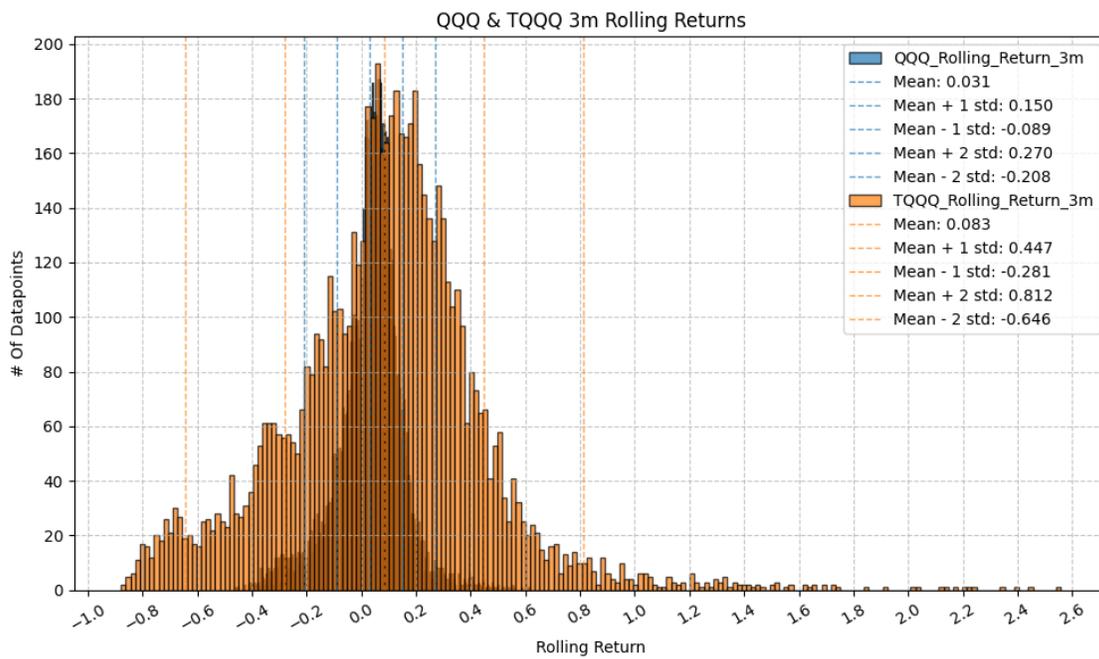
```

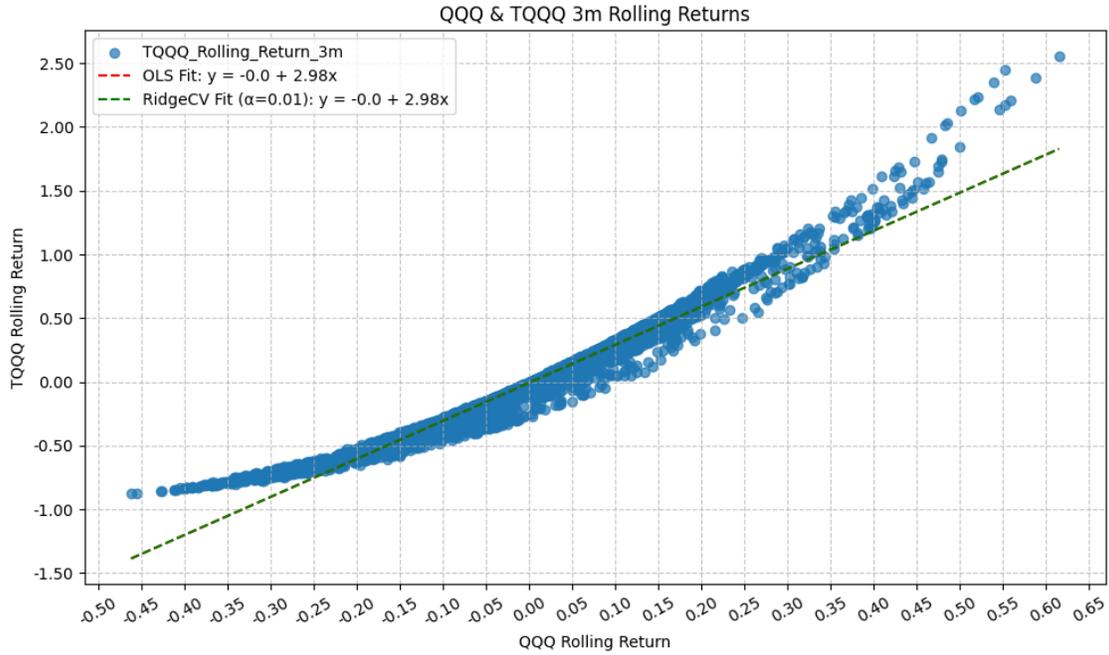
-0.003
 QQQ_Rolling_Return_1m 2.9305 0.005 607.853 0.000 2.921
 2.940

```
=====
Omnibus:                    1627.646      Durbin-Watson:                    0.296
Prob(Omnibus):             0.000      Jarque-Bera (JB):                69016.055
Skew:                      0.357      Prob(JB):                         0.00
Kurtosis:                  18.621      Cond. No.                         14.7
=====
```

Notes:

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





OLS Regression Results

=====

```

Dep. Variable:      TQQQ_Rolling_Return_3m    R-squared:
0.958
Model:              OLS                    Adj. R-squared:
0.958
Method:             Least Squares          F-statistic:
1.549e+05
Date:               Mon, 16 Mar 2026        Prob (F-statistic):
0.00
Time:               14:26:06               Log-Likelihood:
7946.0
No. Observations:  6732                   AIC:
-1.589e+04
Df Residuals:      6730                   BIC:
-1.587e+04
Df Model:           1
Covariance Type:   nonrobust

```

=====

	coef	std err	t	P> t	[0.025
--	------	---------	---	------	--------

0.975]

const	-0.0083	0.001	-8.841	0.000	-0.010
-------	---------	-------	--------	-------	--------

-0.006
 QQQ_Rolling_Return_3m 2.9848 0.008 393.626 0.000 2.970
 3.000

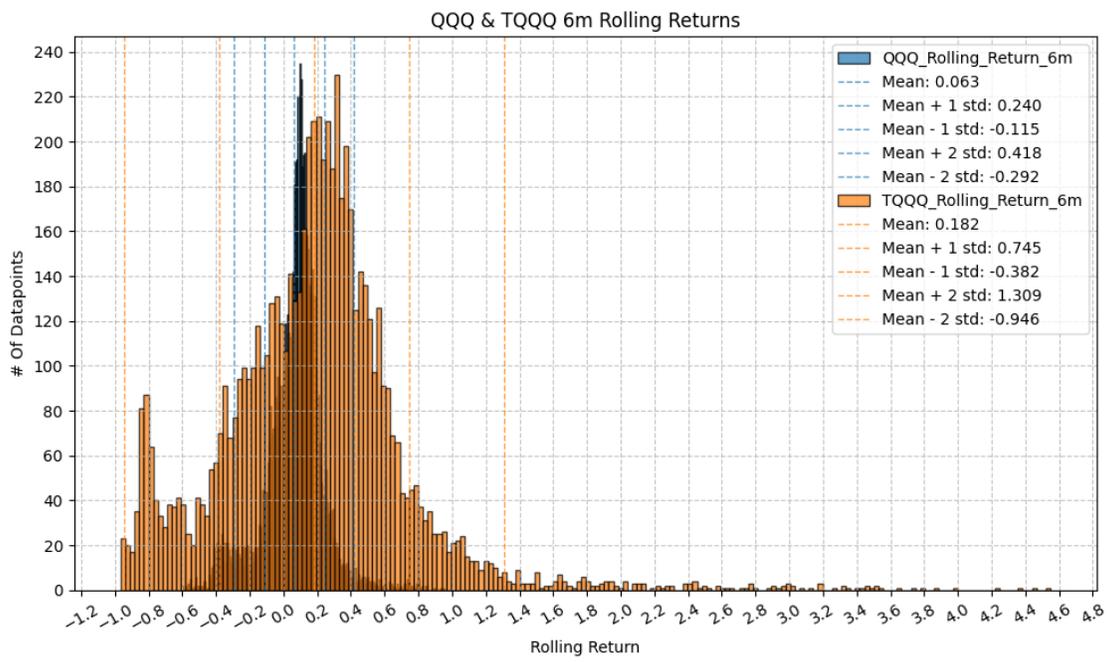
```
=====
```

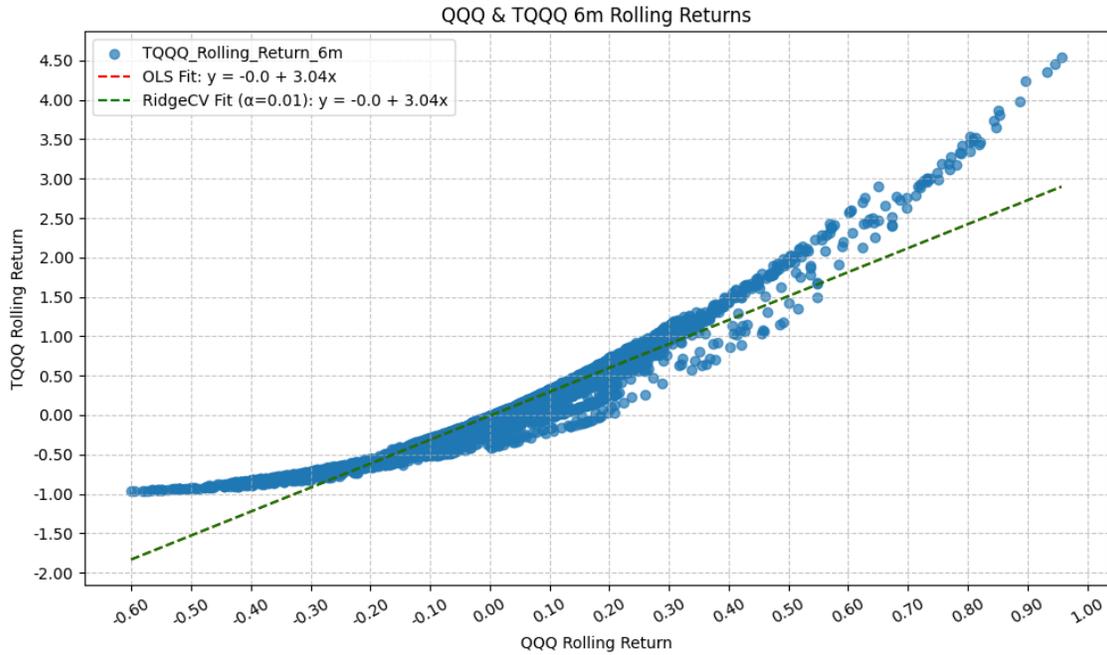
Omnibus:	3461.856	Durbin-Watson:	0.105
Prob(Omnibus):	0.000	Jarque-Bera (JB):	79524.170
Skew:	1.962	Prob(JB):	0.00
Kurtosis:	19.374	Cond. No.	8.38

```
=====
```

Notes:

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





OLS Regression Results

=====

==

```

Dep. Variable:    TQQQ_Rolling_Return_6m    R-squared:
0.916
Model:                OLS    Adj. R-squared:
0.916
Method:              Least Squares    F-statistic:
7.247e+04
Date:                Mon, 16 Mar 2026    Prob (F-statistic):
0.00
Time:                14:26:08    Log-Likelihood:
2610.3
No. Observations:    6669    AIC:
-5217.
Df Residuals:        6667    BIC:
-5203.
Df Model:            1
Covariance Type:    nonrobust

```

=====

```

=====
                coef    std err          t      P>|t|      [0.025
0.975]
-----

```

```

const                -0.0096    0.002    -4.515    0.000    -0.014

```

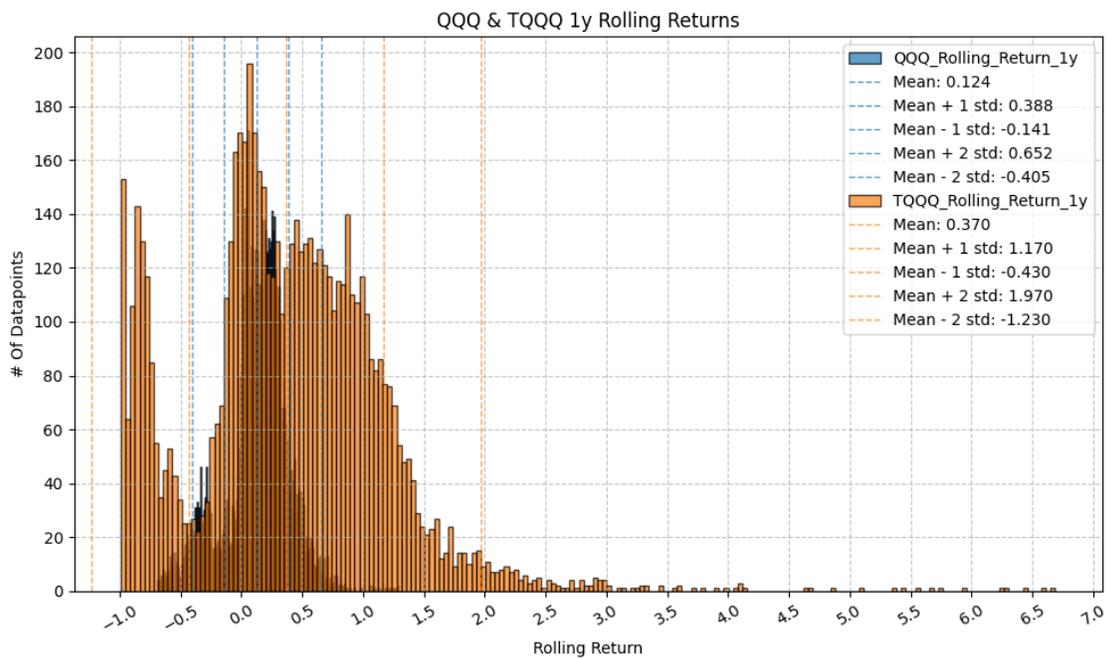
-0.005

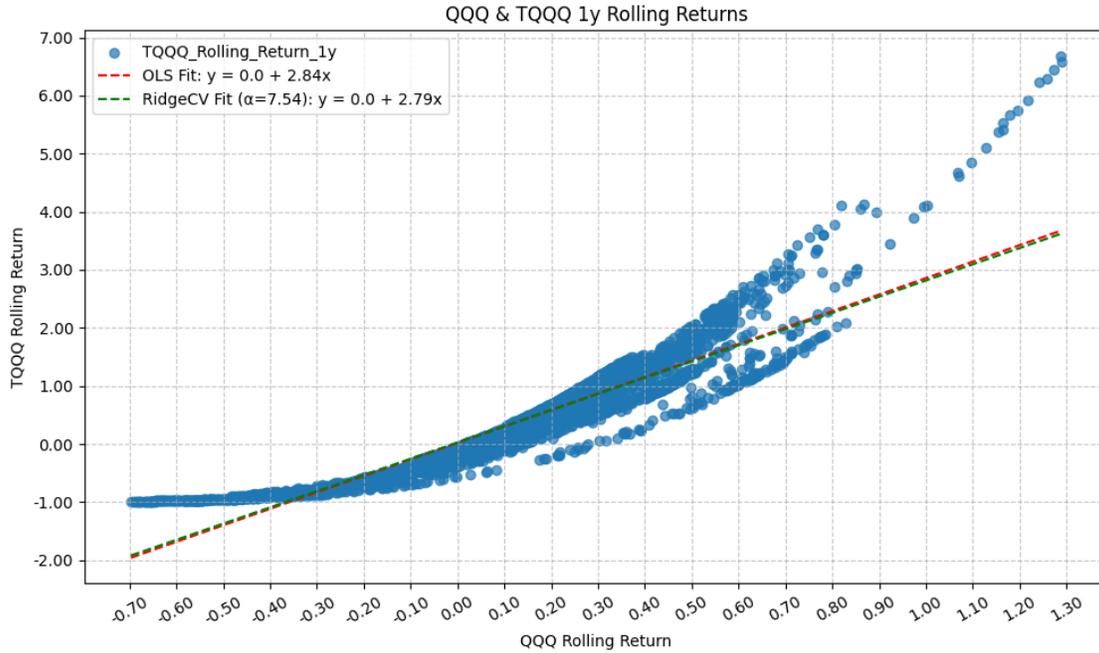
QQQ_Rolling_Return_6m 3.0396 0.011 269.206 0.000 3.017
3.062

```
=====
Omnibus:                    3654.453      Durbin-Watson:                    0.056
Prob(Omnibus):              0.000      Jarque-Bera (JB):                60093.604
Skew:                        2.262      Prob(JB):                        0.00
Kurtosis:                    16.993      Cond. No.                        5.66
=====
```

Notes:

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





OLS Regression Results

=====

==

```

Dep. Variable:      TQQQ_Rolling_Return_1y      R-squared:
0.880
Model:              OLS                        Adj. R-squared:
0.880
Method:             Least Squares              F-statistic:
4.785e+04
Date:               Mon, 16 Mar 2026           Prob (F-statistic):
0.00
Time:               14:26:09                   Log-Likelihood:
-892.54
No. Observations:  6543                       AIC:
1789.
Df Residuals:      6541                       BIC:
1803.
Df Model:           1
Covariance Type:   nonrobust

```

=====

```

=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----

```

```

const                0.0191      0.004      5.035      0.000      0.012

```

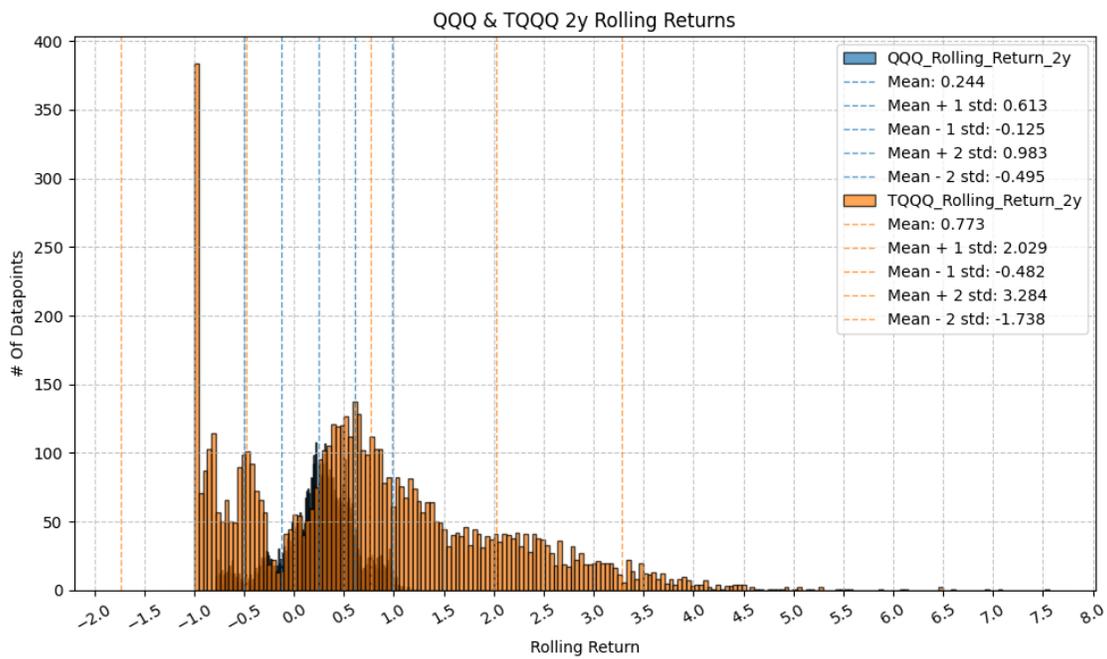
0.026

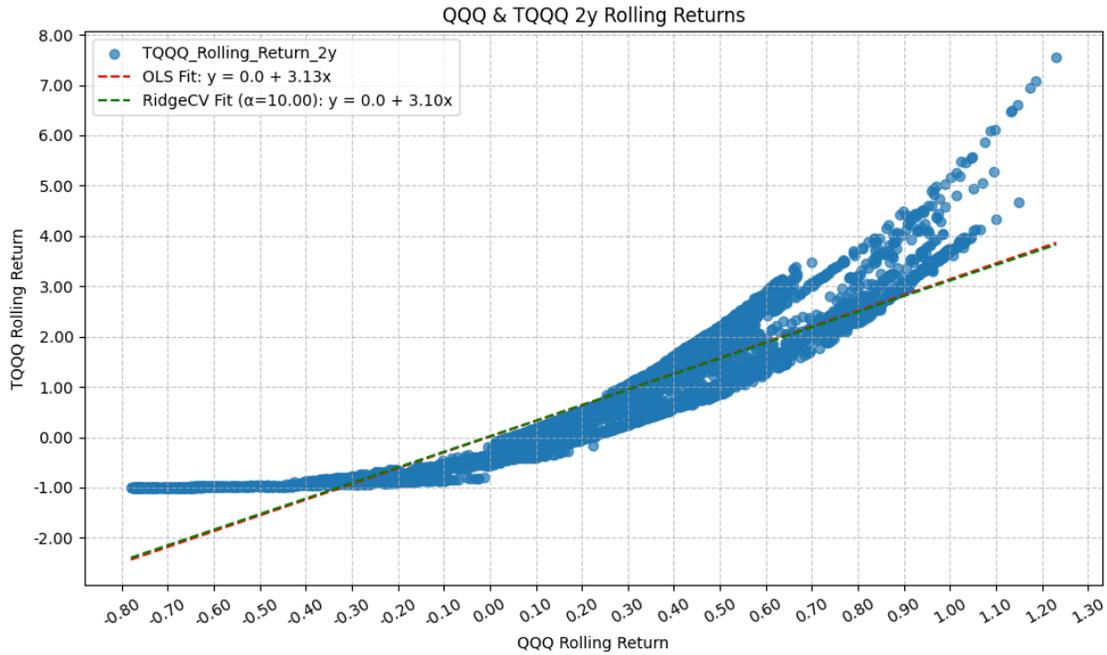
QQQ_Rolling_Return_1y 2.8375 0.013 218.746 0.000 2.812
2.863

```
=====
Omnibus:                    3492.635      Durbin-Watson:                    0.037
Prob(Omnibus):             0.000      Jarque-Bera (JB):                 68111.624
Skew:                        2.122      Prob(JB):                         0.00
Kurtosis:                    18.226      Cond. No.                         3.84
=====
```

Notes:

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





OLS Regression Results

=====

==

```

Dep. Variable:      TQQQ_Rolling_Return_2y      R-squared:
0.849
Model:              OLS                        Adj. R-squared:
0.848
Method:             Least Squares             F-statistic:
3.522e+04
Date:               Mon, 16 Mar 2026          Prob (F-statistic):
0.00
Time:               14:26:10                  Log-Likelihood:
-4421.2
No. Observations:  6291                      AIC:
8846.
Df Residuals:      6289                      BIC:
8860.
Df Model:           1
Covariance Type:   nonrobust

```

=====

```

=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----

```

```

const                0.0096      0.007         1.294     0.196     -0.005

```

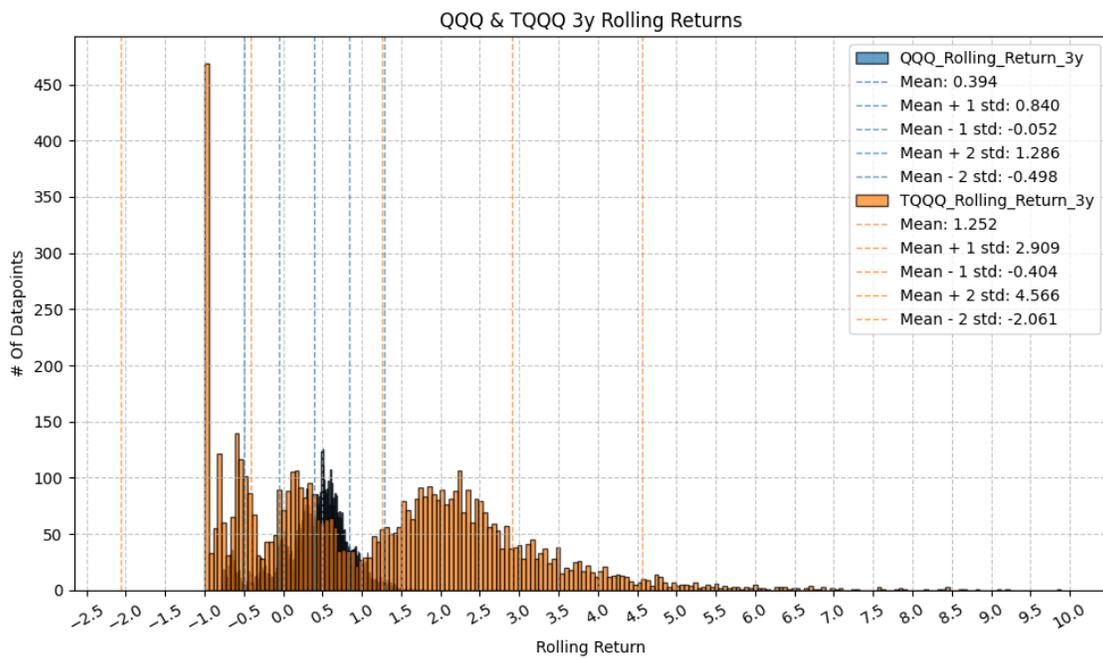
0.024

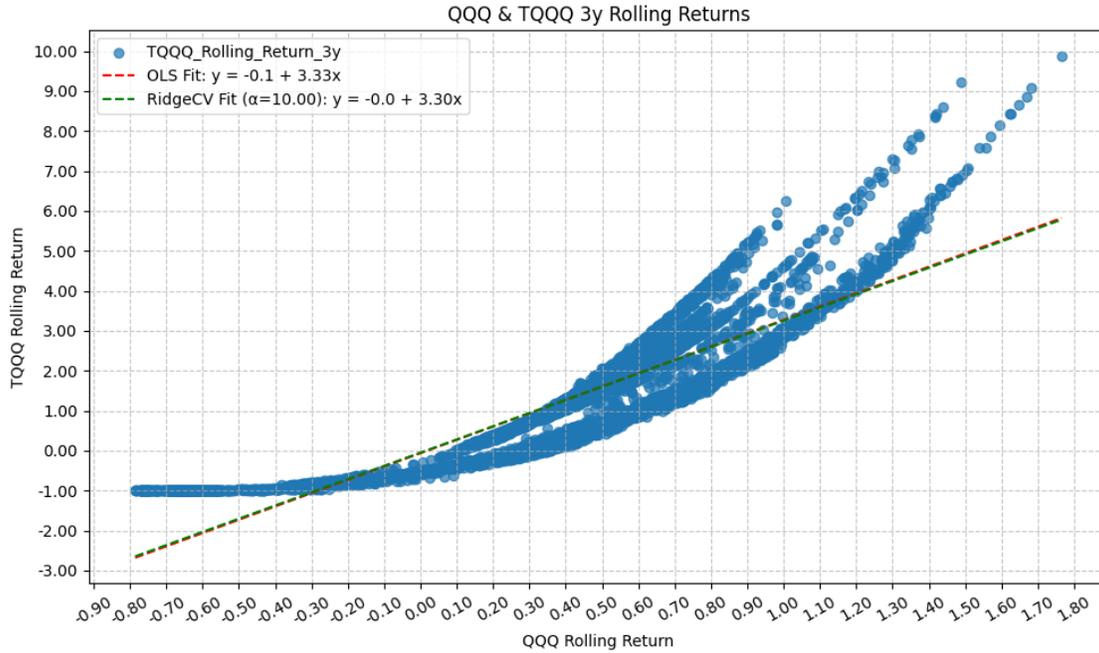
QQQ_Rolling_Return_2y 3.1314 0.017 187.680 0.000 3.099
3.164

```
=====
Omnibus:                    1595.143      Durbin-Watson:                    0.019
Prob(Omnibus):              0.000      Jarque-Bera (JB):                4144.668
Skew:                        1.367      Prob(JB):                         0.00
Kurtosis:                    5.887      Cond. No.                         2.89
=====
```

Notes:

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





OLS Regression Results

=====

==

```

Dep. Variable:      TQQQ_Rolling_Return_3y      R-squared:
0.804
Model:              OLS      Adj. R-squared:
0.804
Method:             Least Squares      F-statistic:
2.481e+04
Date:               Mon, 16 Mar 2026      Prob (F-statistic):
0.00
Time:               14:26:11      Log-Likelihood:
-6691.5
No. Observations:      6039      AIC:
1.339e+04
Df Residuals:         6037      BIC:
1.340e+04
Df Model:              1
Covariance Type:      nonrobust

```

=====

```

=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----

```

```

const                -0.0599      0.013      -4.763      0.000      -0.085

```

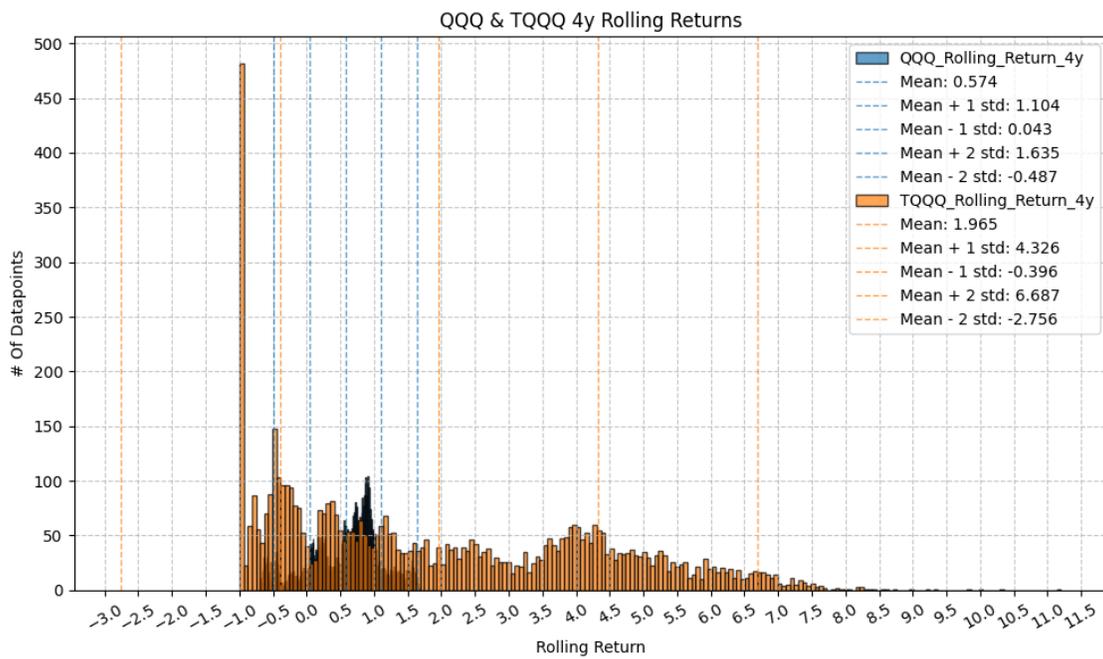
-0.035

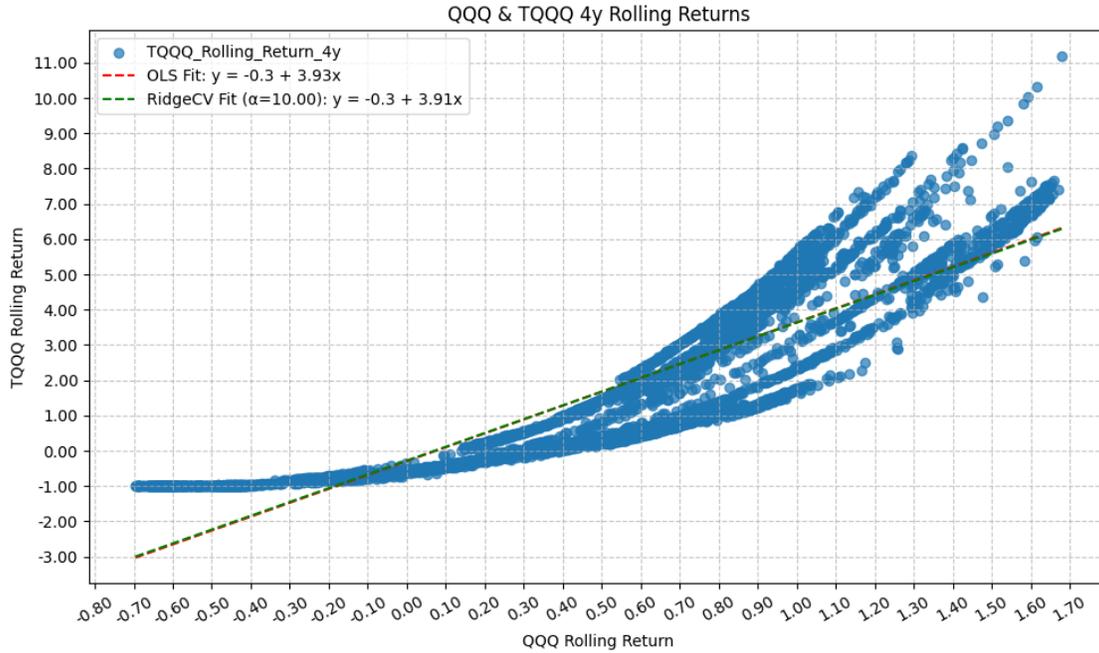
QQQ_Rolling_Return_3y 3.3321 0.021 157.522 0.000 3.291
3.374

```
=====
Omnibus:                    855.515      Durbin-Watson:                    0.015
Prob(Omnibus):              0.000      Jarque-Bera (JB):                1466.078
Skew:                        0.939      Prob(JB):                         0.00
Kurtosis:                    4.516      Cond. No.                         2.66
=====
```

Notes:

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





OLS Regression Results

=====

==

```

Dep. Variable:      TQQQ_Rolling_Return_4y      R-squared:
0.781
Model:              OLS                        Adj. R-squared:
0.781
Method:             Least Squares              F-statistic:
2.068e+04
Date:               Mon, 16 Mar 2026           Prob (F-statistic):
0.00
Time:               14:26:12                   Log-Likelihood:
-8782.4
No. Observations:  5787                       AIC:
1.757e+04
Df Residuals:      5785                       BIC:
1.758e+04
Df Model:           1
Covariance Type:   nonrobust

```

=====

```

=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----

```

```

const                -0.2922      0.021      -13.668      0.000      -0.334

```

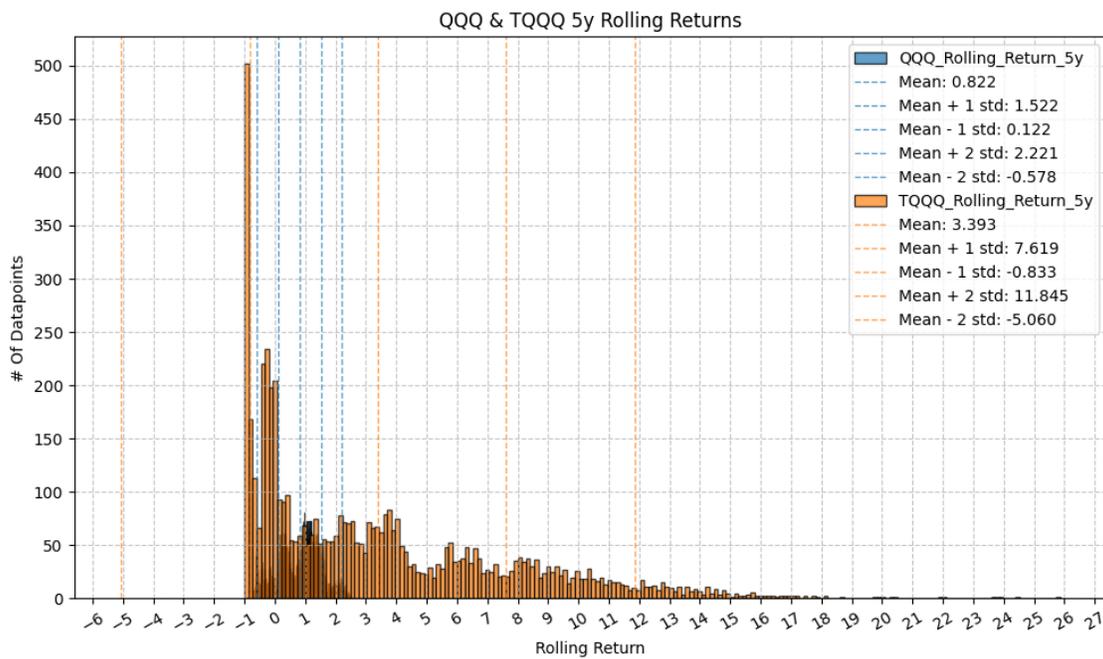
-0.250

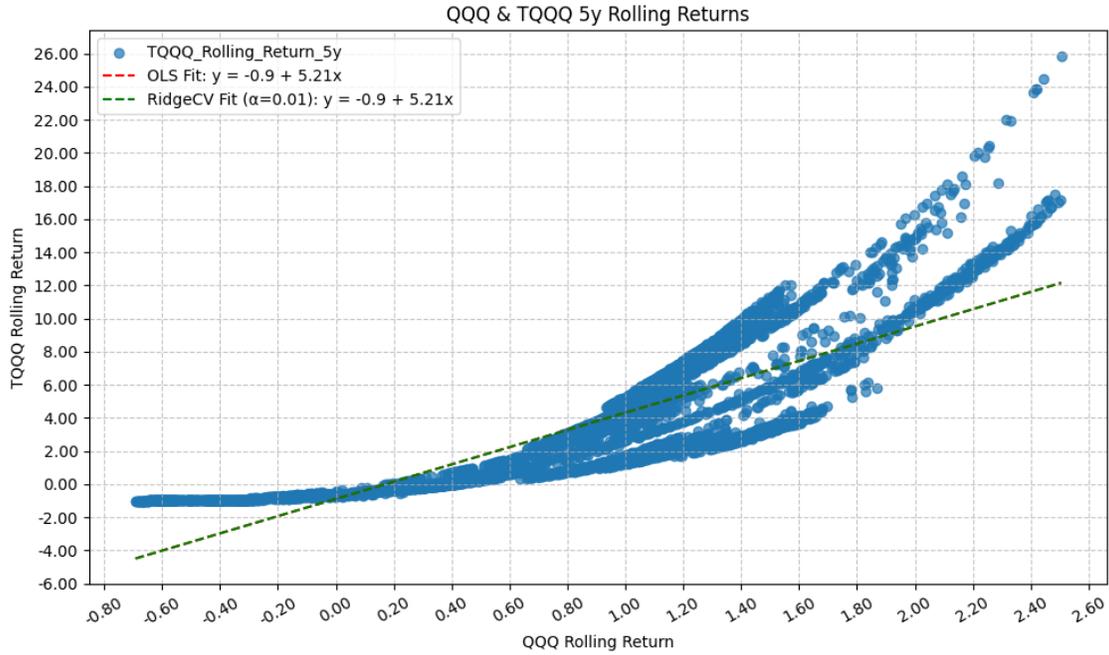
QQQ_Rolling_Return_4y 3.9343 0.027 143.797 0.000 3.881
3.988

```
=====
Omnibus:                    198.061      Durbin-Watson:                    0.010
Prob(Omnibus):             0.000      Jarque-Bera (JB):                 103.519
Skew:                        0.140      Prob(JB):                         3.32e-23
Kurtosis:                    2.407      Cond. No.                         2.66
=====
```

Notes:

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





OLS Regression Results

```

=====
==
Dep. Variable:      TQQQ_Rolling_Return_5y    R-squared:
0.743
Model:              OLS                    Adj. R-squared:
0.743
Method:             Least Squares          F-statistic:
1.599e+04
Date:               Mon, 16 Mar 2026        Prob (F-statistic):
0.00
Time:               14:26:13                Log-Likelihood:
-12071.
No. Observations:  5535                    AIC:
2.415e+04
Df Residuals:      5533                    BIC:
2.416e+04
Df Model:           1
Covariance Type:   nonrobust
=====

```

```

=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const          -0.8853      0.044     -19.926      0.000     -0.972

```

-0.798					
QQQ_Rolling_Return_5y	5.2054	0.041	126.462	0.000	5.125
5.286					
=====					
Omnibus:	314.365	Durbin-Watson:		0.009	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		460.149	
Skew:	0.498	Prob(JB):		1.20e-100	
Kurtosis:	4.002	Cond. No.		2.73	
=====					

Notes:

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

You're welcome to digest each plot, but here's my observations on the above results:

- 1d: TQQQ tracks QQQ as expected (it's a 3x daily return leveraged ETF after all), with a regression coefficient of 2.96 and an R^2 of 0.997, and we extrapolated half the data with the same coefficient.
- 1w: Essentially the same as above. A few outliers, but the regression coefficient is still 2.95 with an R^2 of 0.994. We see a slight skew toward the positive in the rolling returns.
- 1m: The skew toward the positive is more pronounced, and we see more outliers. The regression coefficient has decreased to 2.93 and the R^2 has dropped to 0.98, which is still very high, but we are starting to see some dispersion in the returns.
- 3m: The skew toward the positive is even more pronounced, and we see even more outliers. The regression coefficient has *increased*, to 2.98 and the R^2 has dropped to 0.96.
- 6m: The skew toward the positive is very pronounced, and we see a significant number of outliers with pronounced curvantage in the plot. The regression coefficient has increased again, to 3.4 and the R^2 has dropped to 0.92.
- 1y: At this point, based on the plot and the regression results, we can start to see that the returns of TQQQ are no longer tracking 3x the returns of QQQ as closely as they did in the shorter time periods. The regression coefficient has is now 2.84 and the R^2 has dropped to 0.88.
- 4y and 5y: We can see that there are periods where the rolling returns of TQQQ are significantly higher *and* lower than 3x the returns of QQQ, which is consistent with the idea of volatility decay. For 4y, based on the regression results, we see that if the rolling return of QQQ was 0, then we would expect a return of $-0.30x$ for TQQQ.

$$r_{TQQQ} = -0.30 + 3.93 \times r_{QQQ} = -0.30 + 3.93 \times 0 = -0.30$$

On the other end of the spectrum, if the rolling return of QQQ was 1, then we would expect a return of:

$$r_{TQQQ} = -0.30 + 3.93 \times r_{QQQ} = -0.30 + 3.93 \times 1 = 3.63$$

In general, the positive skew of the rolling returns of TQQQ relative to QQQ is related to the general positive return performance of QQQ. With sustained positive returns, the leverage effect of TQQQ will amplify those returns, leading to a positive skew. However, during periods of negative

returns for QQQ, the leverage effect will also amplify those losses, leading to a negative skew, and to the limit of cumulative return of -1, or a 100% loss. The overall skewness of the rolling returns will depend on the balance of these positive and negative periods.

0.4.7 Rolling Returns Deviation (QQQ & TQQQ)

Next, we will the rolling returns deviation from the expected 3x return for each time period. This will give us a better picture of the volatility decay effect and how it changes over different time horizons.

```
[29]: rolling_returns_stats["Return_Deviation_From_3x"] =
      ↪rolling_returns_stats["Slope"] - 3.0
```

```
[30]: display(rolling_returns_stats)
```

Period	Intercept	Slope	R_Squared	Skew	Average Upside Beta	\
0	1d	-0.000051	2.955114	0.999059	NaN	2.956838
0	1w	-0.000811	2.952376	0.993954	NaN	2.552537
0	1m	-0.003671	2.930530	0.982002	NaN	2.208871
0	3m	-0.008268	2.984796	0.958372	NaN	1.994392
0	6m	-0.009598	3.039561	0.915755	-8.732599	1.485007
0	1y	0.019061	2.837467	0.879741	NaN	1.222436
0	2y	0.009554	3.131370	0.848505	36.154365	1.393182
0	3y	-0.059935	3.332134	0.804313	NaN	-0.091088
0	4y	-0.292179	3.934252	0.781391	19.553878	1.759839
0	5y	-0.885319	5.205432	0.742959	43.020977	2.433454

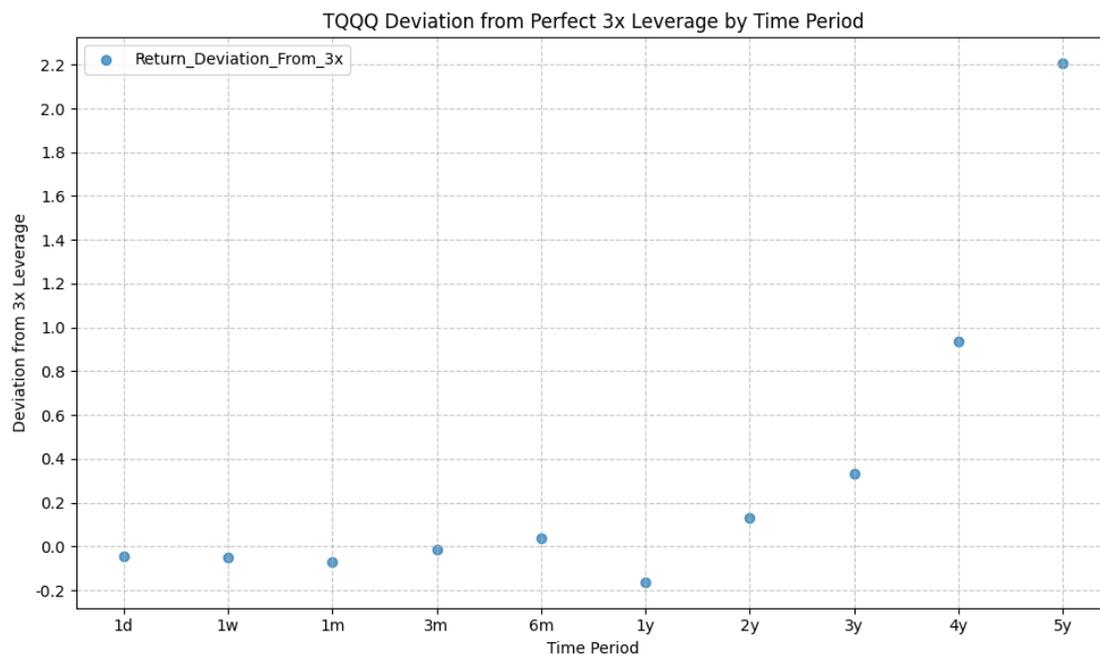
Period	Average Downside Beta	Asymmetry	Return_Deviation_From_3x
0	NaN	NaN	-0.044886
0	NaN	NaN	-0.047624
0	NaN	NaN	-0.069470
0	-inf	inf	-0.015204
0	5.416075	-3.931068	0.039561
0	-inf	inf	-0.162533
0	12.341258	-10.948076	0.131370
0	-inf	inf	0.332134
0	7.211475	-5.451636	0.934252
0	11.479352	-9.045897	2.205432

```
[31]: plot_scatter(
      df=rolling_returns_stats,
      x_plot_column="Period",
      y_plot_columns=["Return_Deviation_From_3x"],
      title="TQQQ Deviation from Perfect 3x Leverage by Time Period",
      x_label="Time Period",
      x_format="String",
      x_format_decimal_places=0,
      x_tick_spacing=1,
```

```

x_tick_rotation=0,
y_label="Deviation from 3x Leverage",
y_format="Decimal",
y_format_decimal_places=1,
y_tick_spacing="Auto",
y_tick_rotation=0,
plot_OLS_regression_line=False,
OLS_column=None,
plot_Ridge_regression_line=False,
Ridge_column=None,
plot_RidgeCV_regression_line=False,
RidgeCV_column=None,
regression_constant=False,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



```

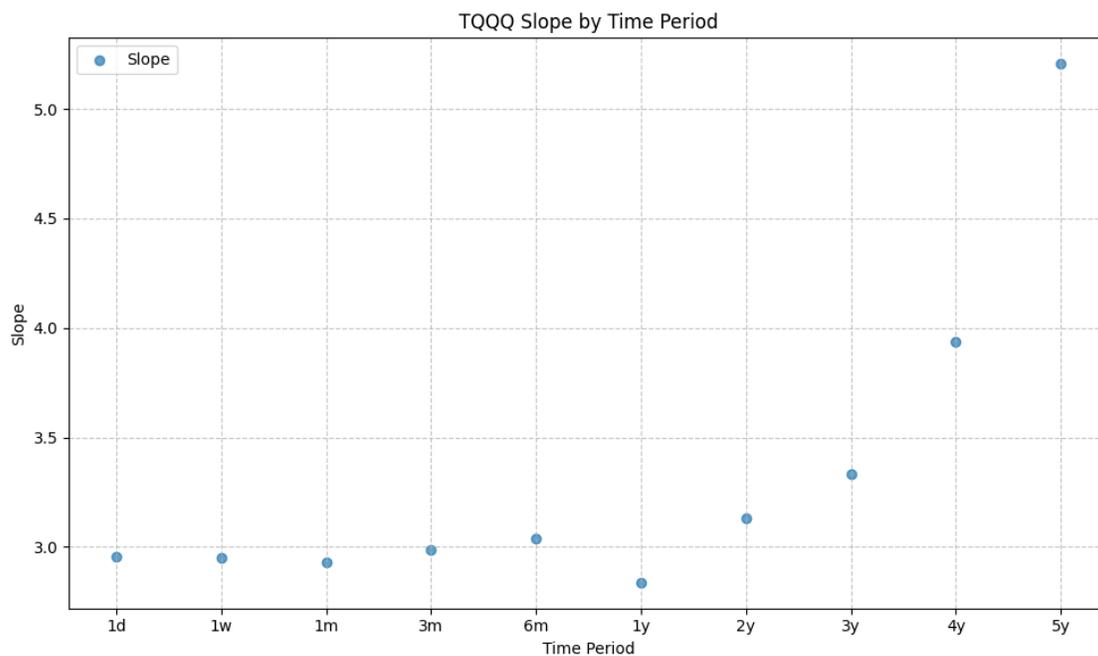
[32]: plot_scatter(
df=rolling_returns_stats,
x_plot_column="Period",
y_plot_columns=["Slope"],
title="TQQQ Slope by Time Period",
x_label="Time Period",
)

```

```

x_format="String",
x_format_decimal_places=0,
x_tick_spacing=1,
x_tick_rotation=0,
y_label="Slope",
y_format="Decimal",
y_format_decimal_places=1,
y_tick_spacing="Auto",
y_tick_rotation=0,
plot_OLS_regression_line=False,
OLS_column=None,
plot_Ridge_regression_line=False,
Ridge_column=None,
plot_RidgeCV_regression_line=False,
RidgeCV_column=None,
regression_constant=False,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



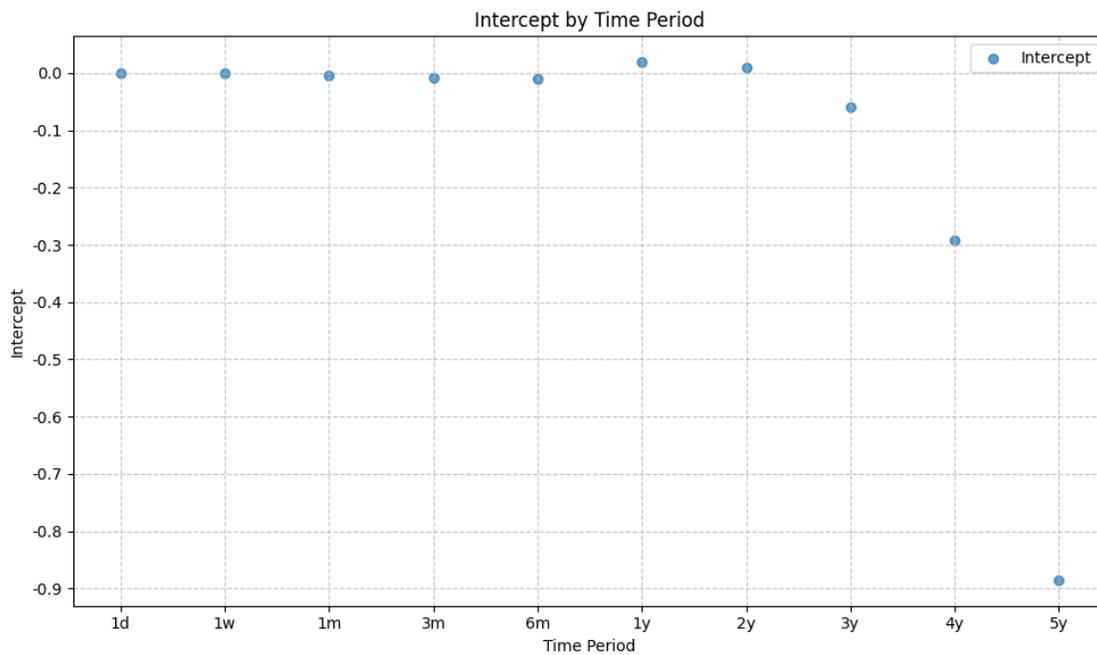
```

[33]: plot_scatter(
    df=rolling_returns_stats,
    x_plot_column="Period",

```

```
y_plot_columns=["Intercept"],
title="Intercept by Time Period",
x_label="Time Period",
x_format="String",
x_format_decimal_places=0,
x_tick_spacing=1,
x_tick_rotation=0,
y_label="Intercept",
y_format="Decimal",
y_format_decimal_places=1,
y_tick_spacing="Auto",
y_tick_rotation=0,
plot_OLS_regression_line=False,
OLS_column=None,
plot_Ridge_regression_line=False,
Ridge_column=None,
plot_RidgeCV_regression_line=False,
RidgeCV_column=None,
regression_constant=False,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
```

)



```
[34]: pandas_set_decimal_places(3)
display(rolling_returns_stats.set_index("Period"))
```

Period	Intercept	Slope	R_Squared	Skew	Average Upside Beta	\
1d	-0.000	2.955	0.999	NaN		2.957
1w	-0.001	2.952	0.994	NaN		2.553
1m	-0.004	2.931	0.982	NaN		2.209
3m	-0.008	2.985	0.958	NaN		1.994
6m	-0.010	3.040	0.916	-8.733		1.485
1y	0.019	2.837	0.880	NaN		1.222
2y	0.010	3.131	0.849	36.154		1.393
3y	-0.060	3.332	0.804	NaN		-0.091
4y	-0.292	3.934	0.781	19.554		1.760
5y	-0.885	5.205	0.743	43.021		2.433

Period	Average Downside Beta	Asymmetry	Return_Deviation_From_3x
1d	NaN	NaN	-0.045
1w	NaN	NaN	-0.048
1m	NaN	NaN	-0.069
3m	-inf	inf	-0.015
6m	5.416	-3.931	0.040
1y	-inf	inf	-0.163
2y	12.341	-10.948	0.131
3y	-inf	inf	0.332
4y	7.211	-5.452	0.934
5y	11.479	-9.046	2.205

This is very interesting. Up to 1 year, there is minimal difference between the mean TQQQ 1 year rolling return and the hypothetical 3x leverage, with an R^2 of greater than 0.9.

However, as we extend the time period, we see that

- The “leverage factor” increases significantly, resulting in a deviation from the perfect 3x leverage.
- The intercept also begins to deviate significantly from 0.

The above highlight the impact of volatility magnification over longer time horizons. This phenomenon is happening likely due to the positive returns that QQQ has achieved over the past 15 years - resulting in TQQQ compounding at a much higher rate than 3x - but it may and likely is not exhibited by other 3x leveraged ETFs that have not had the same positive return profile as QQQ.

With the above results, the next logical question is, when is the opportune time to buy a 3x leveraged ETF like TQQQ? To answer this, we will look at the drawdown levels of TQQQ and the subsequent returns over various time horizons.

0.4.8 Rolling Returns Following Drawdowns (QQQ & TQQQ)

We will identify the drawdown levels of TQQQ and then look at the subsequent rolling returns over various time horizons.

```
[35]: # Copy DataFrame
qqq_tqqq_extrap_future = qqq_tqqq_extrap.copy()

# Create a list of drawdown levels to analyze
drawdown_levels = [-0.10, -0.20, -0.30, -0.40, -0.50, -0.60, -0.70, -0.80]

# Shift the rolling return columns by the number of days in the rolling window
↳to get the returns following the drawdown
for etf in etfs:
    for period_name, window in rolling_windows.items():
        qqq_tqqq_extrap_future[f"{etf}_Rolling_Future_Return_{period_name}"] =
↳qqq_tqqq_extrap_future[f"{etf}_Rolling_Return_{period_name}"].shift(-window)
```

Now, we can analyze the future rolling returns following specific drawdown levels:

```
[36]: # Create a dataframe to hold rolling returns stats
rolling_returns_drawdown_stats = pd.DataFrame()

for drawdown in drawdown_levels:

    for period_name, window in rolling_windows.items():

        try:
            plot_histogram(
                ↳
↳df=qqq_tqqq_extrap_future[qqq_tqqq_extrap_future["TQQQ_Drawdown"] <=
↳drawdown],
                plot_columns=[f"QQQ_Rolling_Future_Return_{period_name}",
↳f"TQQQ_Rolling_Future_Return_{period_name}"],
                title=f"QQQ & TQQQ {period_name} Rolling Future Returns Post
↳{drawdown} TQQQ Drawdown",
                x_label="Rolling Return",
                x_tick_spacing="Auto",
                x_tick_rotation=30,
                y_label="# Of Datapoints",
                y_tick_spacing="Auto",
                y_tick_rotation=0,
                grid=True,
                legend=True,
                export_plot=False,
                plot_file_name=None,
            )
```

```

plot_scatter(
  ␣
↳df=qqq_tqqq_extrap_future[qqq_tqqq_extrap_future["TQQQ_Drawdown"] <=␣
↳drawdown],
  x_plot_column=f"QQQ_Rolling_Future_Return_{period_name}",
  y_plot_columns=[f"TQQQ_Rolling_Future_Return_{period_name}"],
  title=f"QQQ & TQQQ {period_name} Rolling Future Returns Post␣
↳{drawdown} TQQQ Drawdown",
  x_label="QQQ Rolling Return",
  x_format="Decimal",
  x_format_decimal_places=2,
  x_tick_spacing="Auto",
  x_tick_rotation=30,
  y_label="TQQQ Rolling Return",
  y_format="Decimal",
  y_format_decimal_places=2,
  y_tick_spacing="Auto",
  y_tick_rotation=0,
  plot_OLS_regression_line=True,
  OLS_column=f"TQQQ_Rolling_Future_Return_{period_name}",
  plot_Ridge_regression_line=False,
  Ridge_column=None,
  plot_RidgeCV_regression_line=True,
  RidgeCV_column=f"TQQQ_Rolling_Future_Return_{period_name}",
  regression_constant=True,
  grid=True,
  legend=True,
  export_plot=False,
  plot_file_name=None,
)

# Run OLS regression with statsmodels
model = run_linear_regression(
  ␣
↳df=qqq_tqqq_extrap_future[qqq_tqqq_extrap_future["TQQQ_Drawdown"] <=␣
↳drawdown],
  x_plot_column=f"QQQ_Rolling_Future_Return_{period_name}",
  y_plot_column=f"TQQQ_Rolling_Future_Return_{period_name}",
  regression_model="OLS-statsmodels",
  regression_constant=True,
)
print(model.summary())

# Filter by drawdown
drawdown_filter =␣
↳qqq_tqqq_extrap_future[qqq_tqqq_extrap_future["TQQQ_Drawdown"] <= drawdown]

```

```

        # Filter by period, drop rows with missing values
        future_filter =
↪drawdown_filter[[f"TQQQ_Rolling_Future_Return_{period_name}"]].dropna()

        # Find length of future dataframe
        future_length = len(future_filter)

        # Find length of future dataframe where return is positive
        positive_future_length =
↪len(future_filter[future_filter[f"TQQQ_Rolling_Future_Return_{period_name}"]
↪> 0])

        # Calculate percentage of future returns that are positive
        positive_future_percentage = (positive_future_length /
↪future_length) if future_length > 0 else 0

        # Add the regression results to the rolling returns stats dataframe
        intercept = model.params[0]
        # intercept_pvalue = model.pvalues[0] # p-value for Intercept
        slope = model.params[1]
        # slope_pvalue = model.pvalues[1] # p-value for Slope
        r_squared = model.rsquared

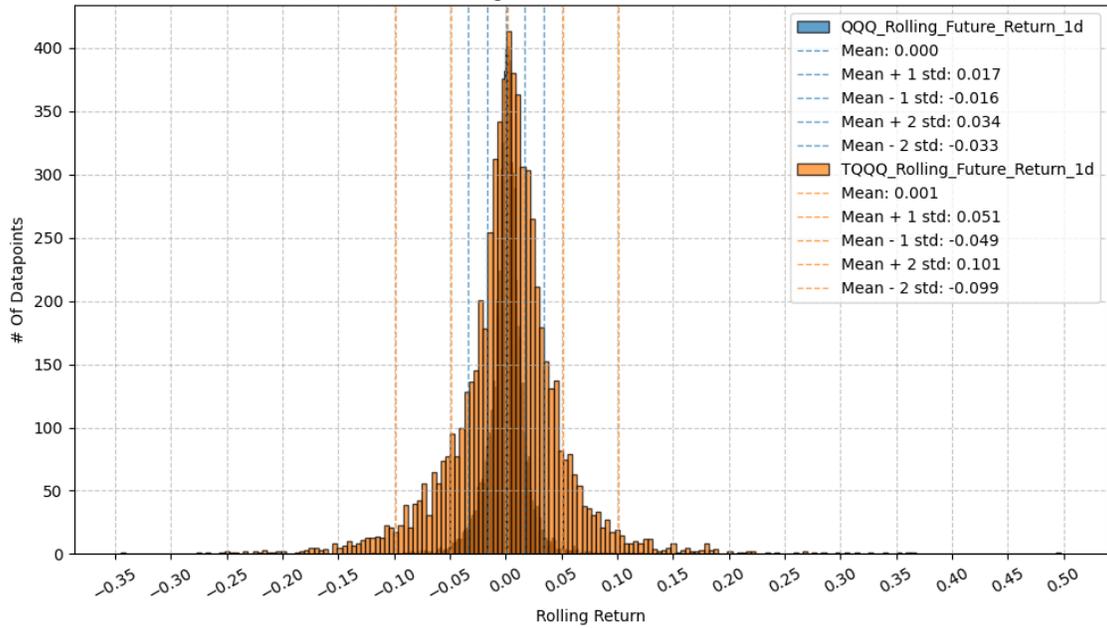
        rolling_returns_slope_int = pd.DataFrame({
            "Drawdown": drawdown,
            "Period": period_name,
            "Intercept": [intercept],
            # "Intercept_PValue": [intercept_pvalue],
            "Slope": [slope],
            # "Slope_PValue": [slope_pvalue],
            "R_Squared": [r_squared],
            "Positive_Future_Percentage": [positive_future_percentage],
        })

        rolling_returns_drawdown_stats = pd.
↪concat([rolling_returns_drawdown_stats, rolling_returns_slope_int])

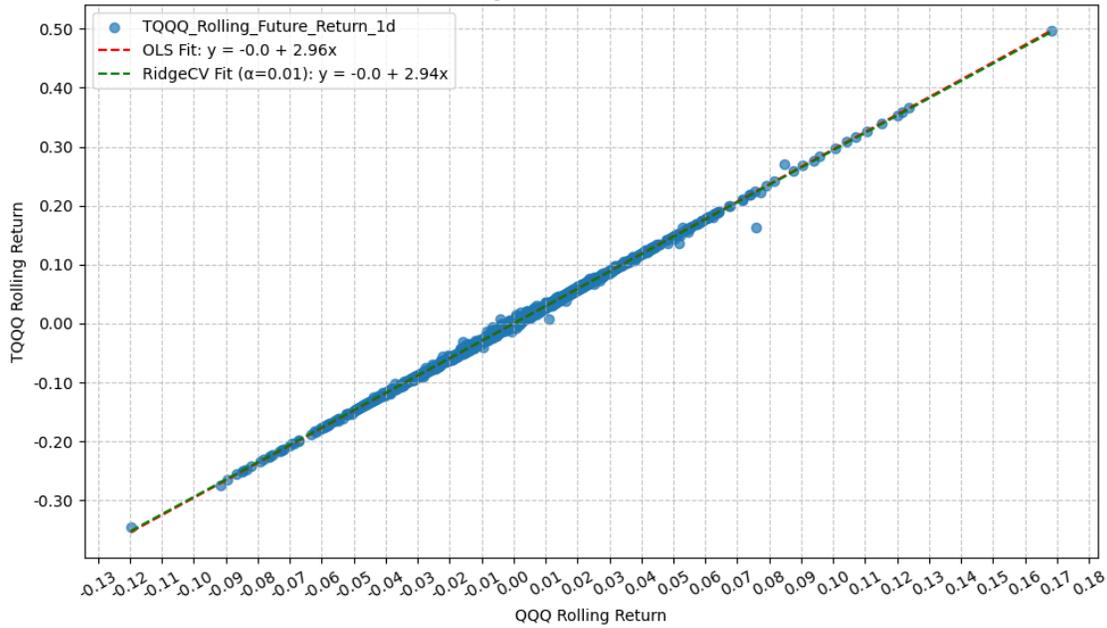
    except:
        print(f"Not enough data points for drawdown level {drawdown} and
↪period {period_name} to run regression.")

```

QQQ & TQQQ 1d Rolling Future Returns Post -0.1 TQQQ Drawdown



QQQ & TQQQ 1d Rolling Future Returns Post -0.1 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1d R-squared:

```

0.999
Model: OLS Adj. R-squared:
0.999
Method: Least Squares F-statistic:
6.825e+06
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:15 Log-Likelihood:
33542.
No. Observations: 6648 AIC:
-6.708e+04
Df Residuals: 6646 BIC:
-6.707e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-5.203e-05	1.91e-05	-2.721	0.007
-8.95e-05 -1.45e-05				
QQQ_Rolling_Future_Return_1d	2.9551	0.001	2612.377	0.000
2.953 2.957				

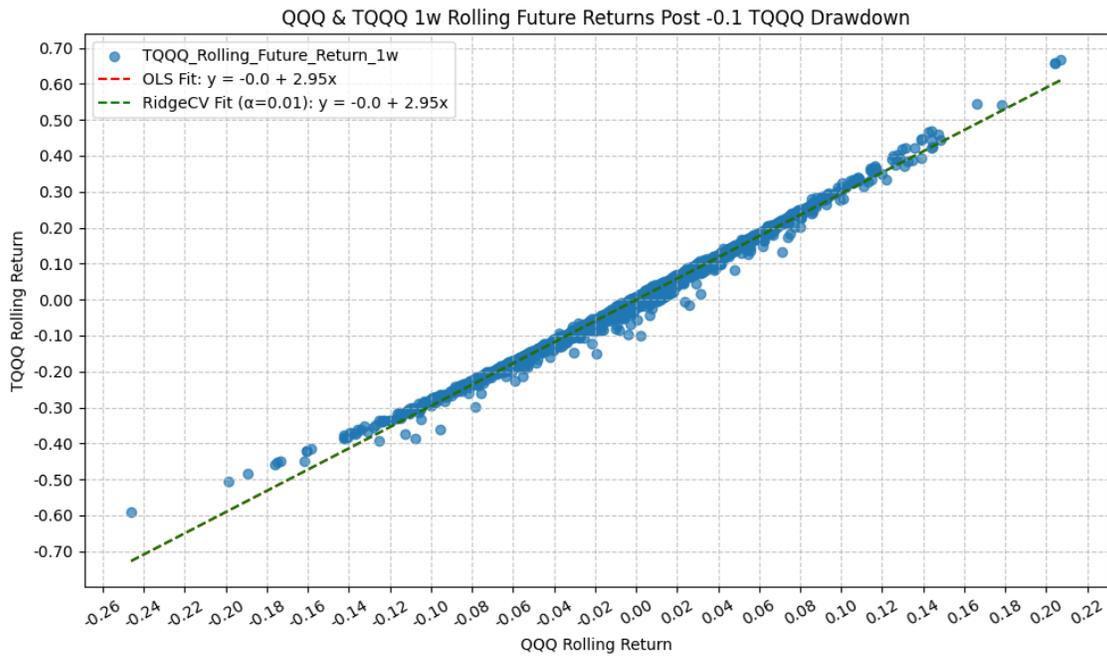
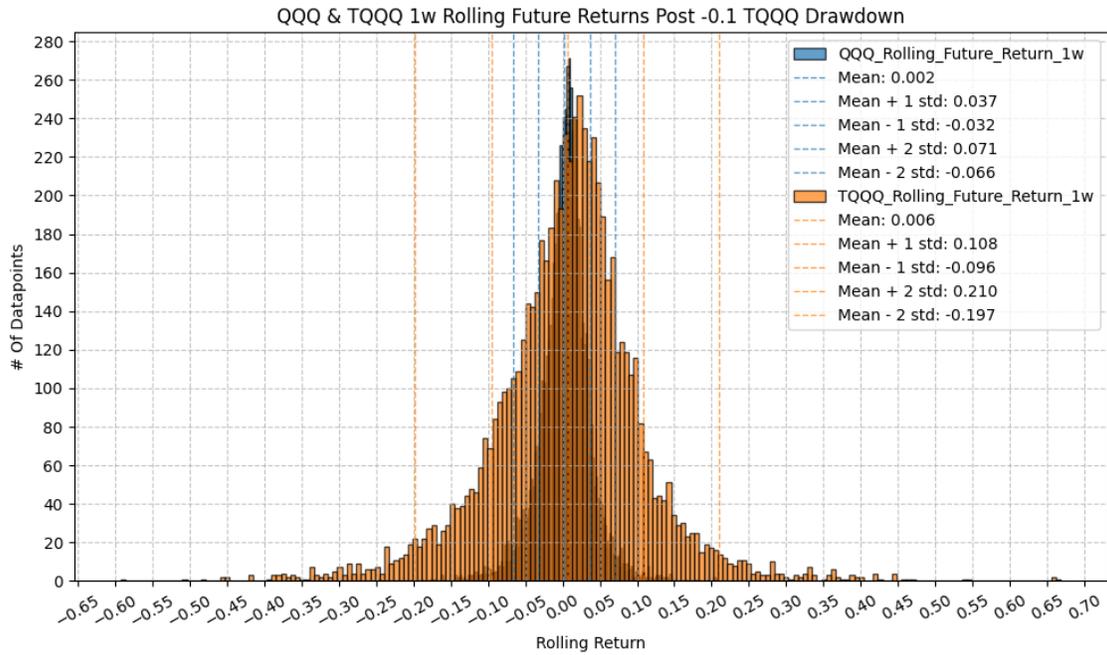
```

=====
Omnibus: 9913.687 Durbin-Watson: 2.565
Prob(Omnibus): 0.000 Jarque-Bera (JB): 41109927.245
Skew: -8.187 Prob(JB): 0.00
Kurtosis: 387.894 Cond. No. 59.2
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1w R-squared:

```

0.994
Model: OLS Adj. R-squared:
0.994
Method: Least Squares F-statistic:
1.088e+06
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:16 Log-Likelihood:
22709.
No. Observations: 6644 AIC:
-4.541e+04
Df Residuals: 6642 BIC:
-4.540e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0008	9.76e-05	-8.221	0.000
-0.001 -0.001				
QQQ_Rolling_Future_Return_1w	2.9526	0.003	1043.242	0.000
2.947 2.958				

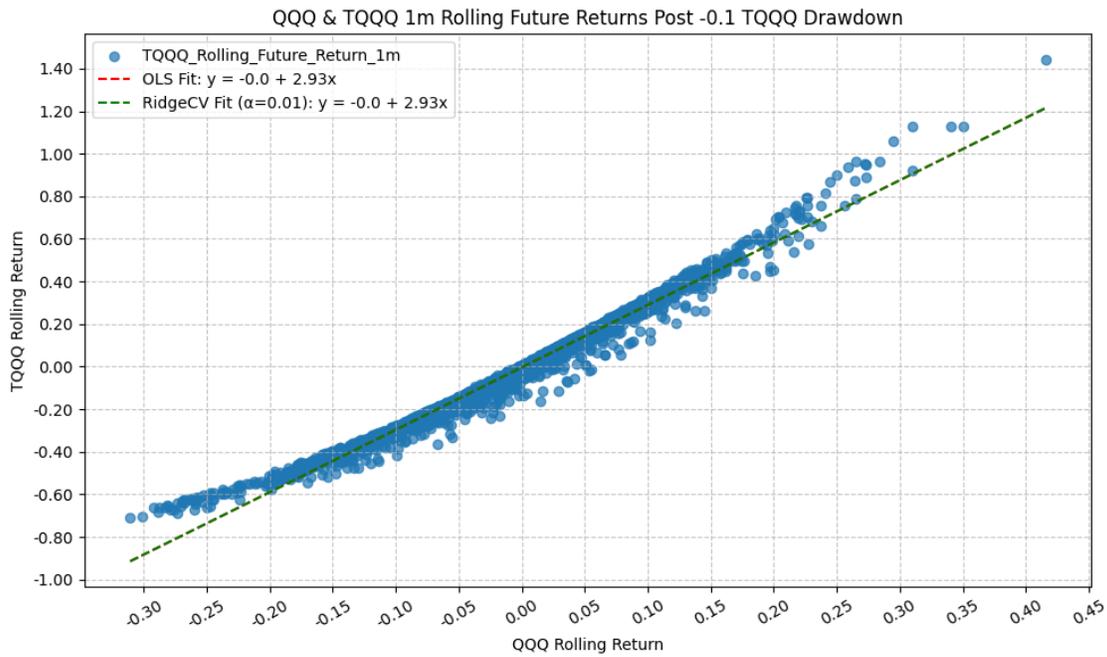
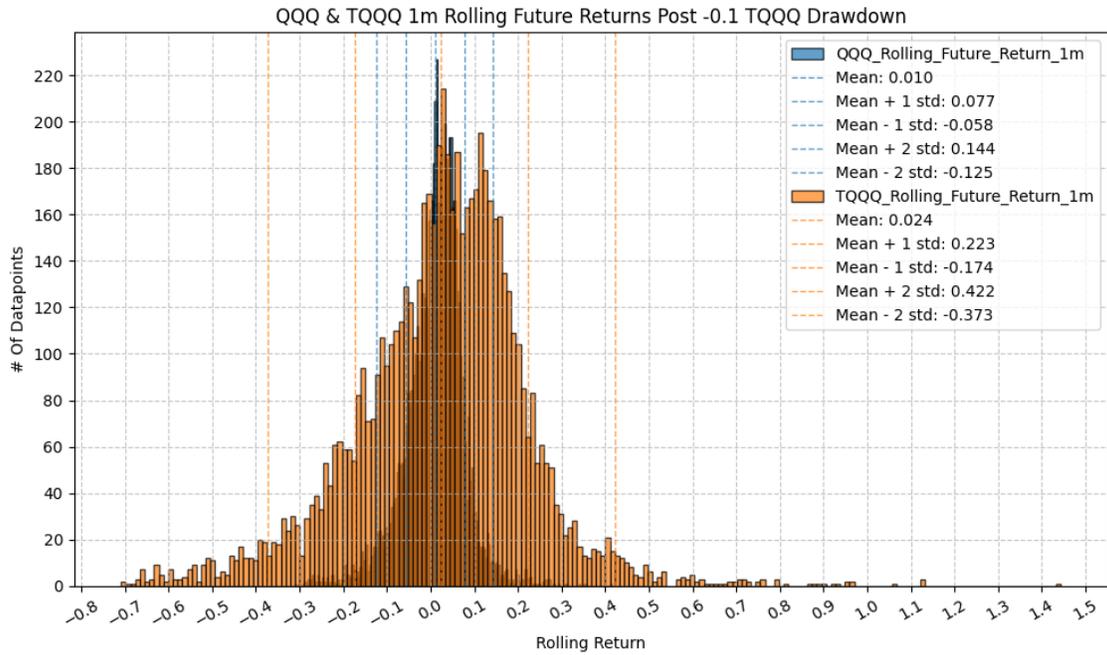
```

=====
Omnibus: 2701.400 Durbin-Watson: 0.939
Prob(Omnibus): 0.000 Jarque-Bera (JB): 586368.143
Skew: -0.779 Prob(JB): 0.00
Kurtosis: 48.997 Cond. No. 29.1
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1m R-squared:

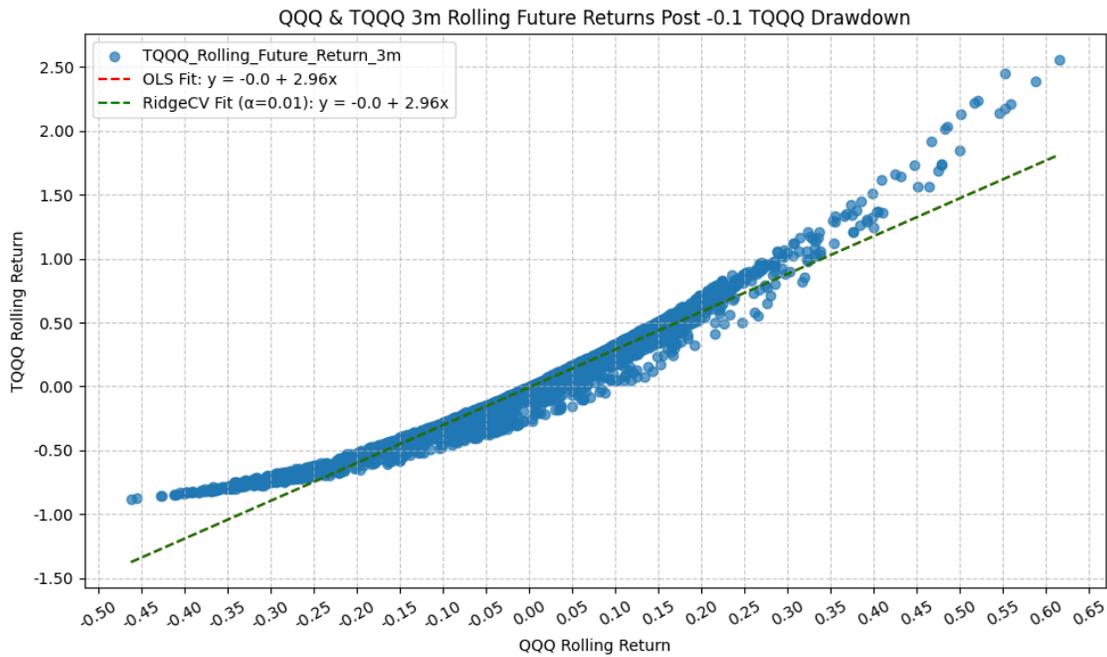
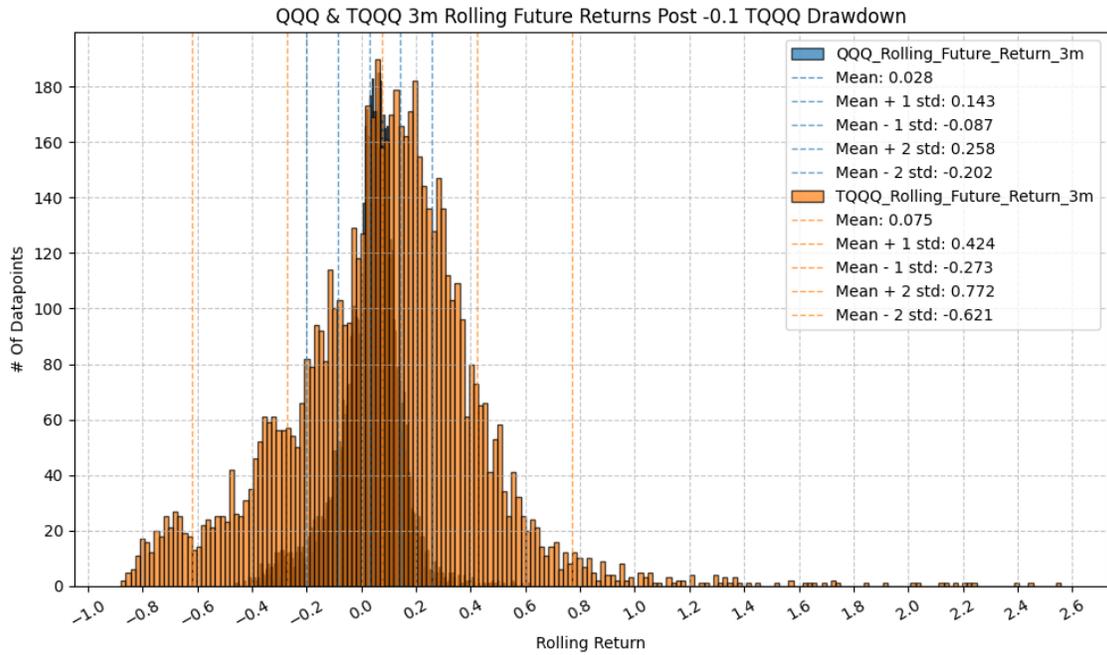
```

0.982
Model:                                OLS   Adj. R-squared:
0.982
Method:                                Least Squares   F-statistic:
3.703e+05
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:17   Log-Likelihood:
14696.
No. Observations:                    6628   AIC:
-2.939e+04
Df Residuals:                        6626   BIC:
-2.937e+04
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0034   0.000   -10.530   0.000
-0.004   -0.003
QQQ_Rolling_Future_Return_1m    2.9304   0.005   608.513   0.000
2.921   2.940
=====
Omnibus:                          1679.490   Durbin-Watson:                0.312
Prob(Omnibus):                     0.000   Jarque-Bera (JB):             80862.122
Skew:                               0.393   Prob(JB):                     0.00
Kurtosis:                          20.093   Cond. No.                     14.9
=====

```

Notes:

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



OLS Regression Results

=====

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3m R-squared:

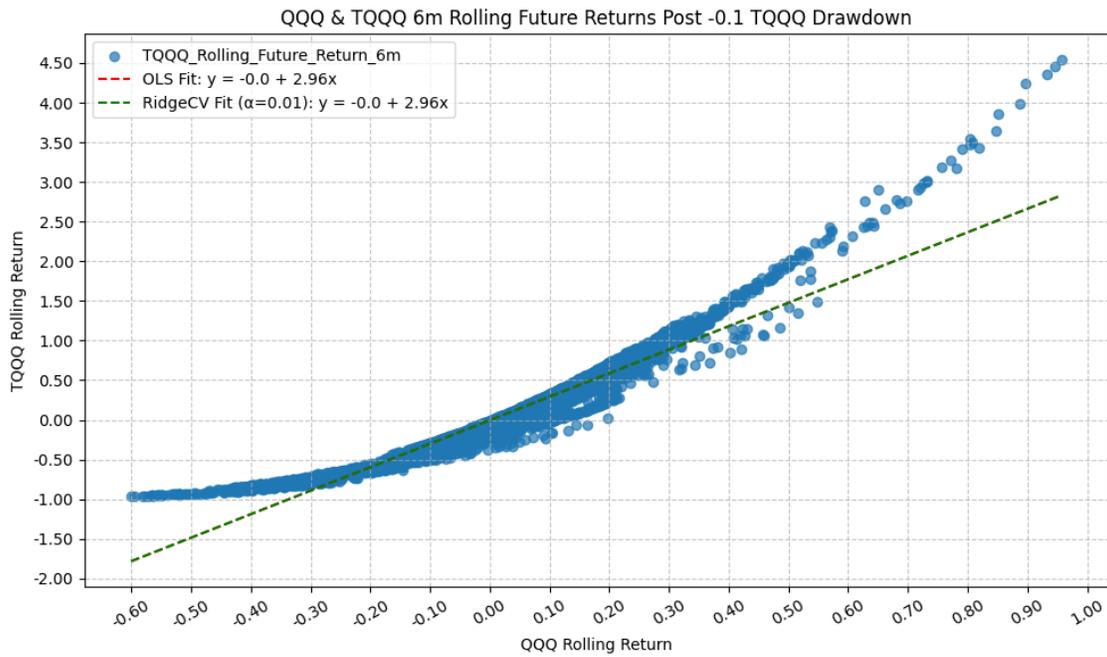
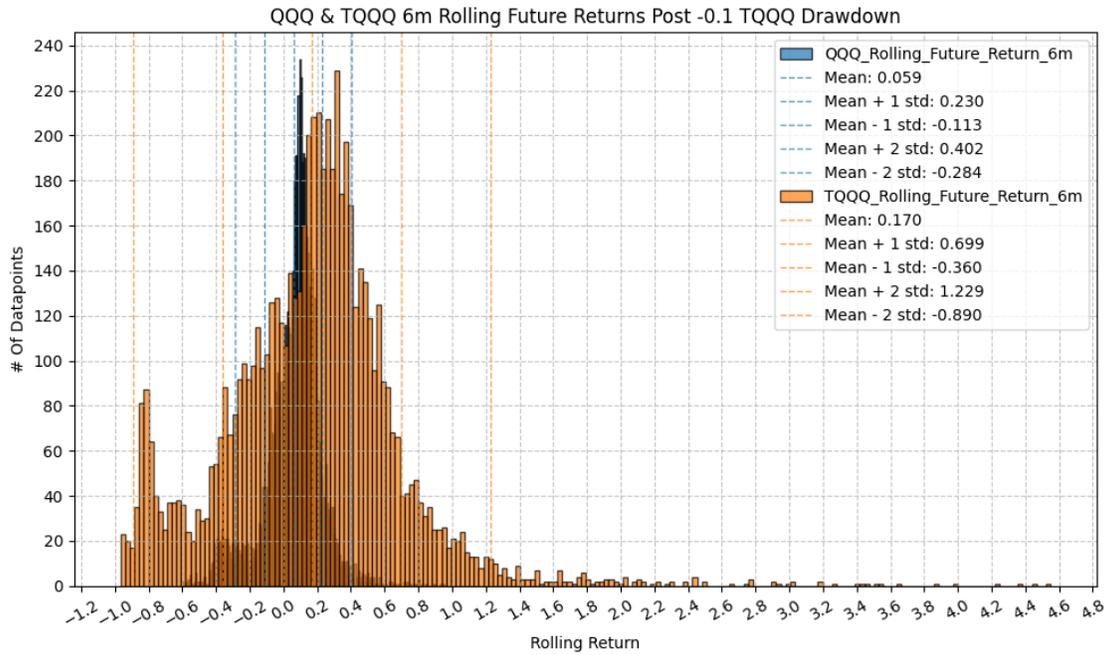
```

0.957
Model:                                OLS   Adj. R-squared:
0.957
Method:                                Least Squares   F-statistic:
1.458e+05
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:18   Log-Likelihood:
7947.5
No. Observations:                    6586   AIC:
-1.589e+04
Df Residuals:                        6584   BIC:
-1.588e+04
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0076   0.001   -8.260   0.000
-0.009   -0.006
QQQ_Rolling_Future_Return_3m    2.9582   0.008   381.884   0.000
2.943   2.973
=====
Omnibus:                          3401.457   Durbin-Watson:                0.113
Prob(Omnibus):                     0.000   Jarque-Bera (JB):             86281.946
Skew:                               1.942   Prob(JB):                     0.00
Kurtosis:                           20.301   Cond. No.                     8.69
=====

```

Notes:

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



OLS Regression Results

=====

=====

Dep. Variable: TQQQ_Rolling_Future_Return_6m R-squared:

```

0.921
Model: OLS Adj. R-squared:
0.921
Method: Least Squares F-statistic:
7.566e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:20 Log-Likelihood:
3154.5
No. Observations: 6523 AIC:
-6305.
Df Residuals: 6521 BIC:
-6291.
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

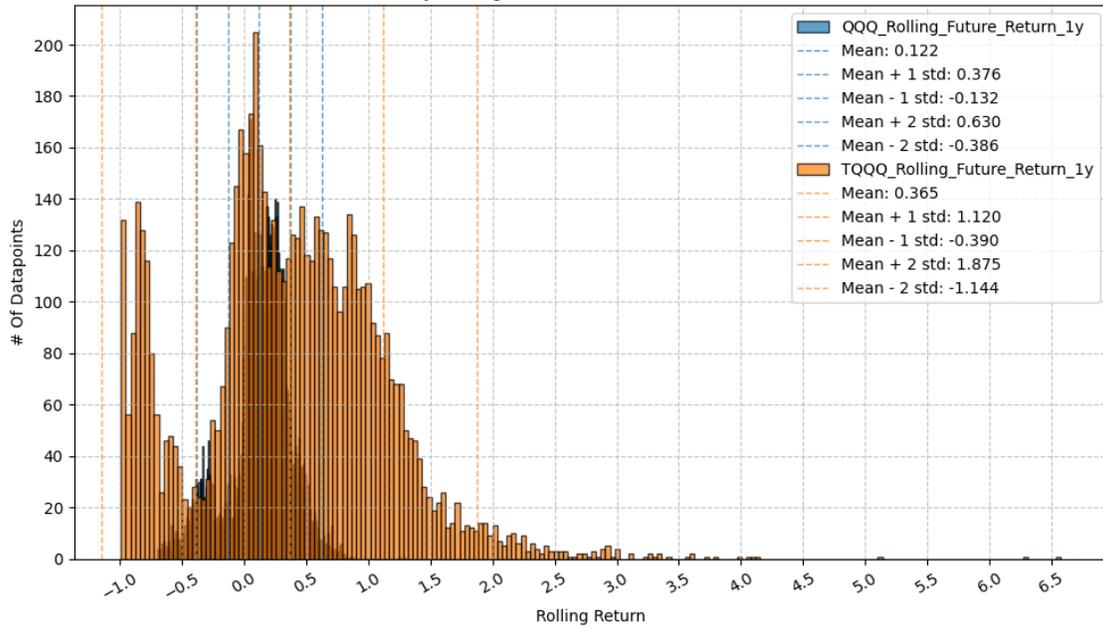
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0042	0.002	-2.132	0.033
-0.008 -0.000				
QQQ_Rolling_Future_Return_6m	2.9626	0.011	275.060	0.000
2.941 2.984				
=====				
Omnibus:	4154.198	Durbin-Watson:		0.065
Prob(Omnibus):	0.000	Jarque-Bera (JB):		100612.082
Skew:	2.647	Prob(JB):		0.00
Kurtosis:	21.498	Cond. No.		5.85
=====				

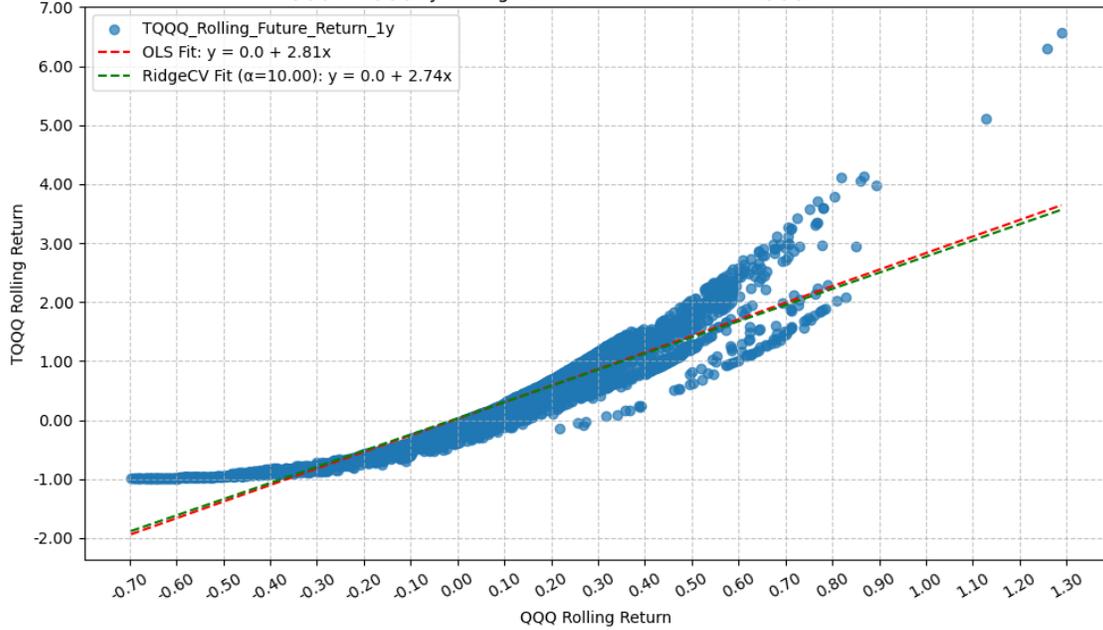
Notes:

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

QQQ & TQQQ 1y Rolling Future Returns Post -0.1 TQQQ Drawdown



QQQ & TQQQ 1y Rolling Future Returns Post -0.1 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1y R-squared:

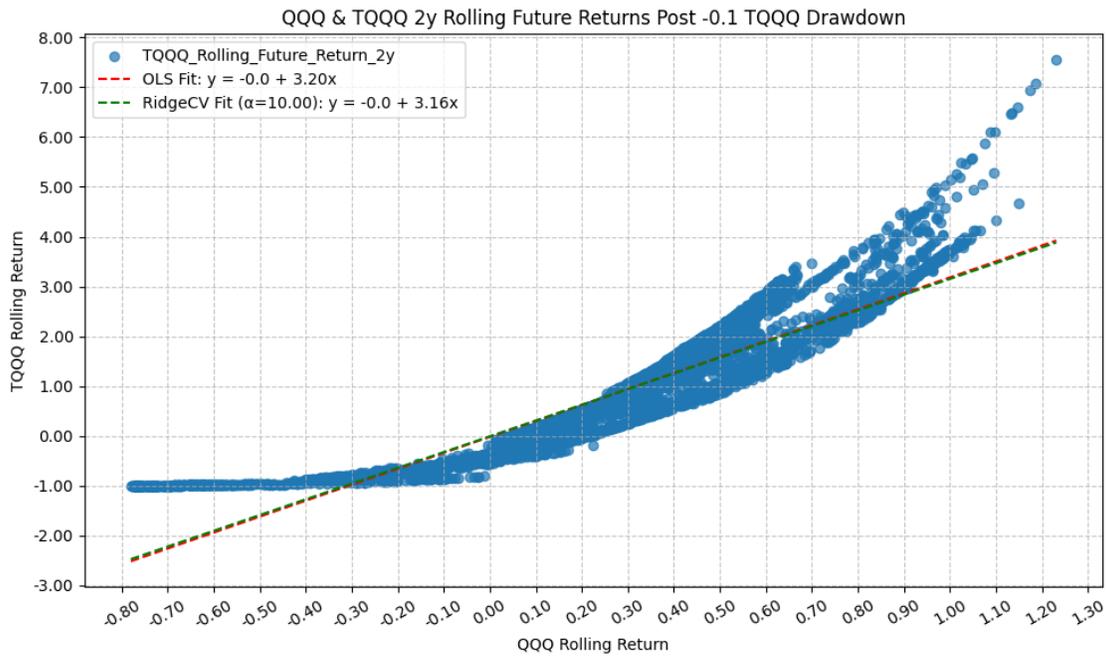
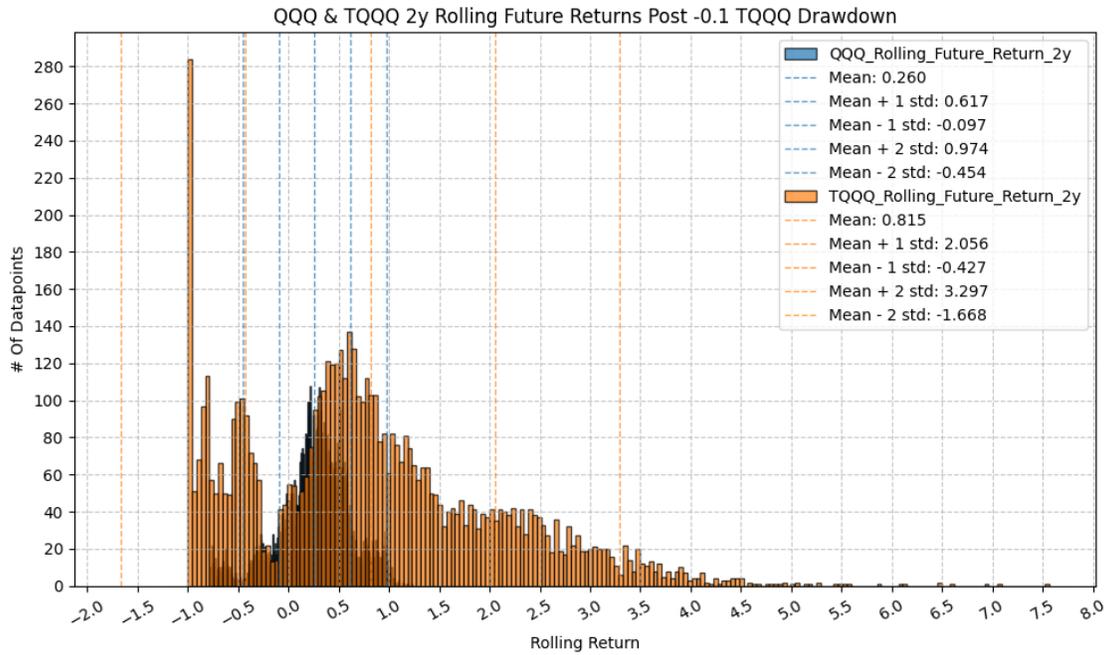
```

0.893
Model:                                OLS   Adj. R-squared:
0.893
Method:                               Least Squares   F-statistic:
5.326e+04
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:26:21   Log-Likelihood:
-135.51
No. Observations:                    6397   AIC:
275.0
Df Residuals:                        6395   BIC:
288.6
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            0.0228   0.003   6.654   0.000
0.016   0.030
QQQ_Rolling_Future_Return_1y    2.8089   0.012  230.784   0.000
2.785   2.833
=====
Omnibus:                         2631.338   Durbin-Watson:                0.052
Prob(Omnibus):                   0.000   Jarque-Bera (JB):            29220.801
Skew:                            1.657   Prob(JB):                    0.00
Kurtosis:                       12.932   Cond. No.                    4.00
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_2y R-squared:

```

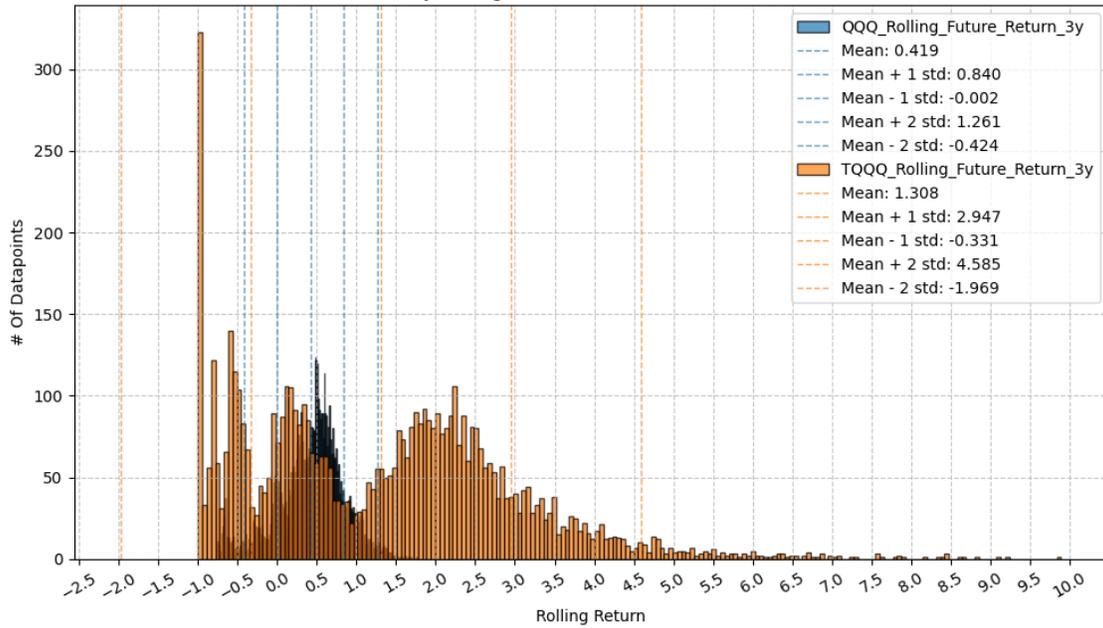
0.848
Model:                                OLS   Adj. R-squared:
0.848
Method:                                Least Squares   F-statistic:
3.426e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:22   Log-Likelihood:
-4260.2
No. Observations:                    6145   AIC:
8524.
Df Residuals:                        6143   BIC:
8538.
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                               -0.0188   0.008   -2.463   0.014
-0.034   -0.004
QQQ_Rolling_Future_Return_2y       3.2014   0.017   185.083   0.000
3.167   3.235
=====
Omnibus:                            1670.286   Durbin-Watson:                0.019
Prob(Omnibus):                       0.000   Jarque-Bera (JB):             4641.855
Skew:                                 1.436   Prob(JB):                     0.00
Kurtosis:                             6.143   Cond. No.                     3.02
=====

```

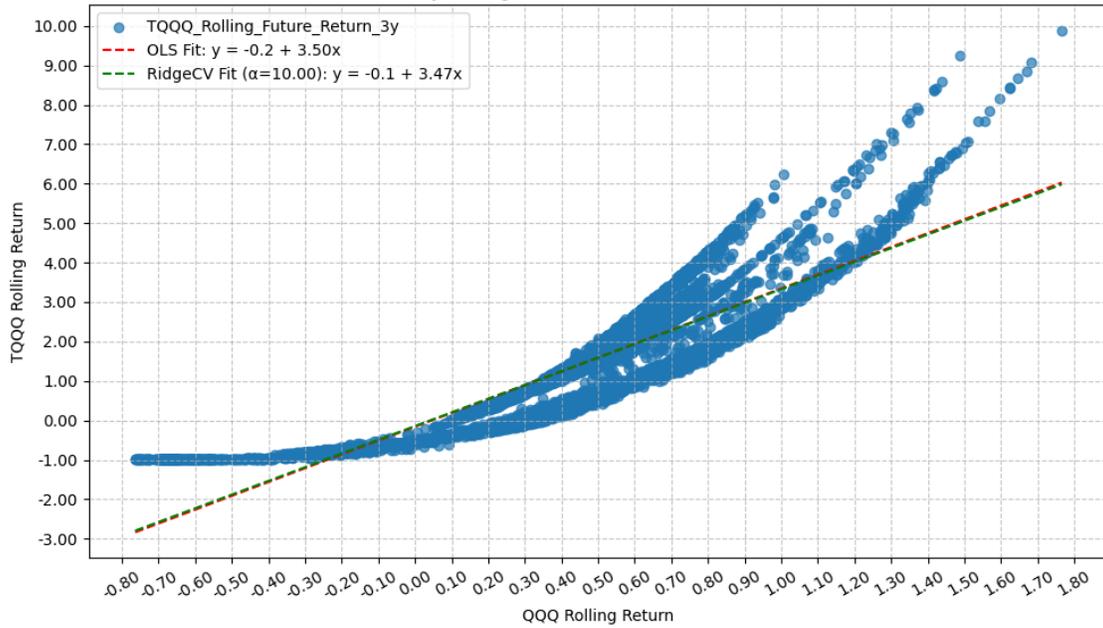
Notes:

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

QQQ & TQQQ 3y Rolling Future Returns Post -0.1 TQQQ Drawdown



QQQ & TQQQ 3y Rolling Future Returns Post -0.1 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3y R-squared:

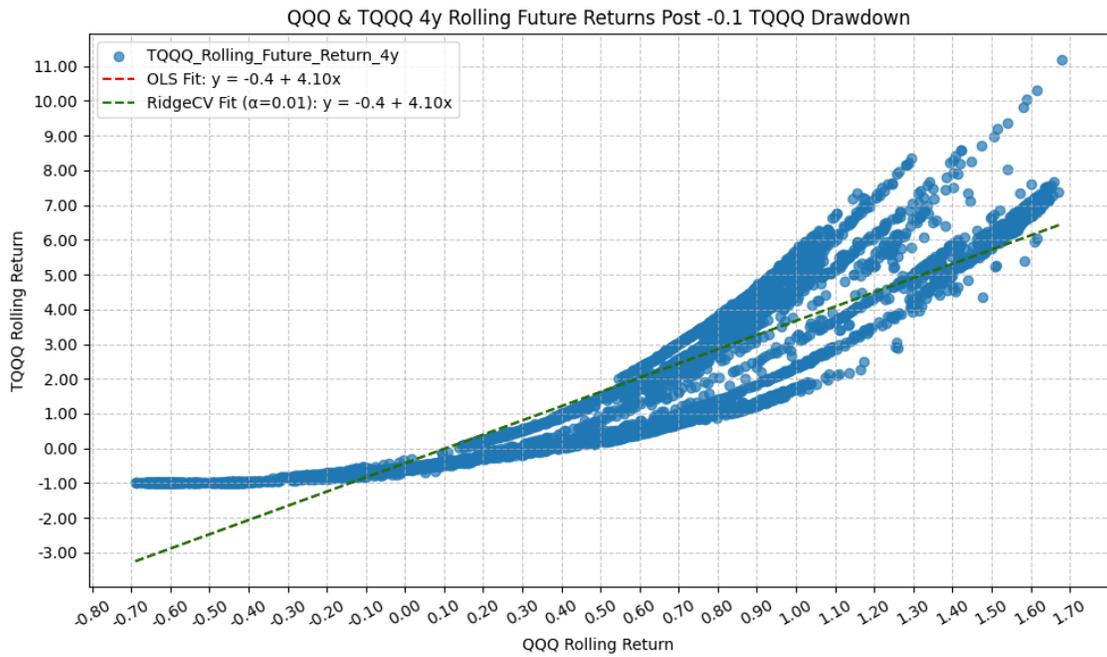
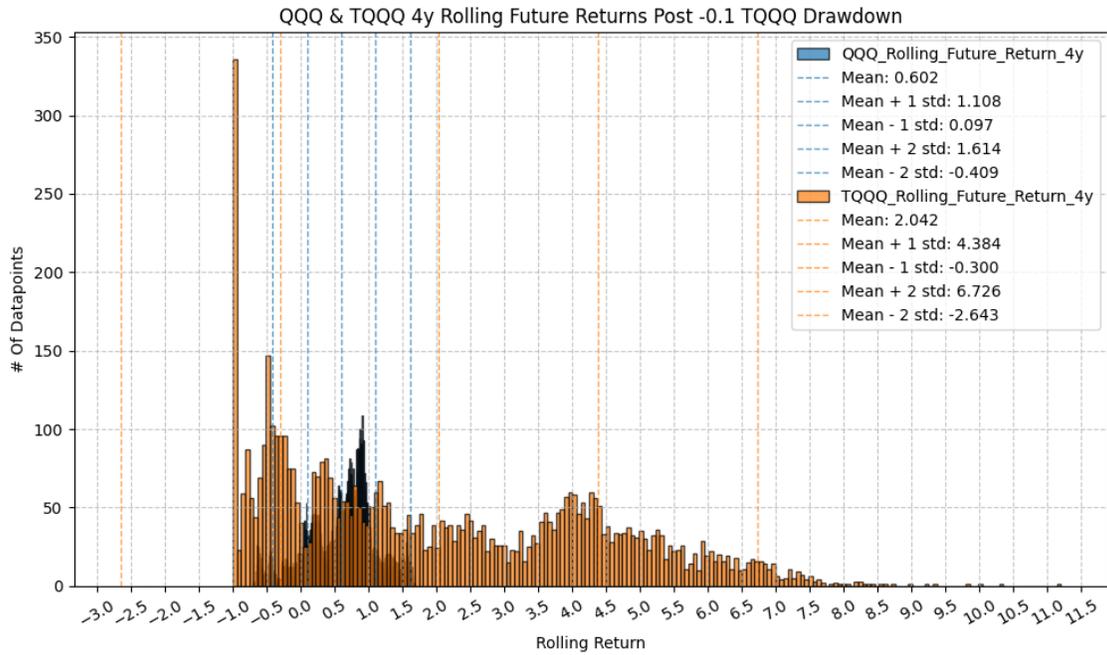
```

0.811
Model:                                OLS   Adj. R-squared:
0.811
Method:                                Least Squares   F-statistic:
2.522e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:23   Log-Likelihood:
-6367.9
No. Observations:                    5893   AIC:
1.274e+04
Df Residuals:                        5891   BIC:
1.275e+04
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.1590   0.013   -12.136   0.000
-0.185   -0.133
QQQ_Rolling_Future_Return_3y     3.5025   0.022   158.807   0.000
3.459   3.546
=====
Omnibus:                          868.866   Durbin-Watson:                0.015
Prob(Omnibus):                     0.000   Jarque-Bera (JB):            1529.067
Skew:                               0.959   Prob(JB):                     0.00
Kurtosis:                           4.595   Cond. No.                     2.86
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_4y R-squared:

```

0.783
Model: OLS Adj. R-squared:
0.783
Method: Least Squares F-statistic:
2.039e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:24 Log-Likelihood:
-8491.0
No. Observations: 5641 AIC:
1.699e+04
Df Residuals: 5639 BIC:
1.700e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

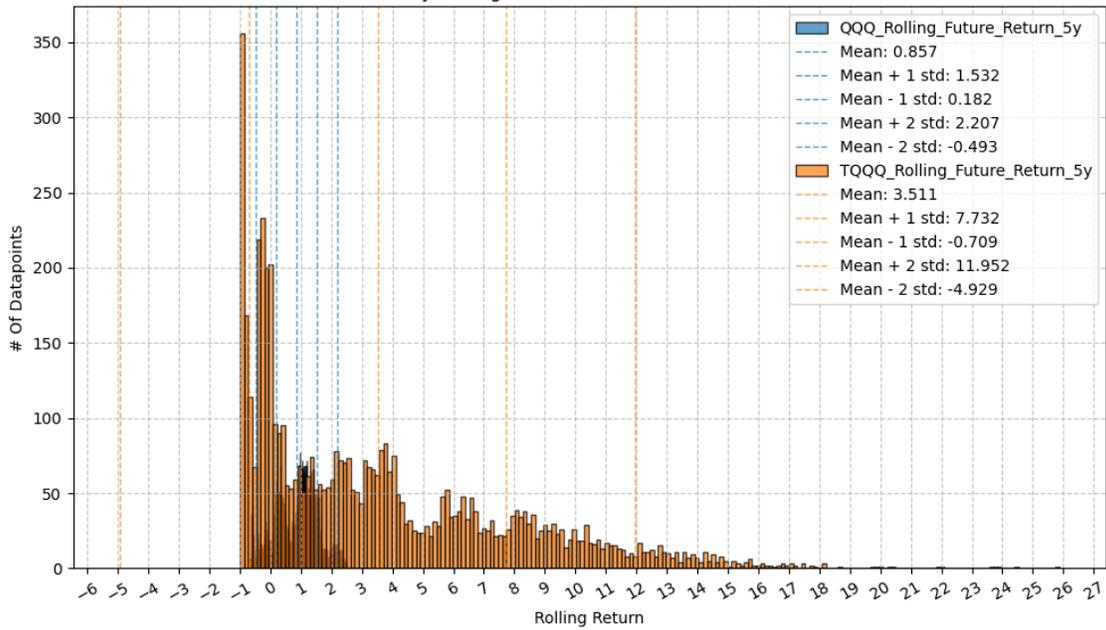
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.4268	0.023	-18.906	0.000
-0.471 -0.383				
QQQ_Rolling_Future_Return_4y	4.0976	0.029	142.777	0.000
4.041 4.154				
=====				
Omnibus:	125.491	Durbin-Watson:		0.010
Prob(Omnibus):	0.000	Jarque-Bera (JB):		78.475
Skew:	0.148	Prob(JB):		9.11e-18
Kurtosis:	2.504	Cond. No.		2.85
=====				

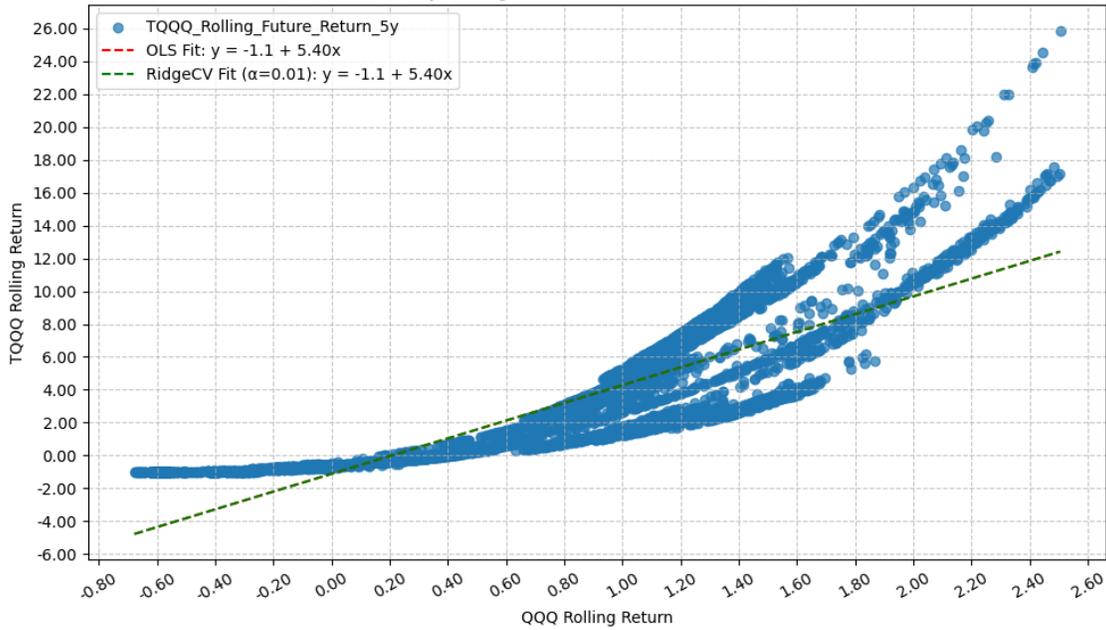
Notes:

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

QQQ & TQQQ 5y Rolling Future Returns Post -0.1 TQQQ Drawdown



QQQ & TQQQ 5y Rolling Future Returns Post -0.1 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_5y R-squared:

```

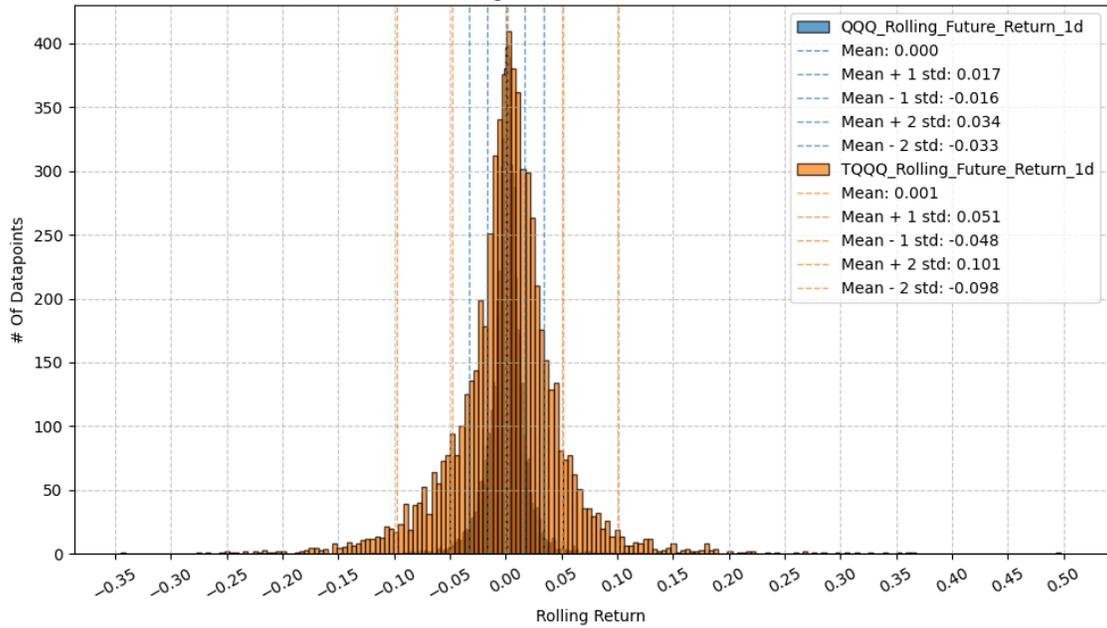
0.745
Model:                                OLS   Adj. R-squared:
0.745
Method:                               Least Squares   F-statistic:
1.578e+04
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:26:25   Log-Likelihood:
-11719.
No. Observations:                    5389   AIC:
2.344e+04
Df Residuals:                        5387   BIC:
2.345e+04
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -1.1137   0.047   -23.759   0.000
-1.206   -1.022
QQQ_Rolling_Future_Return_5y    5.3970   0.043   125.610   0.000
5.313   5.481
=====
Omnibus:                          275.950   Durbin-Watson:                0.009
Prob(Omnibus):                     0.000   Jarque-Bera (JB):            406.209
Skew:                              0.459   Prob(JB):                    6.21e-89
Kurtosis:                          3.983   Cond. No.                     2.90
=====

```

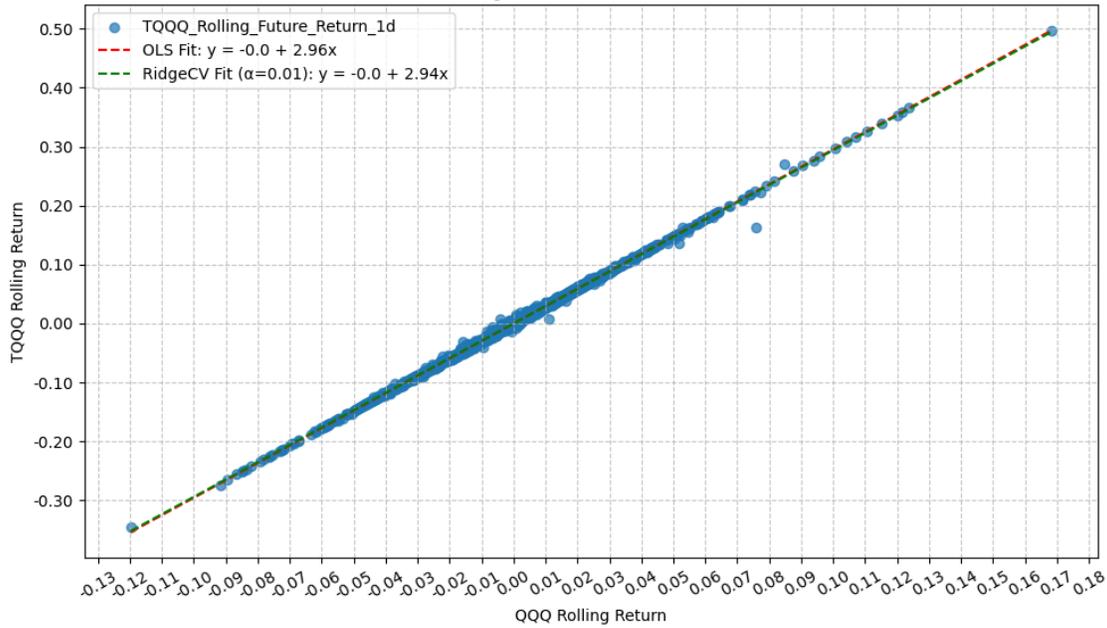
Notes:

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

QQQ & TQQQ 1d Rolling Future Returns Post -0.2 TQQQ Drawdown



QQQ & TQQQ 1d Rolling Future Returns Post -0.2 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1d R-squared:

```

0.999
Model: OLS Adj. R-squared:
0.999
Method: Least Squares F-statistic:
6.602e+06
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:27 Log-Likelihood:
33115.
No. Observations: 6571 AIC:
-6.623e+04
Df Residuals: 6569 BIC:
-6.621e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

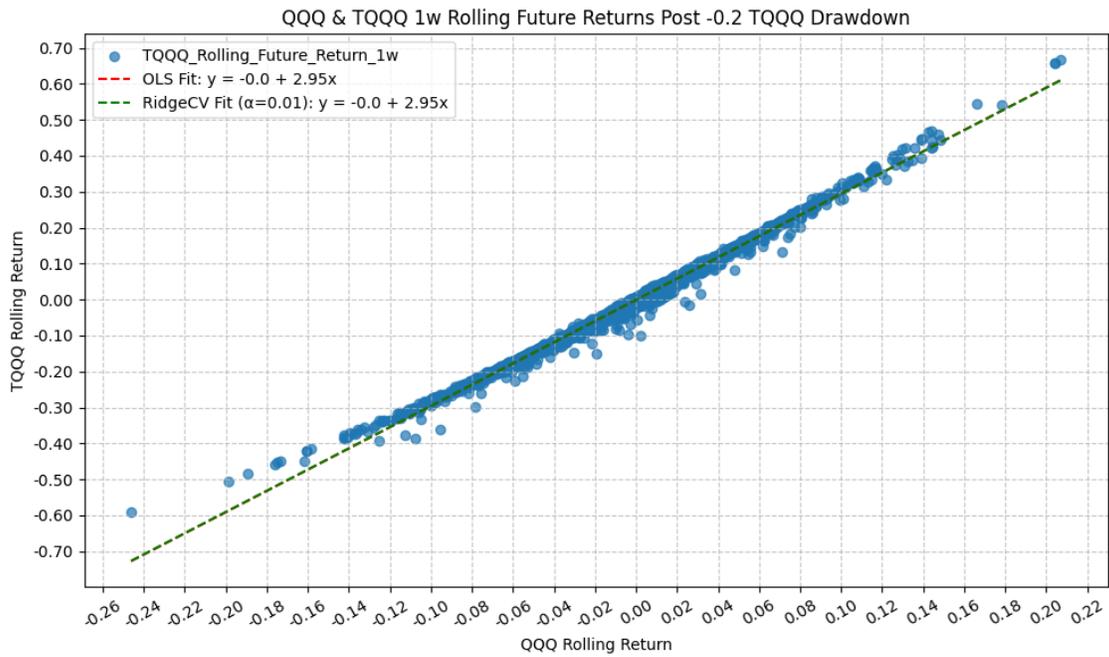
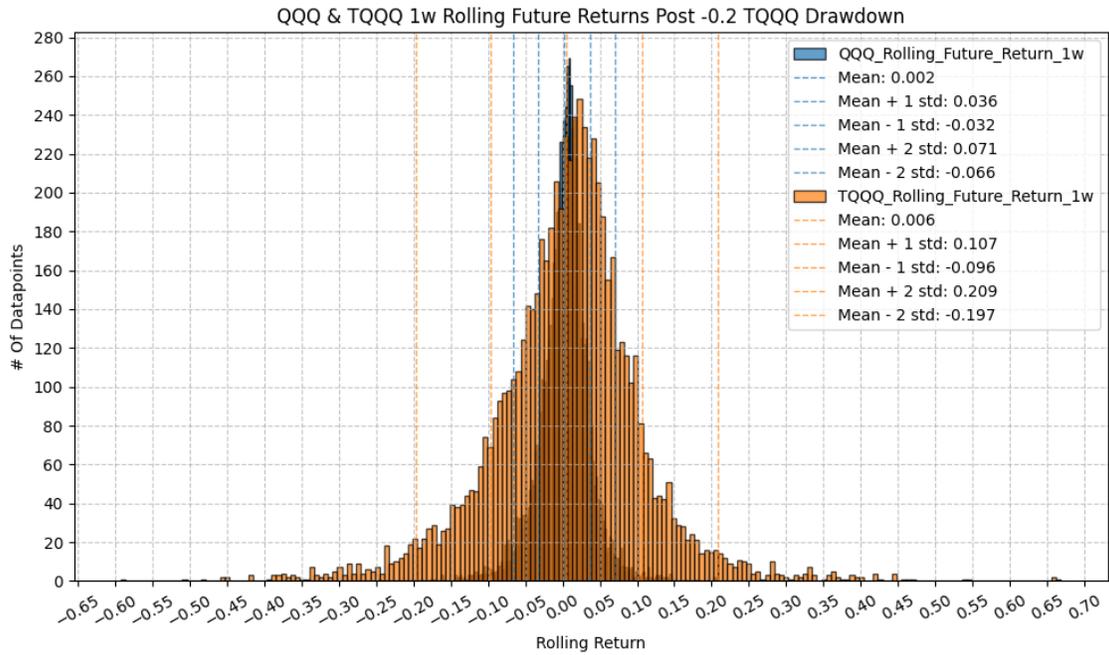
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-5.264e-05	1.93e-05	-2.721	0.007
-9.06e-05 -1.47e-05				
QQQ_Rolling_Future_Return_1d	2.9551	0.001	2569.475	0.000
2.953 2.957				
=====				
Omnibus:	9769.052	Durbin-Watson:		2.565
Prob(Omnibus):	0.000	Jarque-Bera (JB):		39689255.457
Skew:	-8.139	Prob(JB):		0.00
Kurtosis:	383.390	Cond. No.		59.5
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1w R-squared:

```

0.994
Model:                                OLS   Adj. R-squared:
0.994
Method:                               Least Squares   F-statistic:
1.069e+06
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:26:28   Log-Likelihood:
22453.
No. Observations:                     6567   AIC:
-4.490e+04
Df Residuals:                         6565   BIC:
-4.489e+04
Df Model:                              1
Covariance Type:                      nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0008	9.8e-05	-8.016	0.000
-0.001 -0.001				
QQQ_Rolling_Future_Return_1w	2.9517	0.003	1033.957	0.000
2.946 2.957				
=====				

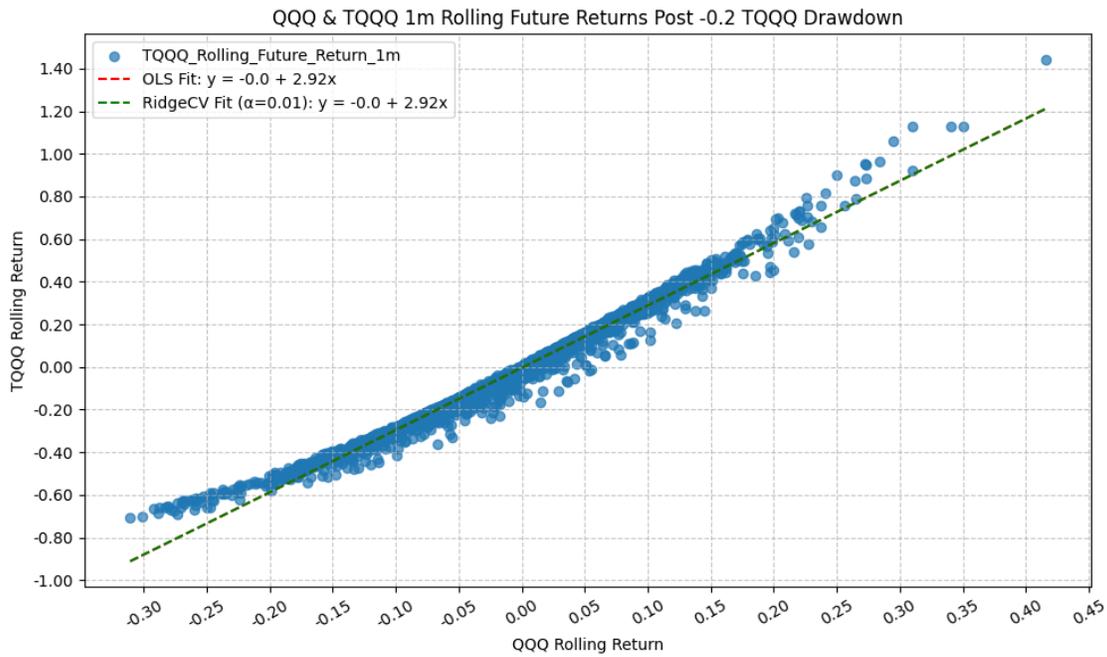
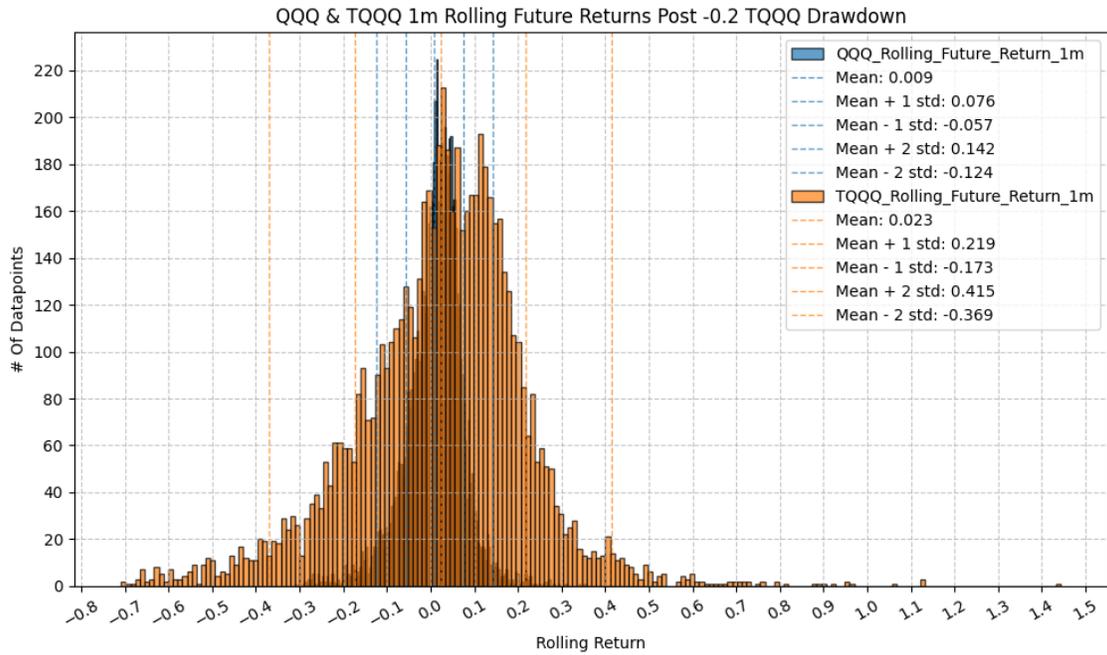
```

Omnibus:                             2705.152   Durbin-Watson:                0.933
Prob(Omnibus):                        0.000   Jarque-Bera (JB):            594917.588
Skew:                                  -0.803   Prob(JB):                     0.00
Kurtosis:                              49.601   Cond. No.                     29.2
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1m R-squared:

```

0.983
Model:                                OLS   Adj. R-squared:
0.983
Method:                                Least Squares   F-statistic:
3.703e+05
Date:                                   Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                   14:26:29   Log-Likelihood:
14653.
No. Observations:                      6551   AIC:
-2.930e+04
Df Residuals:                          6549   BIC:
-2.929e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0035	0.000	-10.801	0.000
-0.004 -0.003				
QQQ_Rolling_Future_Return_1m	2.9224	0.005	608.511	0.000
2.913 2.932				

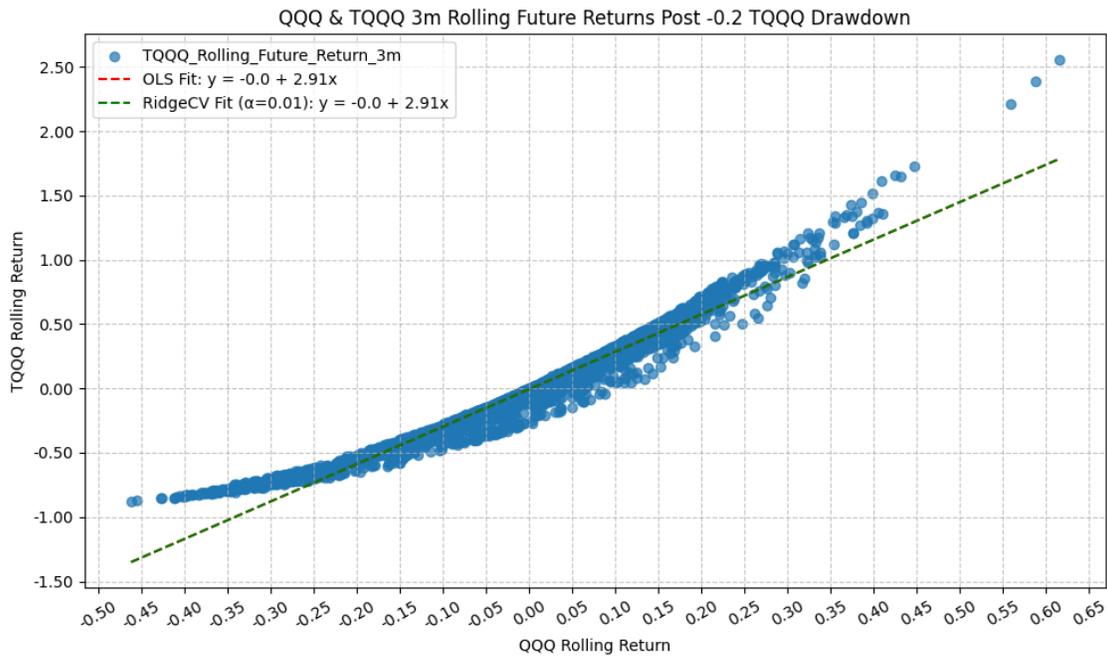
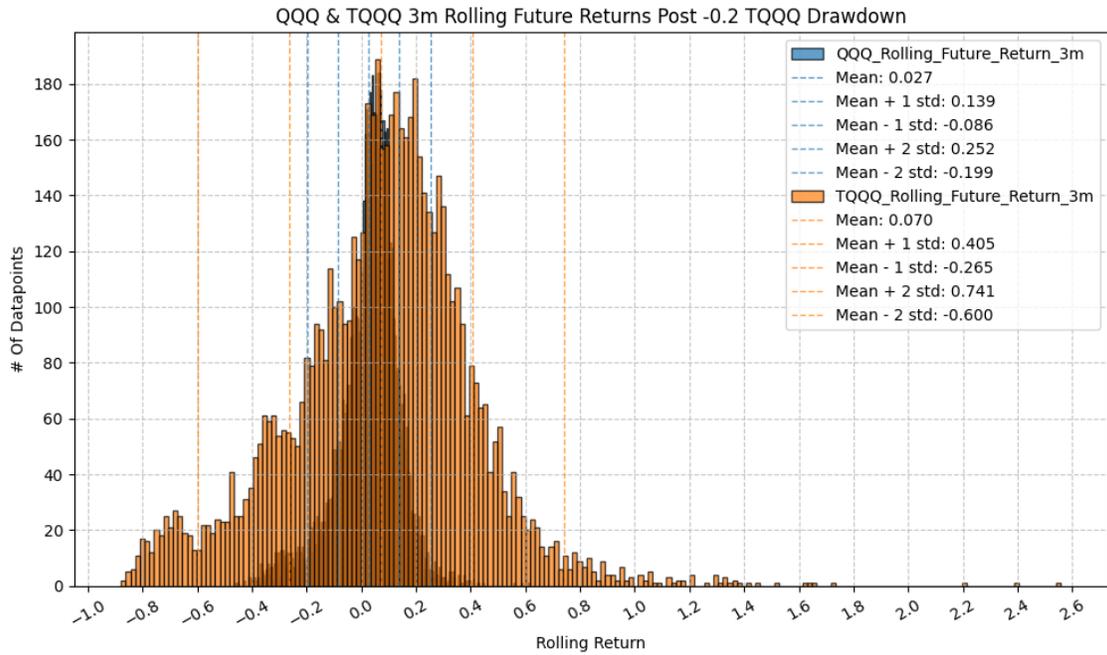
```

=====
Omnibus:                               1535.850   Durbin-Watson:                0.317
Prob(Omnibus):                          0.000   Jarque-Bera (JB):            81019.960
Skew:                                     0.160   Prob(JB):                    0.00
Kurtosis:                                20.226   Cond. No.                     15.0
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3m R-squared:

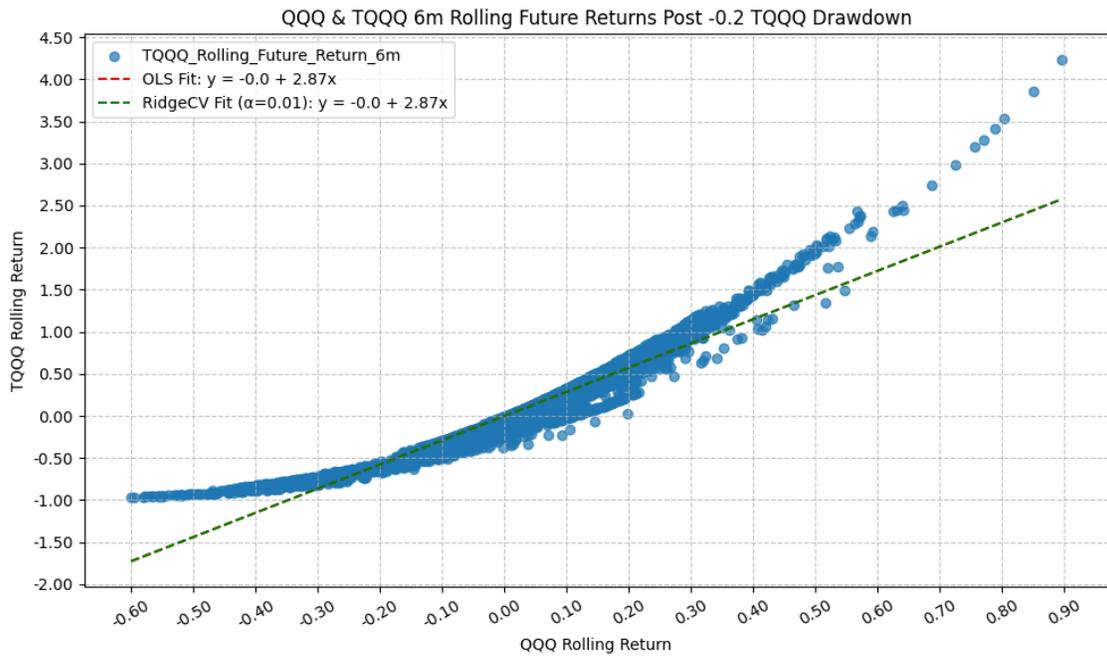
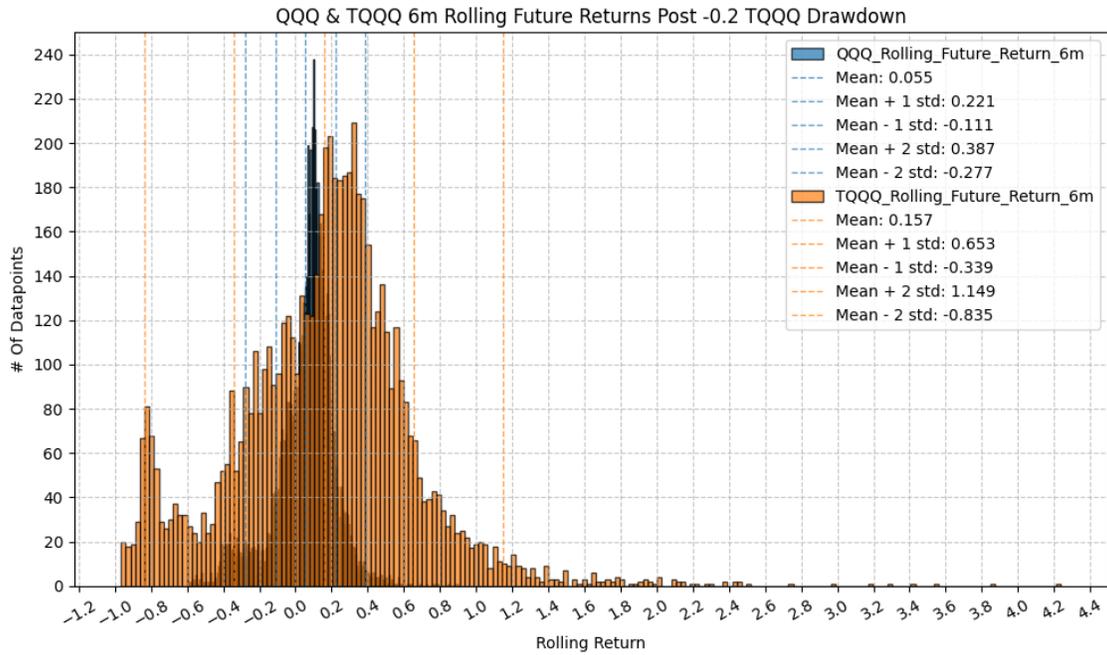
```

0.960
Model:                                OLS   Adj. R-squared:
0.960
Method:                                Least Squares   F-statistic:
1.544e+05
Date:                                  Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                  14:26:30   Log-Likelihood:
8321.1
No. Observations:                      6509   AIC:
-1.664e+04
Df Residuals:                          6507   BIC:
-1.662e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0070   0.001   -8.175   0.000
-0.009   -0.005
QQQ_Rolling_Future_Return_3m     2.9103   0.007   392.952   0.000
2.896   2.925
=====
Omnibus:                          2145.969   Durbin-Watson:                0.136
Prob(Omnibus):                     0.000   Jarque-Bera (JB):            38765.286
Skew:                               1.109   Prob(JB):                    0.00
Kurtosis:                          14.748   Cond. No.                    8.87
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_6m R-squared:

```

0.926
Model: OLS Adj. R-squared:
0.926
Method: Least Squares F-statistic:
8.102e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:32 Log-Likelihood:
3779.1
No. Observations: 6446 AIC:
-7554.
Df Residuals: 6444 BIC:
-7541.
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

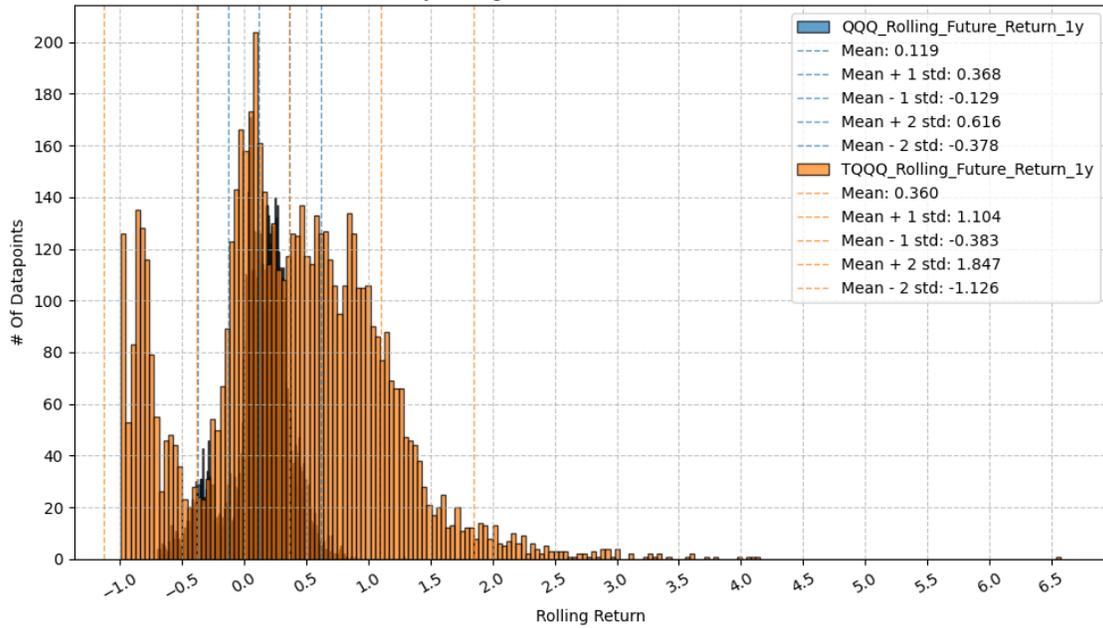
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0015	0.002	-0.860	0.390
-0.005 0.002				
QQQ_Rolling_Future_Return_6m	2.8743	0.010	284.646	0.000
2.855 2.894				
=====				
Omnibus:	3183.205	Durbin-Watson:		0.077
Prob(Omnibus):	0.000	Jarque-Bera (JB):		49759.451
Skew:	1.977	Prob(JB):		0.00
Kurtosis:	16.024	Cond. No.		6.04
=====				

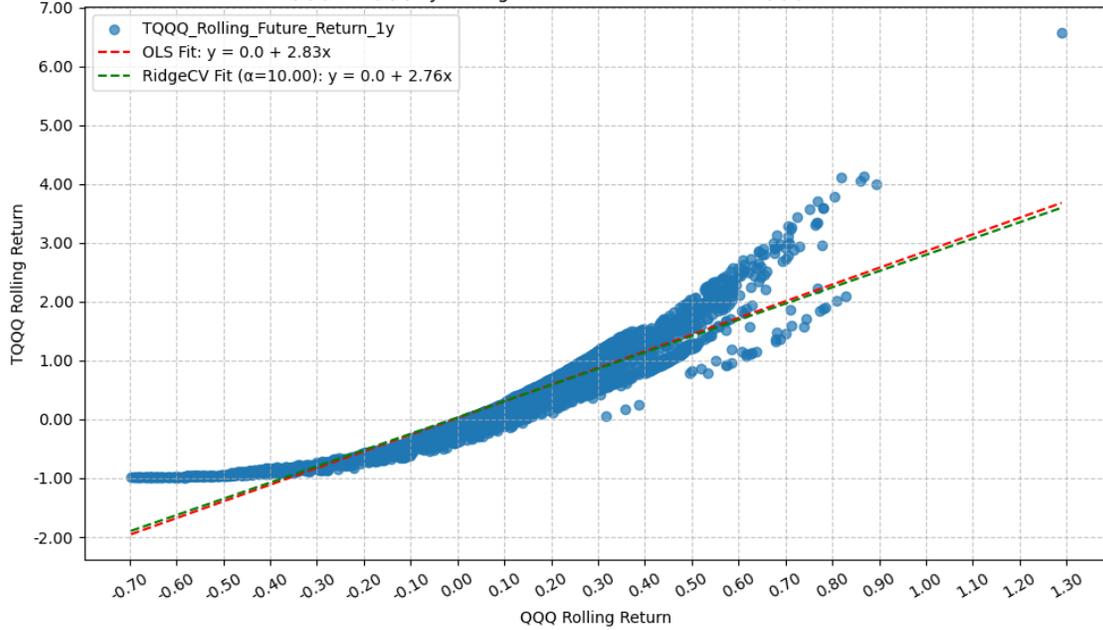
Notes:

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

QQQ & TQQQ 1y Rolling Future Returns Post -0.2 TQQQ Drawdown



QQQ & TQQQ 1y Rolling Future Returns Post -0.2 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1y R-squared:

```

0.898
Model:                                OLS   Adj. R-squared:
0.898
Method:                                Least Squares   F-statistic:
5.551e+04
Date:                                   Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                   14:26:33   Log-Likelihood:
115.86
No. Observations:                       6320   AIC:
-227.7
Df Residuals:                           6318   BIC:
-214.2
Df Model:                                1
Covariance Type:                        nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0227	0.003	6.836	0.000
0.016 0.029				
QQQ_Rolling_Future_Return_1y	2.8344	0.012	235.614	0.000
2.811 2.858				

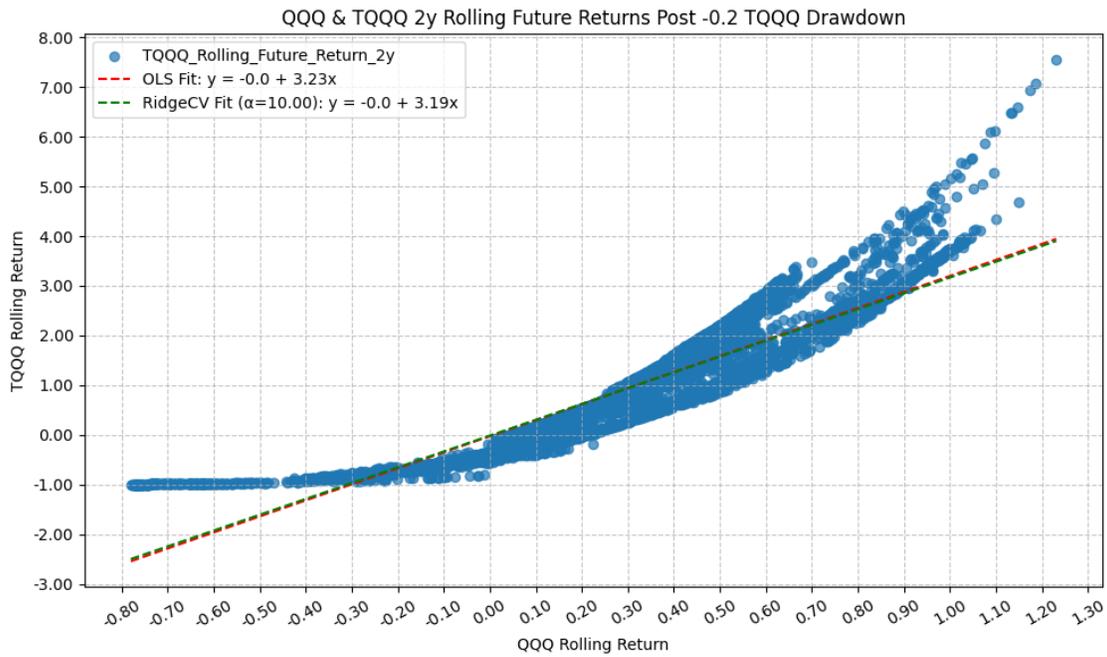
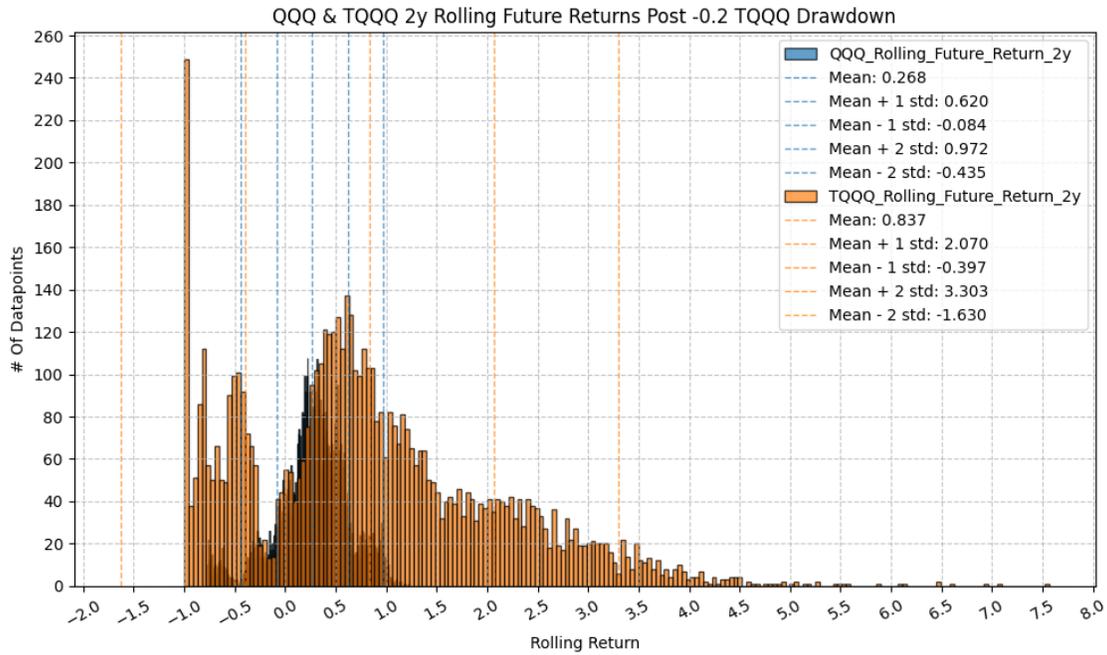
```

=====
Omnibus:                               2422.820   Durbin-Watson:                0.068
Prob(Omnibus):                          0.000   Jarque-Bera (JB):            19442.842
Skew:                                    1.621   Prob(JB):                    0.00
Kurtosis:                               10.958   Cond. No.:                   4.09
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_2y R-squared:

```

0.847
Model: OLS Adj. R-squared:
0.847
Method: Least Squares F-statistic:
3.365e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:34 Log-Likelihood:
-4181.2
No. Observations: 6068 AIC:
8366.
Df Residuals: 6066 BIC:
8380.
Df Model: 1
Covariance Type: nonrobust
=====
=====

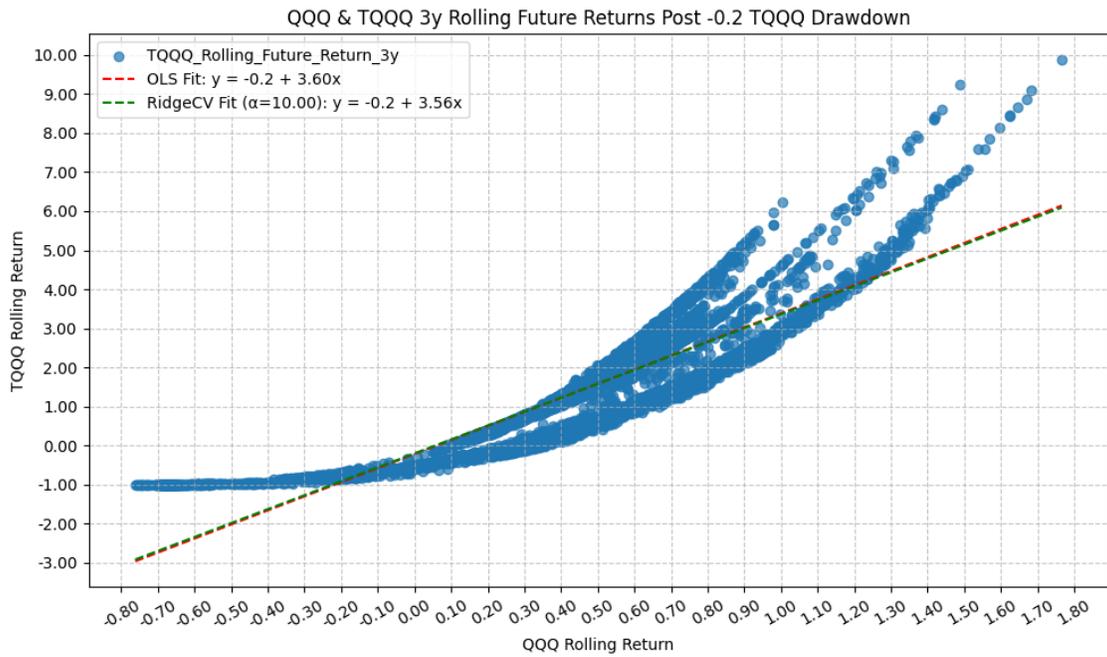
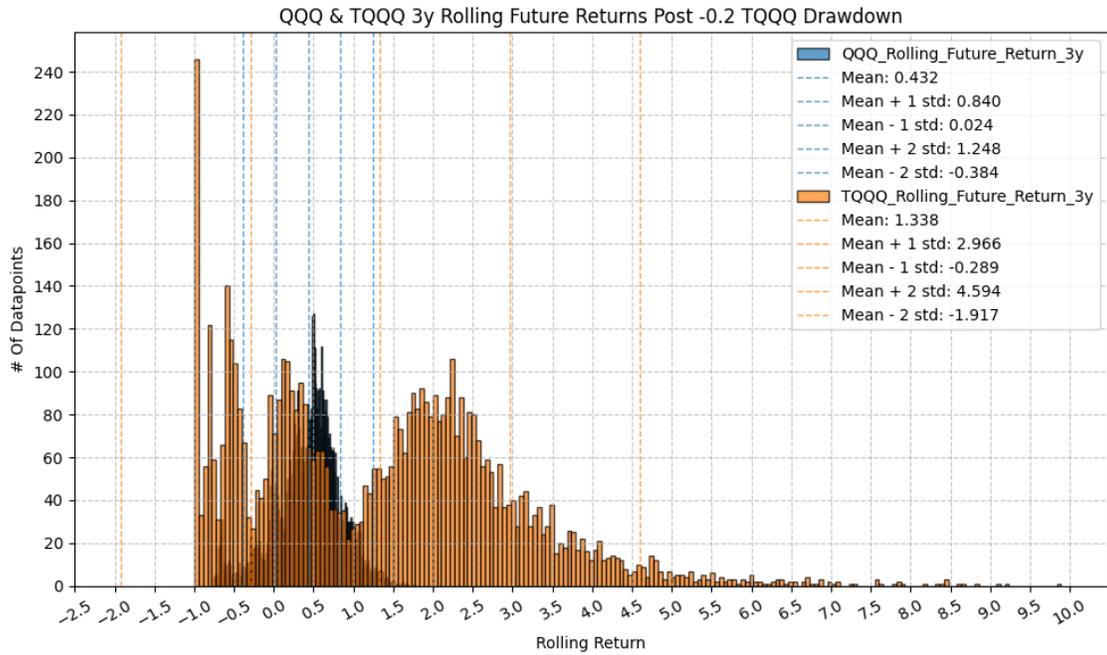
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0288	0.008	-3.698	0.000
-0.044 -0.014				
QQQ_Rolling_Future_Return_2y	3.2276	0.018	183.436	0.000
3.193 3.262				
=====				
Omnibus:	1695.729	Durbin-Watson:		0.019
Prob(Omnibus):	0.000	Jarque-Bera (JB):		4868.218
Skew:	1.463	Prob(JB):		0.00
Kurtosis:	6.270	Cond. No.		3.07
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3y R-squared:

```

0.814
Model:                                OLS   Adj. R-squared:
0.814
Method:                                Least Squares   F-statistic:
2.547e+04
Date:                                   Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                   14:26:35   Log-Likelihood:
-6191.6
No. Observations:                      5816   AIC:
1.239e+04
Df Residuals:                          5814   BIC:
1.240e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.2170	0.013	-16.189	0.000
-0.243 -0.191				
QQQ_Rolling_Future_Return_3y	3.6008	0.023	159.606	0.000
3.557 3.645				
=====				

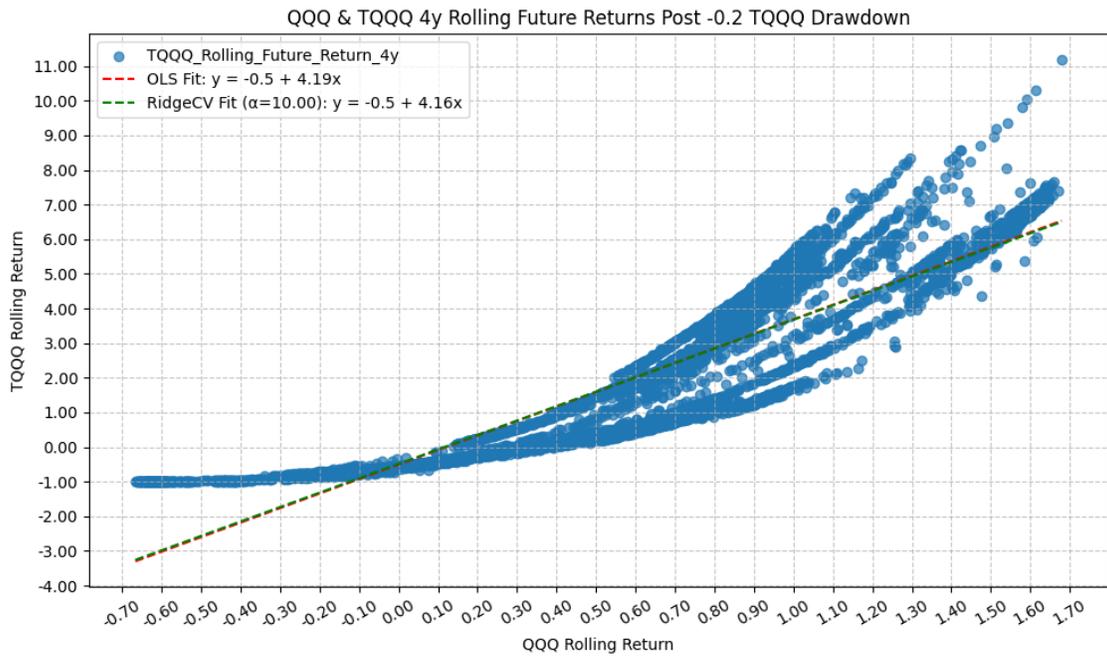
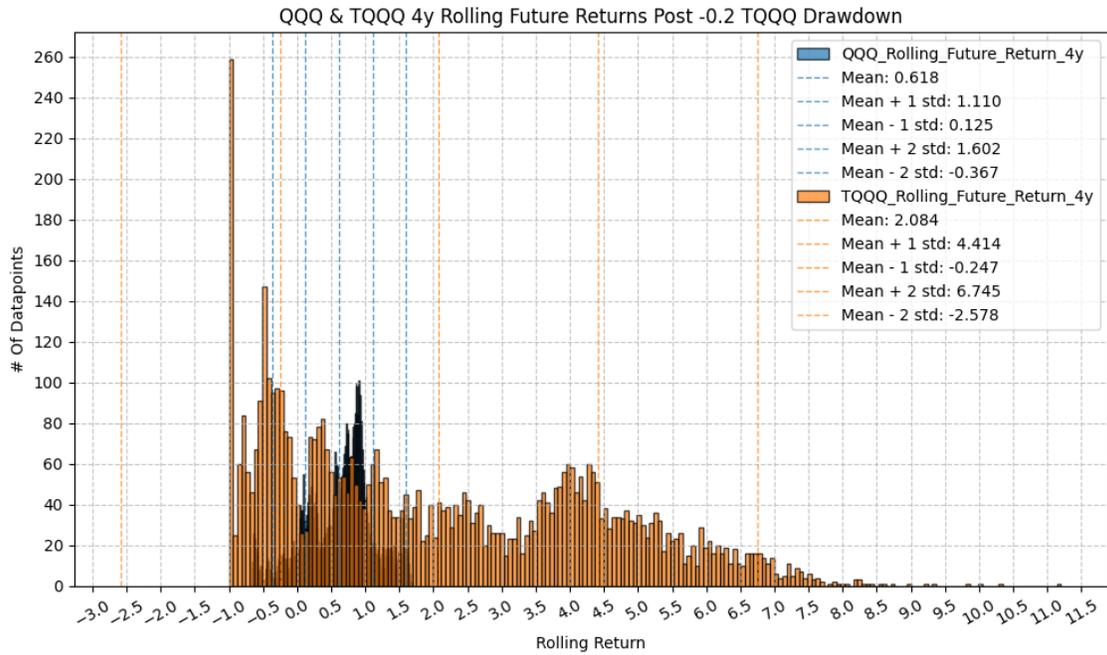
```

Omnibus:                               874.268   Durbin-Watson:                0.015
Prob(Omnibus):                          0.000   Jarque-Bera (JB):            1570.330
Skew:                                     0.966   Prob(JB):                    0.00
Kurtosis:                                4.657   Cond. No.:                   2.98
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_4y R-squared:

```

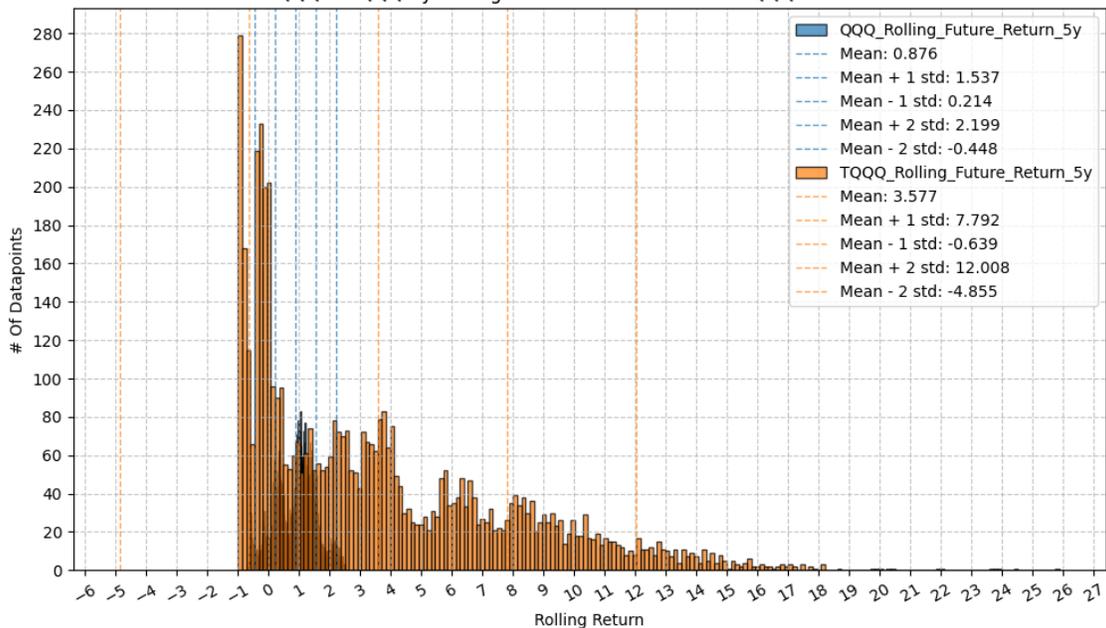
0.784
Model:                                OLS   Adj. R-squared:
0.784
Method:                               Least Squares   F-statistic:
2.024e+04
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:26:36   Log-Likelihood:
-8333.7
No. Observations:                    5564   AIC:
1.667e+04
Df Residuals:                        5562   BIC:
1.668e+04
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.5059   0.023   -21.736   0.000
-0.552   -0.460
QQQ_Rolling_Future_Return_4y    4.1927   0.029   142.267   0.000
4.135   4.250
=====
Omnibus:                         89.406   Durbin-Watson:           0.010
Prob(Omnibus):                   0.000   Jarque-Bera (JB):       63.314
Skew:                             0.153   Prob(JB):                1.78e-14
Kurtosis:                        2.576   Cond. No.                2.96
=====

```

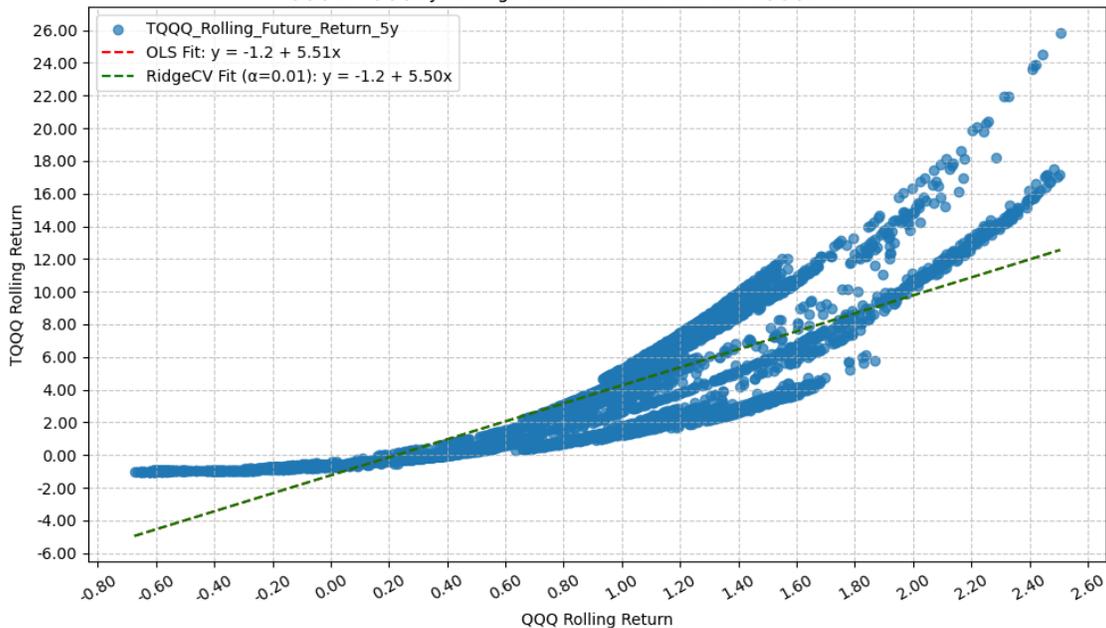
Notes:

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

QQQ & TQQQ 5y Rolling Future Returns Post -0.2 TQQQ Drawdown



QQQ & TQQQ 5y Rolling Future Returns Post -0.2 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_5y R-squared:

```

0.747
Model:                                OLS   Adj. R-squared:
0.747
Method:                                Least Squares   F-statistic:
1.566e+04
Date:                                  Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                  14:26:37   Log-Likelihood:
-11532.
No. Observations:                      5312   AIC:
2.307e+04
Df Residuals:                          5310   BIC:
2.308e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-1.2438	0.048	-25.759	0.000
-1.338 -1.149				
QQQ_Rolling_Future_Return_5y	5.5050	0.044	125.134	0.000
5.419 5.591				
=====				

```

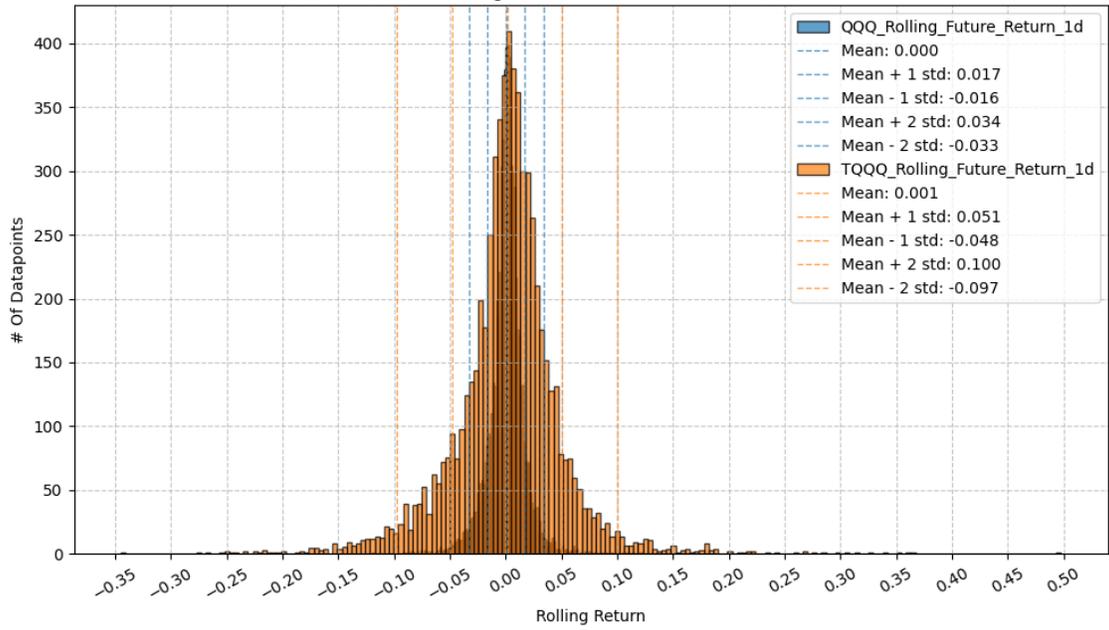
Omnibus:                               256.613   Durbin-Watson:                0.009
Prob(Omnibus):                          0.000   Jarque-Bera (JB):             381.078
Skew:                                     0.437   Prob(JB):                     1.78e-83
Kurtosis:                                3.979   Cond. No.                      3.00
=====
=====

```

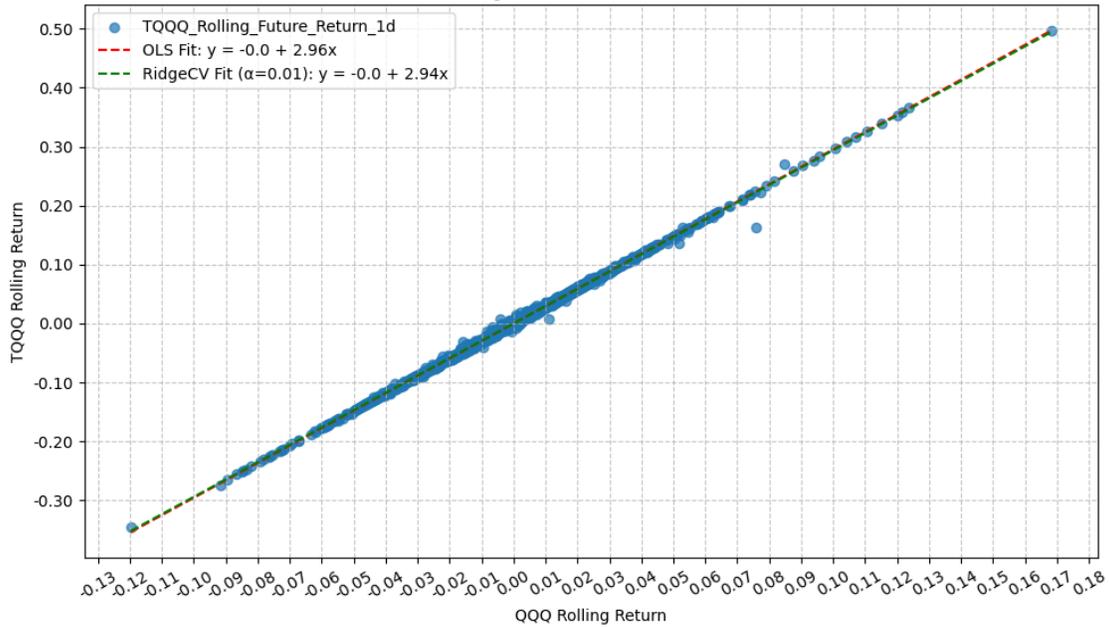
Notes:

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

QQQ & TQQQ 1d Rolling Future Returns Post -0.3 TQQQ Drawdown



QQQ & TQQQ 1d Rolling Future Returns Post -0.3 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1d R-squared:

```

0.999
Model: OLS Adj. R-squared:
0.999
Method: Least Squares F-statistic:
6.433e+06
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:39 Log-Likelihood:
32894.
No. Observations: 6531 AIC:
-6.578e+04
Df Residuals: 6529 BIC:
-6.577e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

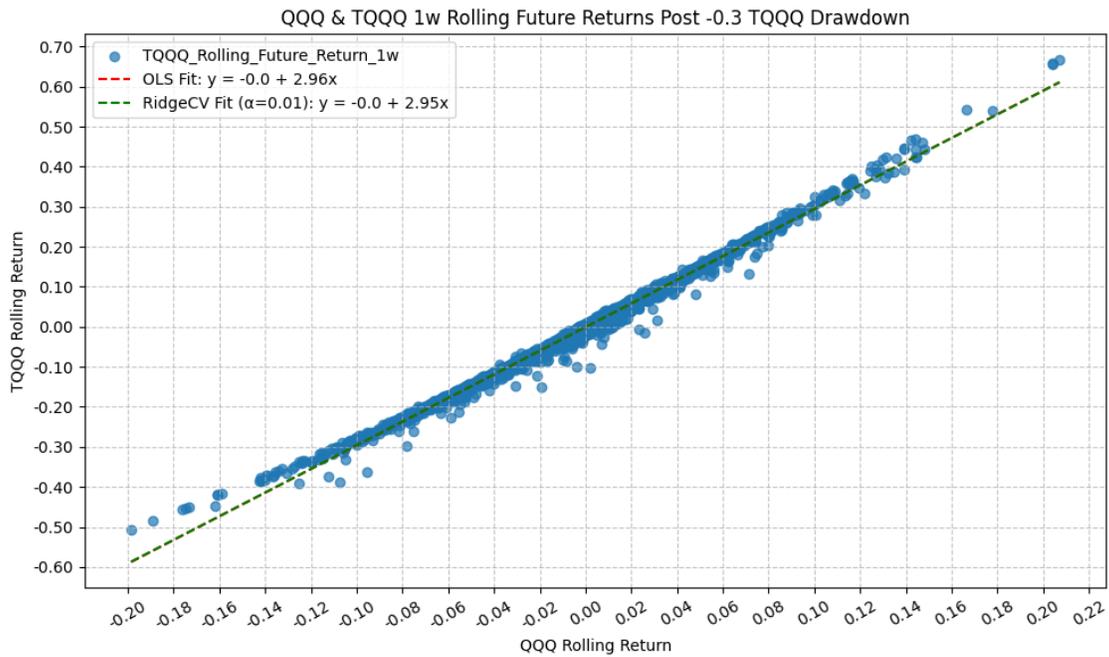
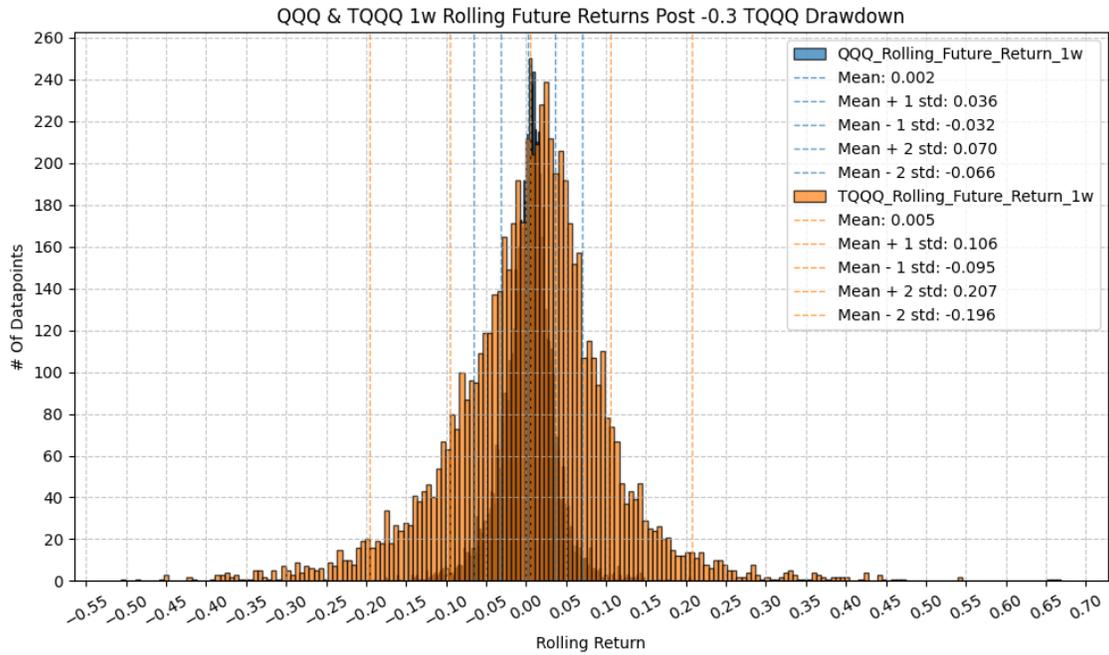
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-5.296e-05	1.95e-05	-2.721	0.007
-9.11e-05 -1.48e-05				
QQQ_Rolling_Future_Return_1d	2.9551	0.001	2536.404	0.000
2.953 2.957				
=====				
Omnibus:	9694.083	Durbin-Watson:		2.565
Prob(Omnibus):	0.000	Jarque-Bera (JB):		38964571.195
Skew:	-8.113	Prob(JB):		0.00
Kurtosis:	381.052	Cond. No.		59.9
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1w R-squared:

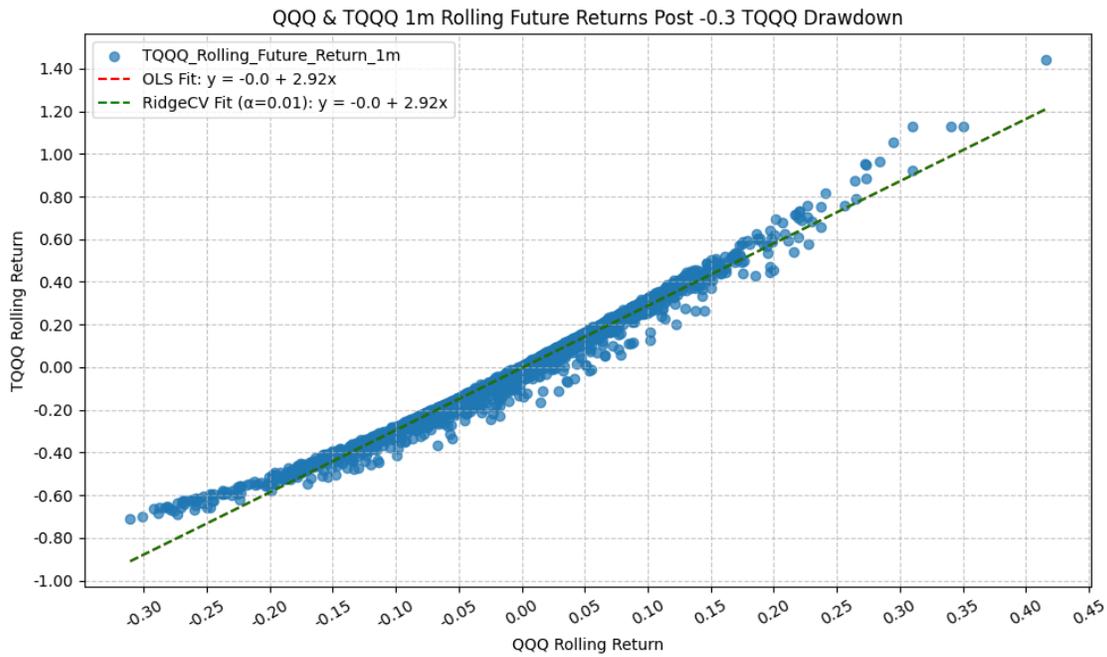
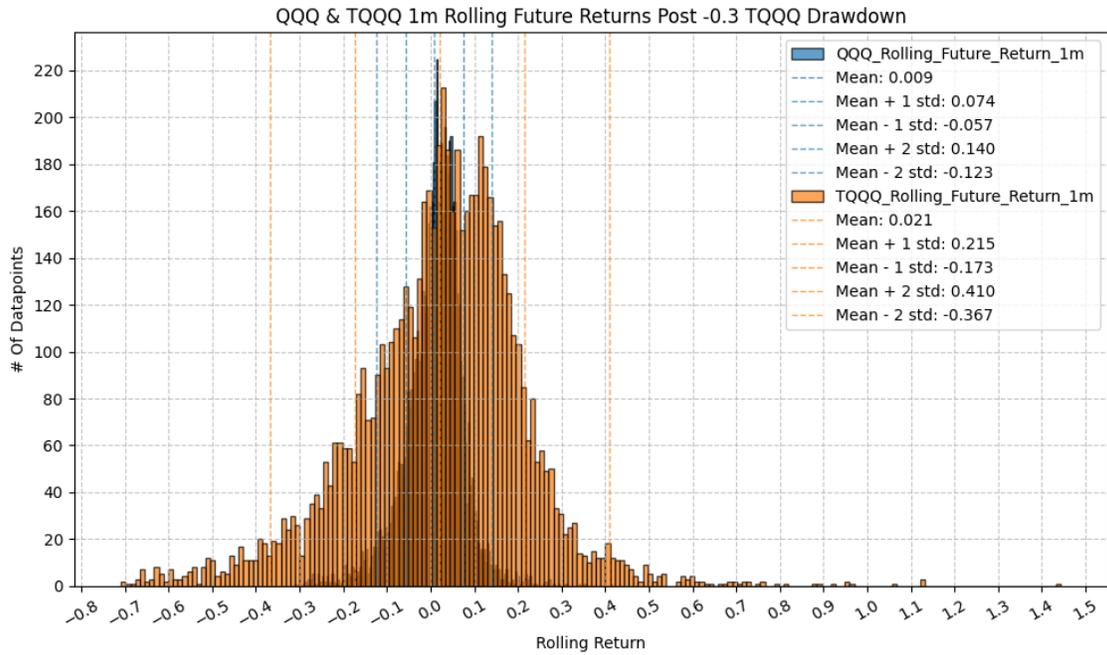
```

0.994
Model:                                OLS   Adj. R-squared:
0.994
Method:                               Least Squares   F-statistic:
1.119e+06
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:26:40   Log-Likelihood:
22520.
No. Observations:                    6527   AIC:
-4.504e+04
Df Residuals:                        6525   BIC:
-4.502e+04
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0008   9.53e-05   -8.333   0.000
-0.001   -0.001
QQQ_Rolling_Future_Return_1w    2.9552    0.003   1057.792   0.000
2.950   2.961
=====
Omnibus:                          3463.566   Durbin-Watson:          0.902
Prob(Omnibus):                     0.000   Jarque-Bera (JB):      388402.497
Skew:                               -1.580   Prob(JB):              0.00
Kurtosis:                          40.659   Cond. No.              29.4
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1m R-squared:

```

0.983
Model:                                OLS   Adj. R-squared:
0.983
Method:                                Least Squares   F-statistic:
3.675e+05
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:41   Log-Likelihood:
14623.
No. Observations:                    6511   AIC:
-2.924e+04
Df Residuals:                        6509   BIC:
-2.923e+04
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0035	0.000	-11.033	0.000
-0.004 -0.003				
QQQ_Rolling_Future_Return_1m	2.9176	0.005	606.191	0.000
2.908 2.927				

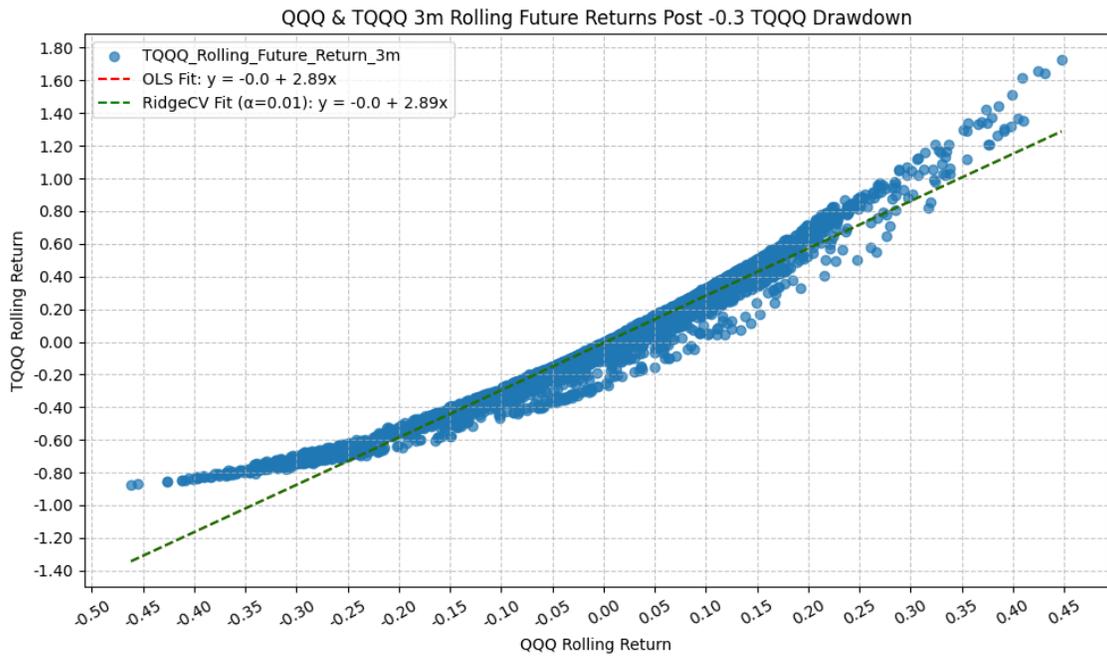
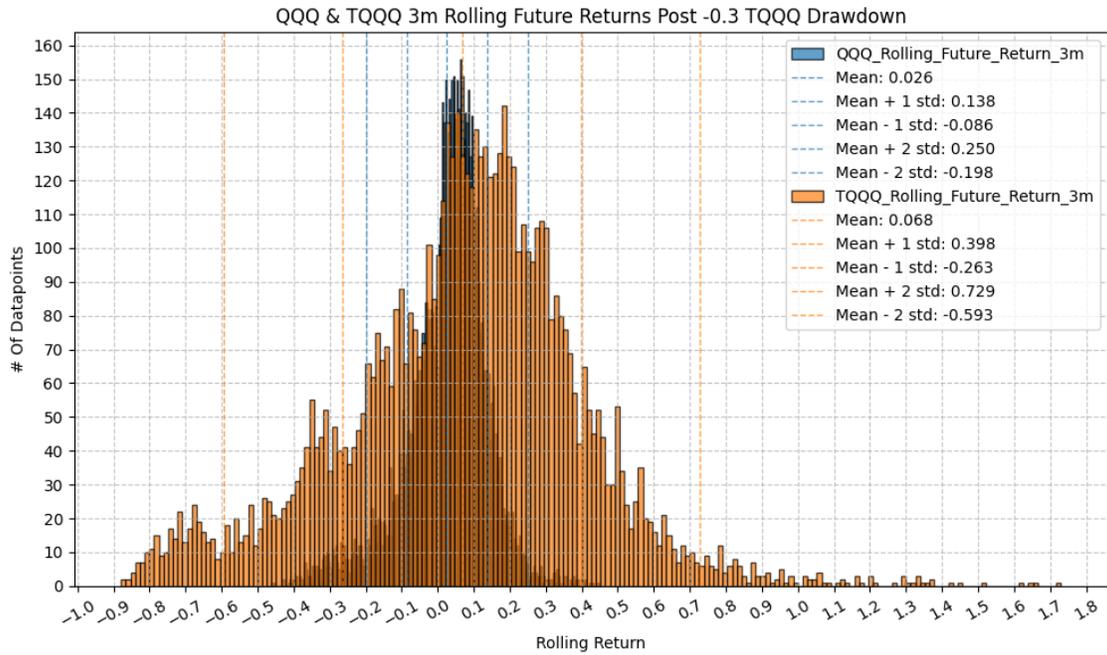
```

=====
Omnibus:                            1511.925   Durbin-Watson:                0.308
Prob(Omnibus):                       0.000   Jarque-Bera (JB):             81855.191
Skew:                                 0.083   Prob(JB):                     0.00
Kurtosis:                             20.369   Cond. No.                     15.2
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3m R-squared:

```

0.961
Model:                                OLS   Adj. R-squared:
0.961
Method:                                Least Squares   F-statistic:
1.585e+05
Date:                                   Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                   14:26:42   Log-Likelihood:
8457.5
No. Observations:                      6469   AIC:
-1.691e+04
Df Residuals:                          6467   BIC:
-1.690e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0067	0.001	-8.040	0.000
-0.008 -0.005				
QQQ_Rolling_Future_Return_3m	2.8943	0.007	398.066	0.000
2.880 2.909				

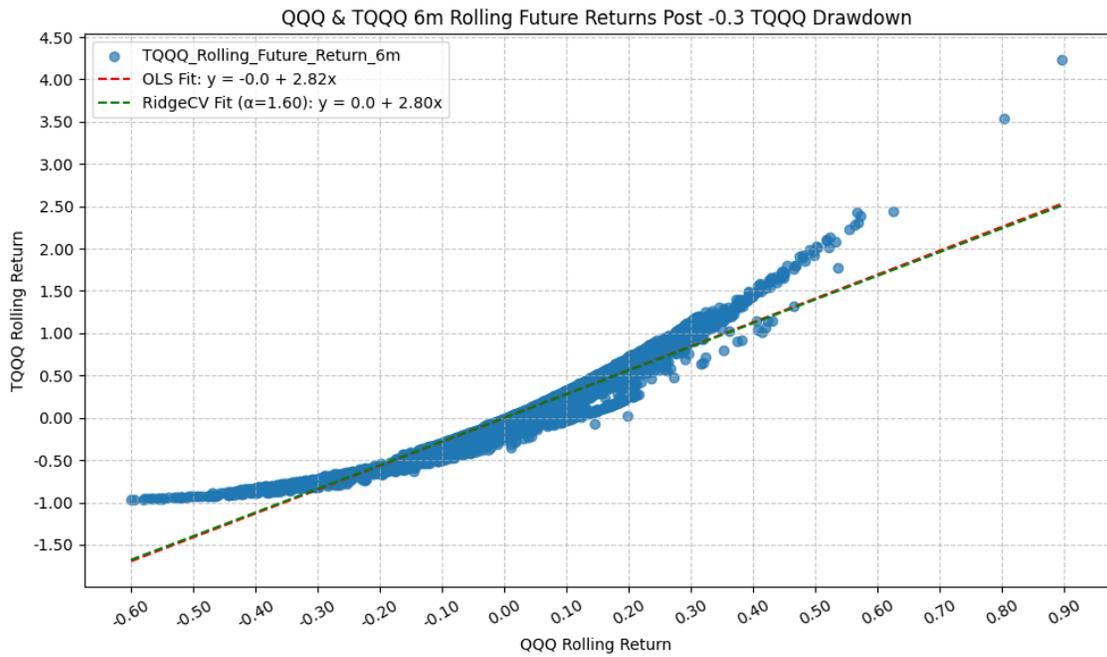
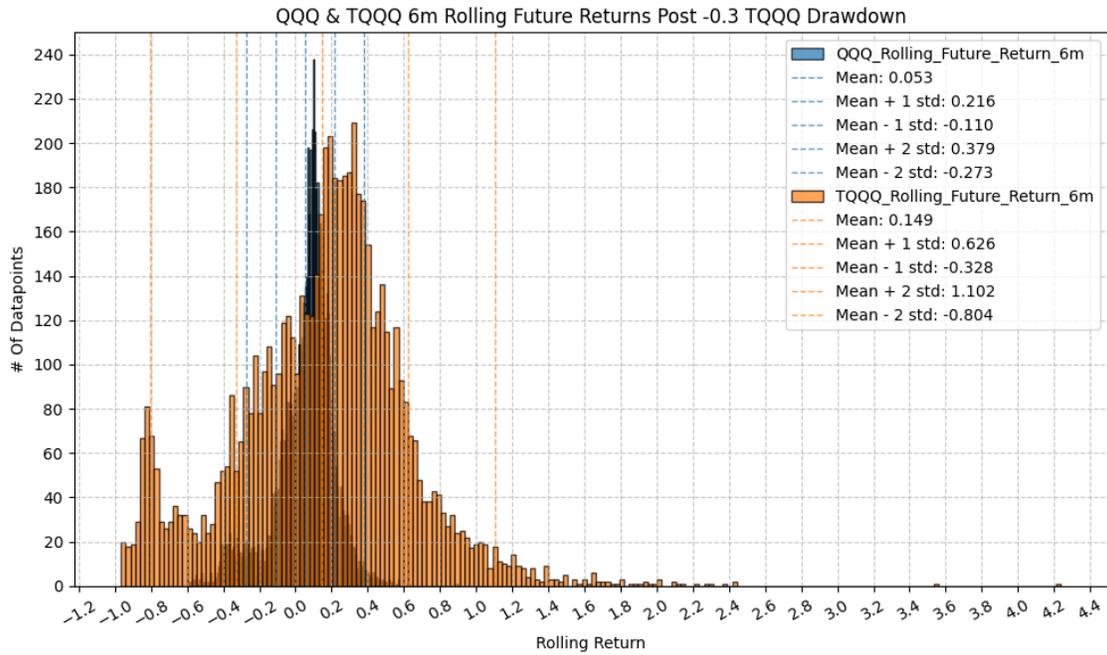
```

=====
Omnibus:                               1346.125   Durbin-Watson:                0.103
Prob(Omnibus):                         0.000   Jarque-Bera (JB):            15267.066
Skew:                                   0.666   Prob(JB):                    0.00
Kurtosis:                               10.407   Cond. No.                     8.94
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_6m R-squared:

```

0.929
Model: OLS Adj. R-squared:
0.929
Method: Least Squares F-statistic:
8.378e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:43 Log-Likelihood:
4128.3
No. Observations: 6406 AIC:
-8253.
Df Residuals: 6404 BIC:
-8239.
Df Model: 1
Covariance Type: nonrobust
=====
=====

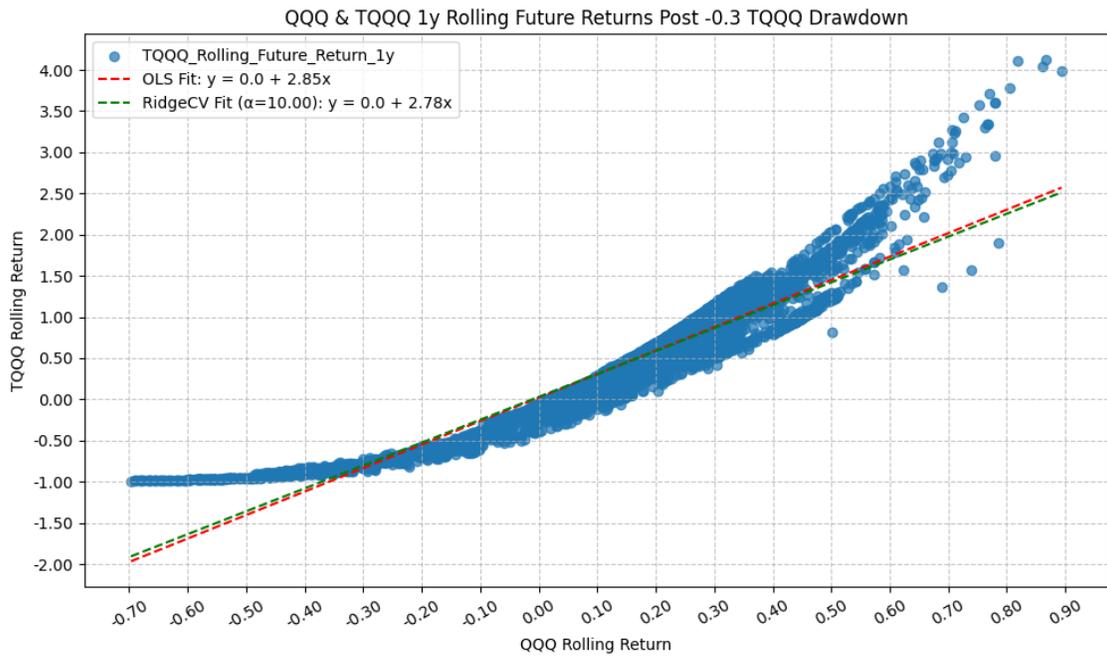
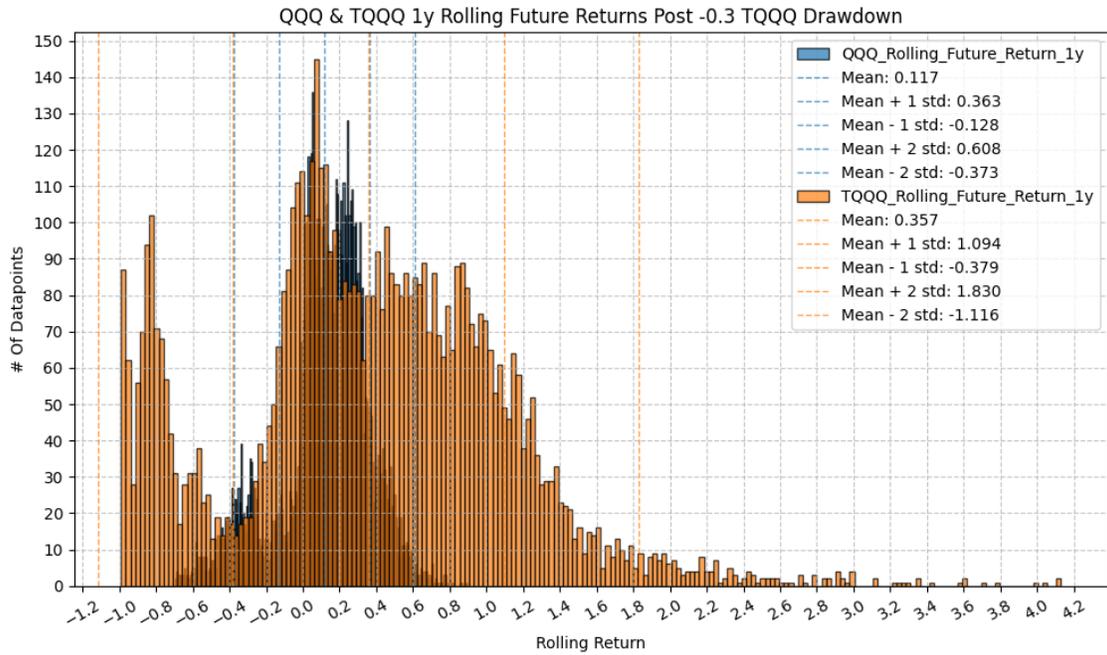
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0006	0.002	-0.337	0.736
-0.004 0.003				
QQQ_Rolling_Future_Return_6m	2.8222	0.010	289.447	0.000
2.803 2.841				
=====				
Omnibus:	2682.468	Durbin-Watson:		0.109
Prob(Omnibus):	0.000	Jarque-Bera (JB):		36485.982
Skew:	1.629	Prob(JB):		0.00
Kurtosis:	14.228	Cond. No.		6.16
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1y R-squared:

```

0.902
Model:                                OLS   Adj. R-squared:
0.902
Method:                                Least Squares   F-statistic:
5.754e+04
Date:                                   Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                   14:26:45   Log-Likelihood:
291.84
No. Observations:                       6280   AIC:
-579.7
Df Residuals:                            6278   BIC:
-566.2
Df Model:                                 1
Covariance Type:                         nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0224	0.003	6.919	0.000
0.016 0.029				
QQQ_Rolling_Future_Return_1y	2.8516	0.012	239.879	0.000
2.828 2.875				

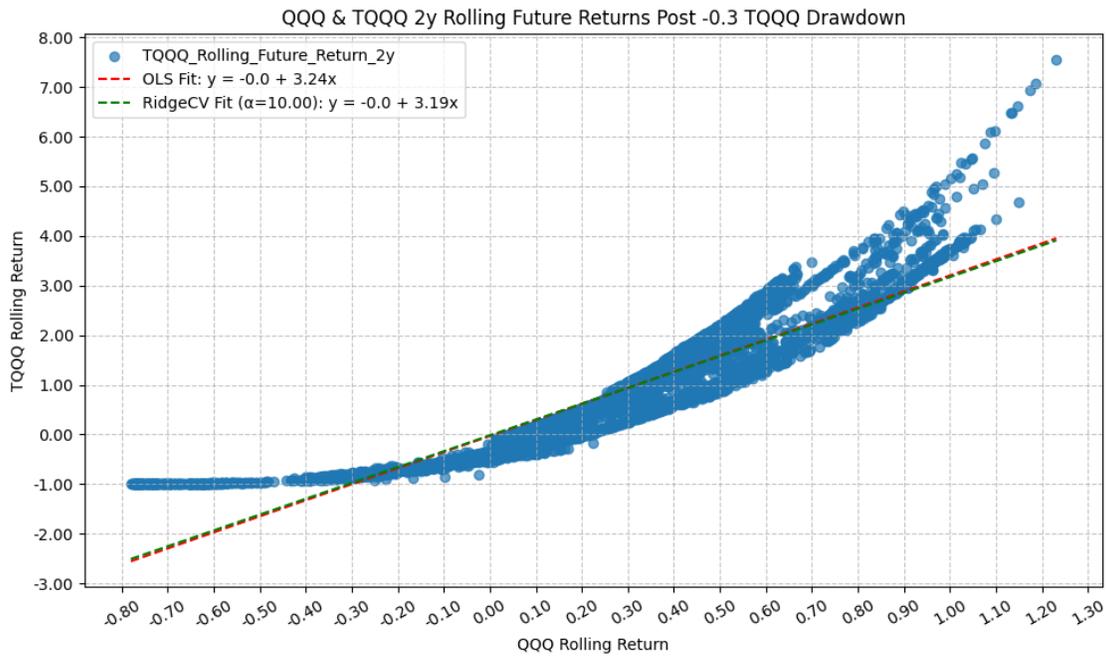
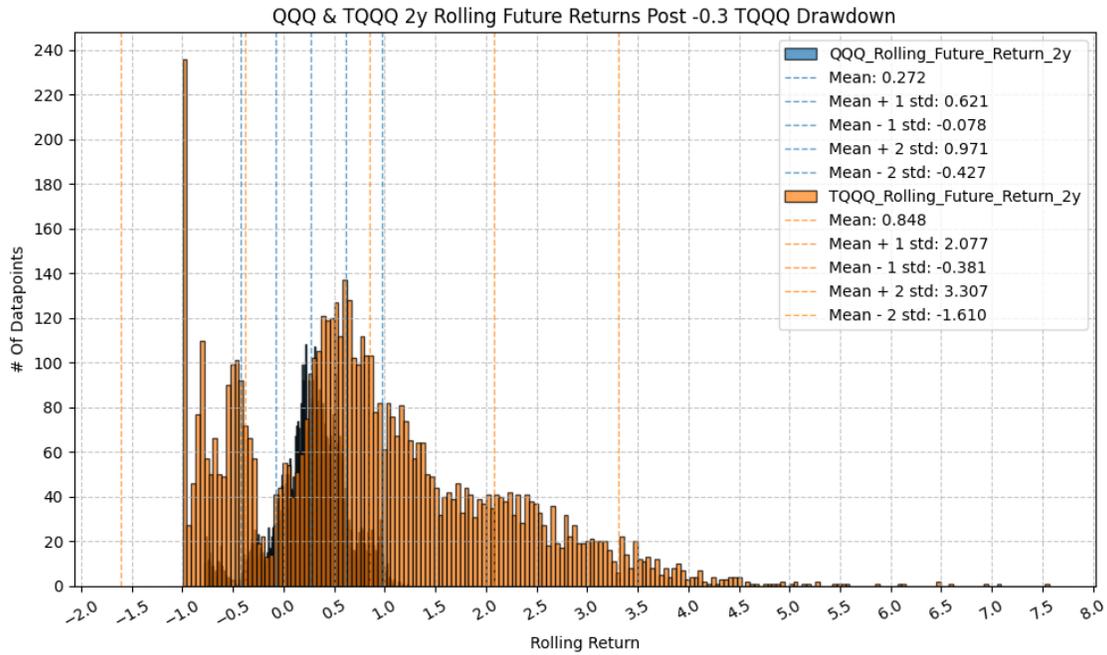
```

=====
Omnibus:                                1986.661   Durbin-Watson:                                0.043
Prob(Omnibus):                           0.000   Jarque-Bera (JB):                            8583.652
Skew:                                     1.493   Prob(JB):                                    0.00
Kurtosis:                                 7.887   Cond. No.                                    4.14
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_2y R-squared:

```

0.847
Model:                                OLS   Adj. R-squared:
0.847
Method:                                Least Squares   F-statistic:
3.331e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:46   Log-Likelihood:
-4141.4
No. Observations:                    6028   AIC:
8287.
Df Residuals:                        6026   BIC:
8300.
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0317	0.008	-4.039	0.000
-0.047 -0.016				
QQQ_Rolling_Future_Return_2y	3.2366	0.018	182.524	0.000
3.202 3.271				
=====				

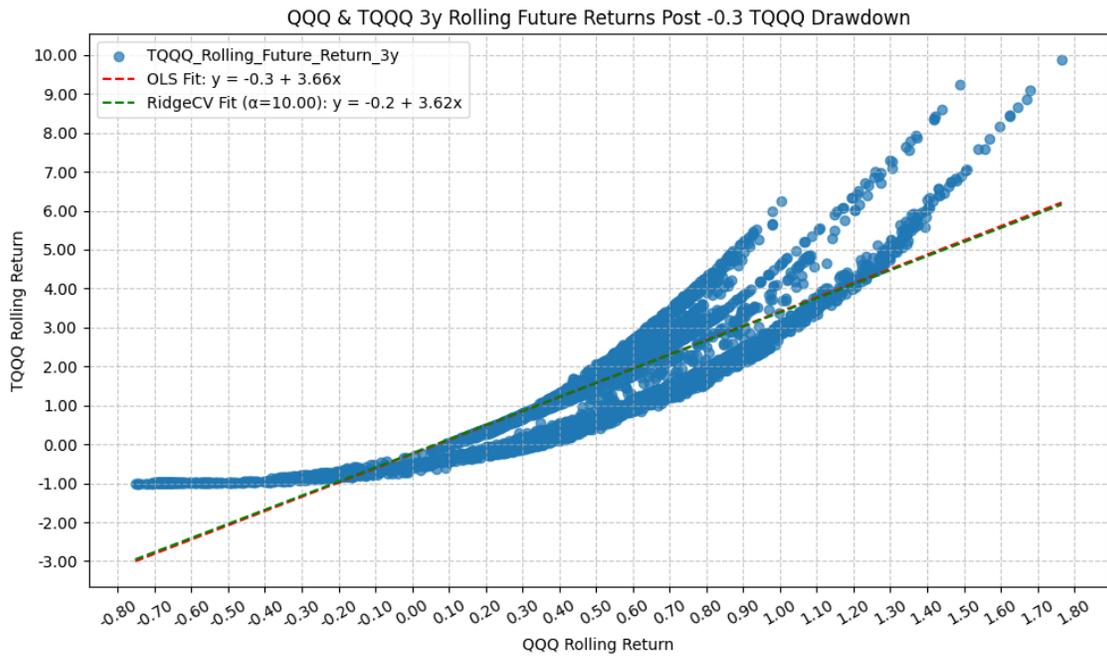
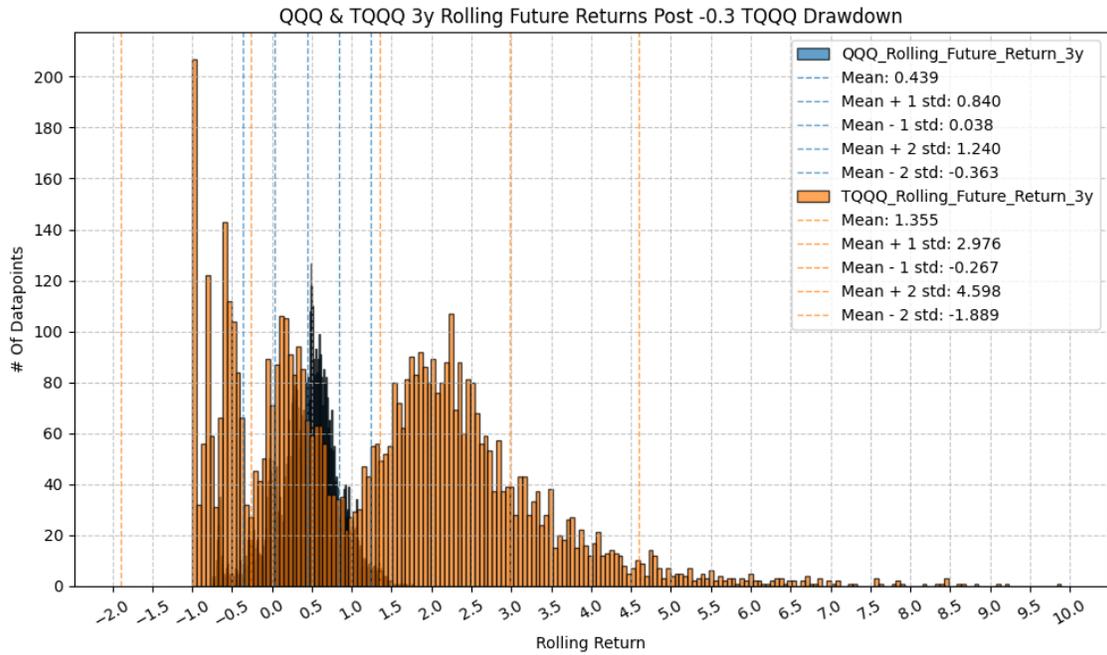
```

Omnibus:                            1703.262   Durbin-Watson:                0.019
Prob(Omnibus):                       0.000   Jarque-Bera (JB):             4959.569
Skew:                                 1.473   Prob(JB):                     0.00
Kurtosis:                             6.326   Cond. No.:                    3.10
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3y R-squared:

```

0.816
Model: OLS Adj. R-squared:
0.816
Method: Least Squares F-statistic:
2.566e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:47 Log-Likelihood:
-6094.3
No. Observations: 5776 AIC:
1.219e+04
Df Residuals: 5774 BIC:
1.221e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

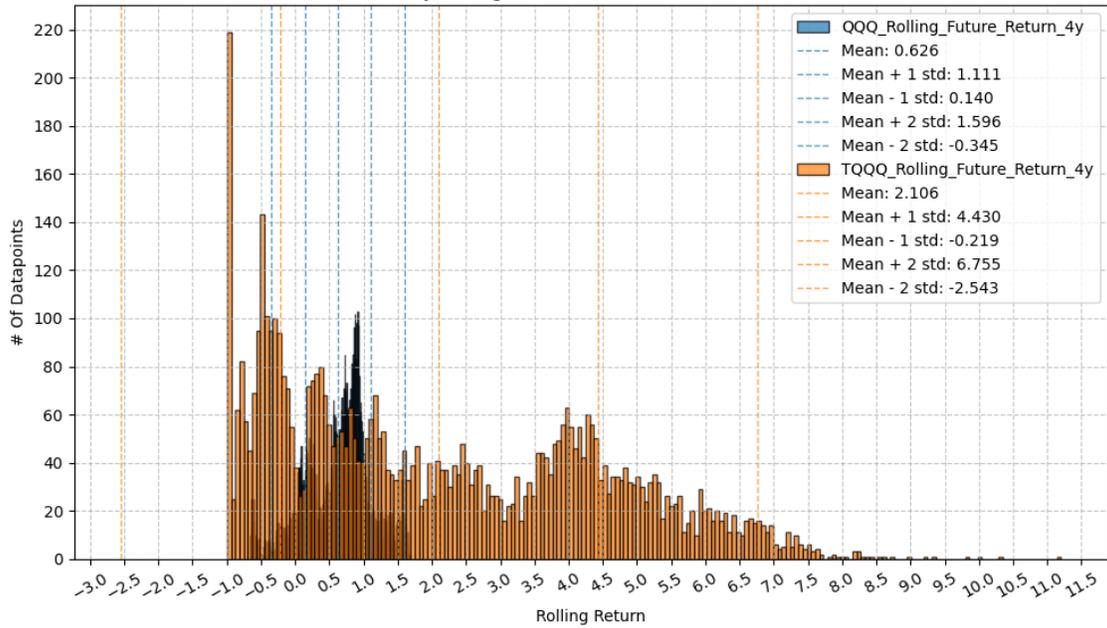
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.2502	0.014	-18.446	0.000
-0.277 -0.224				
QQQ_Rolling_Future_Return_3y	3.6568	0.023	160.193	0.000
3.612 3.702				
=====				
Omnibus:	876.215	Durbin-Watson:		0.015
Prob(Omnibus):	0.000	Jarque-Bera (JB):		1596.509
Skew:	0.967	Prob(JB):		0.00
Kurtosis:	4.700	Cond. No.		3.05
=====				

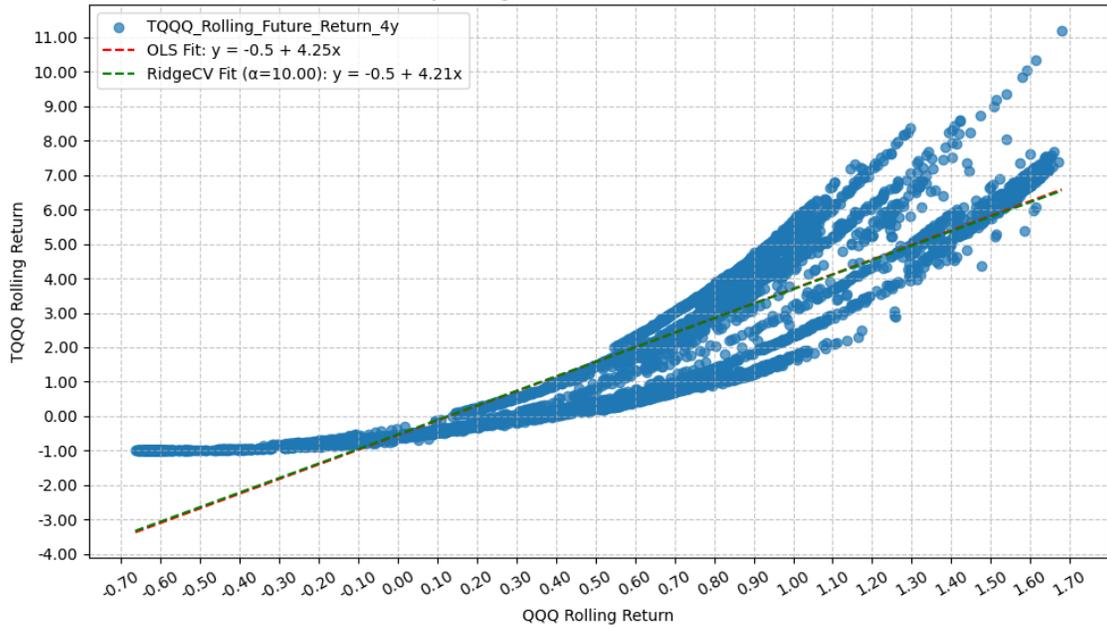
Notes:

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

QQQ & TQQQ 4y Rolling Future Returns Post -0.3 TQQQ Drawdown



QQQ & TQQQ 4y Rolling Future Returns Post -0.3 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_4y R-squared:

```

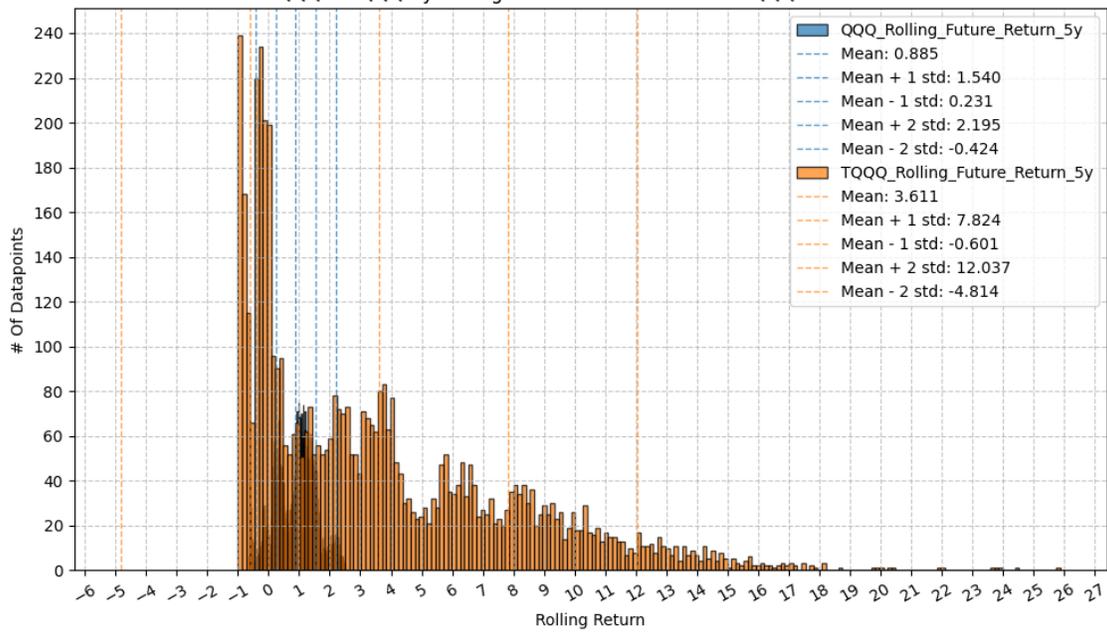
0.785
Model:                                OLS   Adj. R-squared:
0.785
Method:                                Least Squares   F-statistic:
2.017e+04
Date:                                  Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                  14:26:48   Log-Likelihood:
-8250.6
No. Observations:                      5524   AIC:
1.651e+04
Df Residuals:                           5522   BIC:
1.652e+04
Df Model:                                1
Covariance Type:                        nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                               -0.5497   0.024   -23.230   0.000
-0.596   -0.503
QQQ_Rolling_Future_Return_4y        4.2450   0.030   142.023   0.000
4.186   4.304
=====
Omnibus:                             72.624   Durbin-Watson:           0.010
Prob(Omnibus):                        0.000   Jarque-Bera (JB):       55.217
Skew:                                  0.155   Prob(JB):                1.02e-12
Kurtosis:                              2.620   Cond. No.                3.02
=====

```

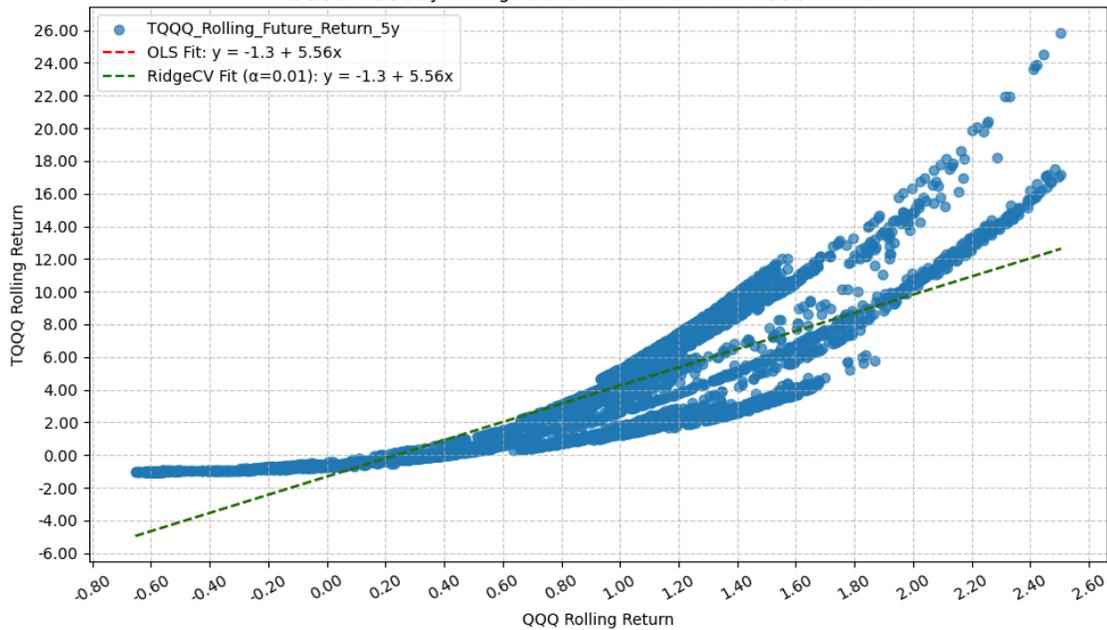
Notes:

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

QQQ & TQQQ 5y Rolling Future Returns Post -0.3 TQQQ Drawdown



QQQ & TQQQ 5y Rolling Future Returns Post -0.3 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_5y R-squared:

```

0.748
Model: OLS Adj. R-squared:
0.747
Method: Least Squares F-statistic:
1.560e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:49 Log-Likelihood:
-11434.
No. Observations: 5272 AIC:
2.287e+04
Df Residuals: 5270 BIC:
2.288e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-1.3156	0.049	-26.822	0.000
-1.412 -1.219				
QQQ_Rolling_Future_Return_5y	5.5645	0.045	124.913	0.000
5.477 5.652				

```

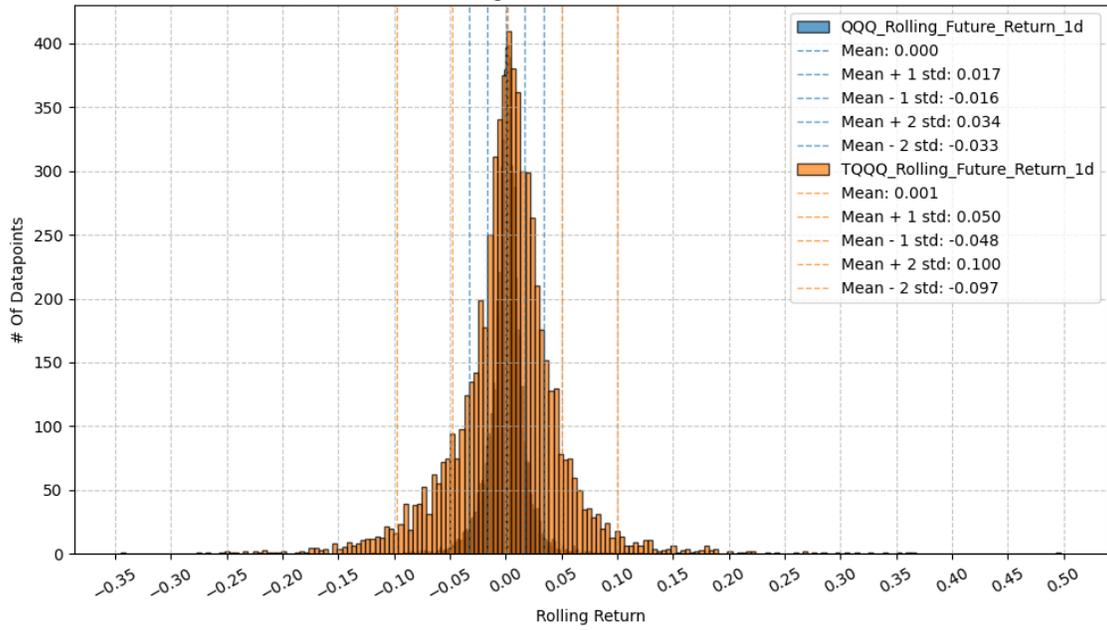
=====
Omnibus: 246.317 Durbin-Watson: 0.009
Prob(Omnibus): 0.000 Jarque-Bera (JB): 368.513
Skew: 0.424 Prob(JB): 9.51e-81
Kurtosis: 3.980 Cond. No. 3.05
=====

```

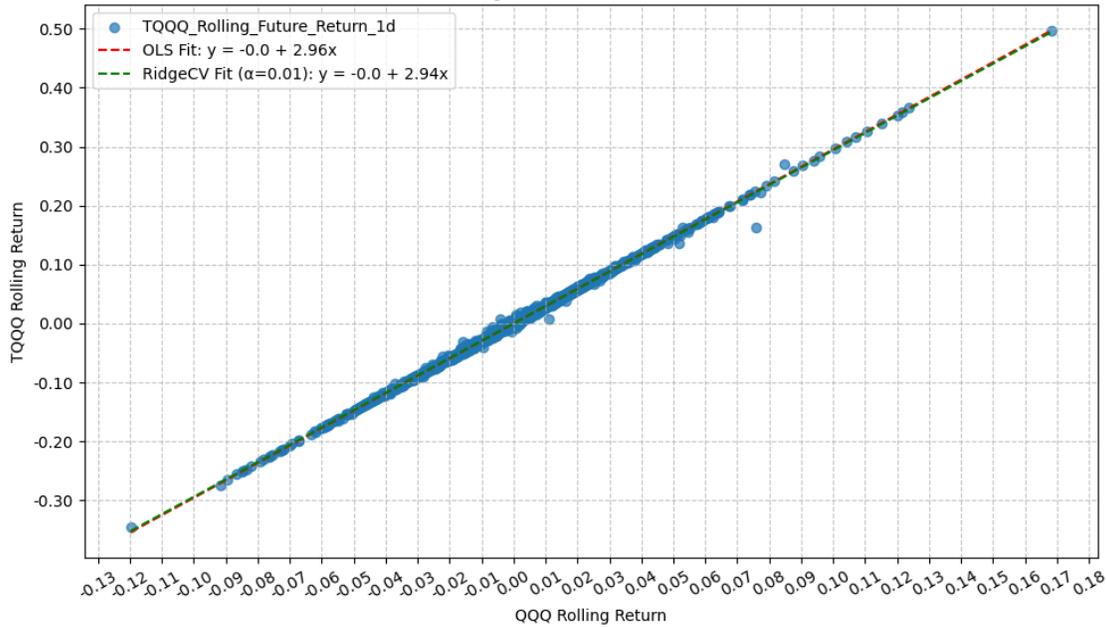
Notes:

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

QQQ & TQQQ 1d Rolling Future Returns Post -0.4 TQQQ Drawdown



QQQ & TQQQ 1d Rolling Future Returns Post -0.4 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1d R-squared:

```

0.999
Model: OLS Adj. R-squared:
0.999
Method: Least Squares F-statistic:
6.385e+06
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:50 Log-Likelihood:
32833.
No. Observations: 6520 AIC:
-6.566e+04
Df Residuals: 6518 BIC:
-6.565e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

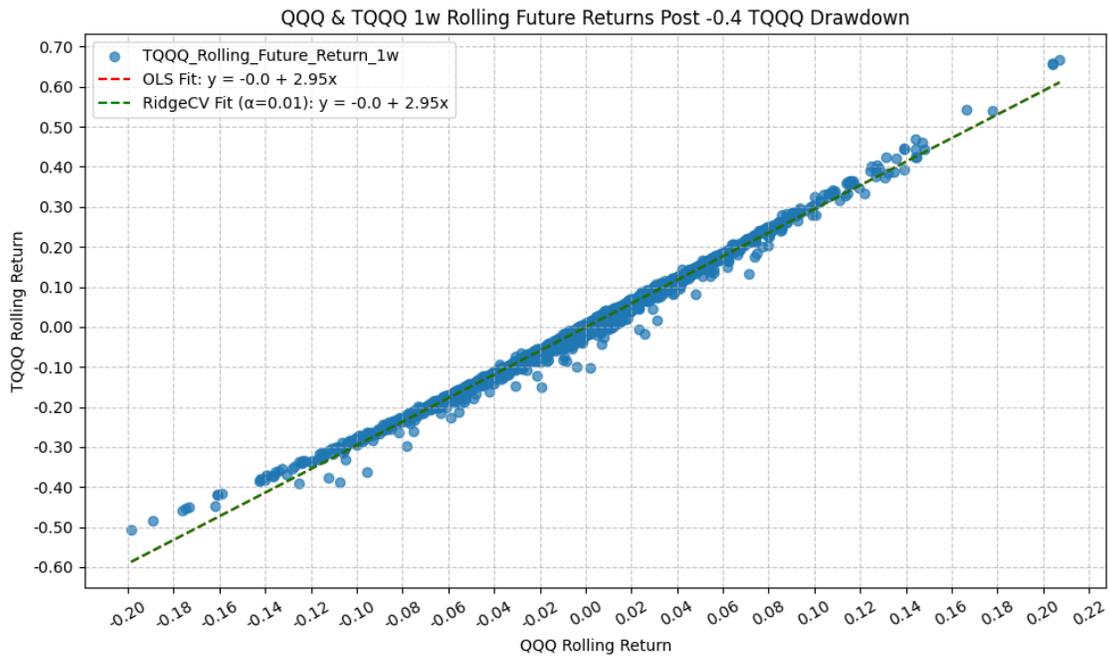
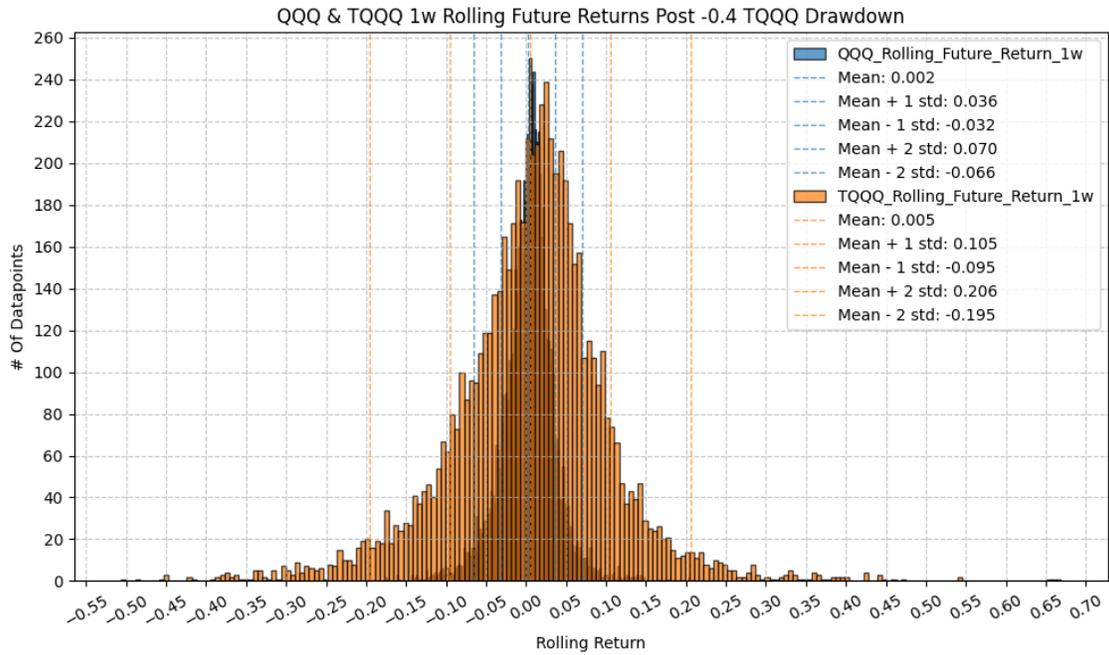
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-5.305e-05	1.95e-05	-2.721	0.007
-9.13e-05 -1.48e-05				
QQQ_Rolling_Future_Return_1d	2.9551	0.001	2526.915	0.000
2.953 2.957				
=====				
Omnibus:	9673.351	Durbin-Watson:		2.565
Prob(Omnibus):	0.000	Jarque-Bera (JB):		38764591.768
Skew:	-8.106	Prob(JB):		0.00
Kurtosis:	380.398	Cond. No.		60.0
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1w R-squared:

```

0.994
Model:                                OLS   Adj. R-squared:
0.994
Method:                               Least Squares   F-statistic:
1.118e+06
Date:                                  Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                  14:26:52   Log-Likelihood:
22527.
No. Observations:                     6516   AIC:
-4.505e+04
Df Residuals:                         6514   BIC:
-4.504e+04
Df Model:                              1
Covariance Type:                      nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0008	9.47e-05	-8.566	0.000
-0.001 -0.001				
QQQ_Rolling_Future_Return_1w	2.9535	0.003	1057.421	0.000
2.948 2.959				

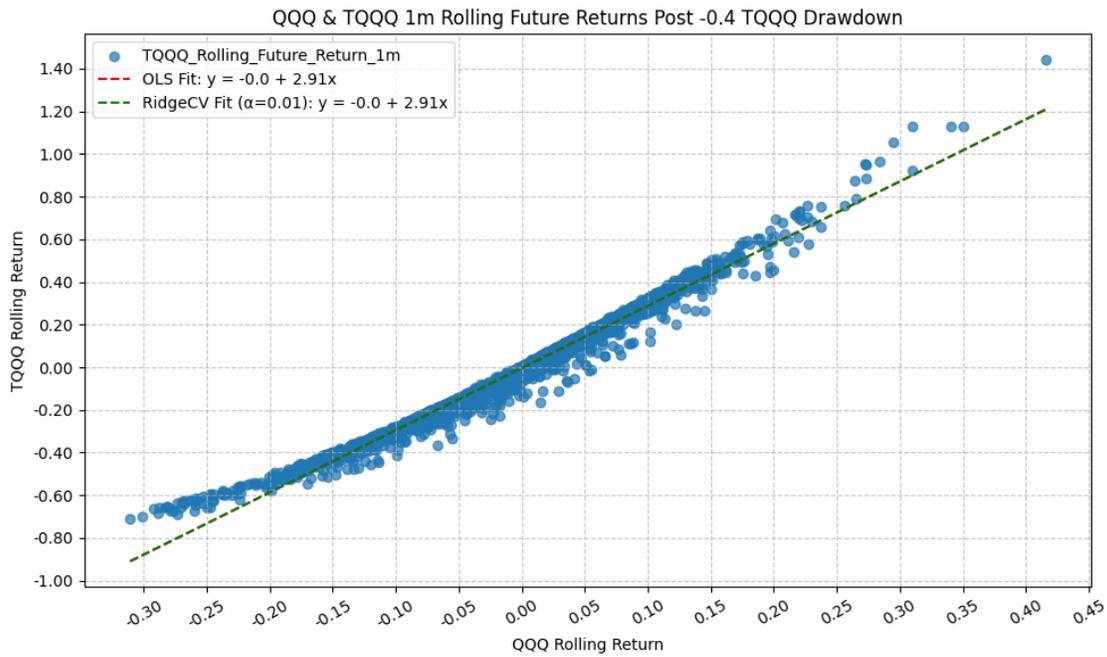
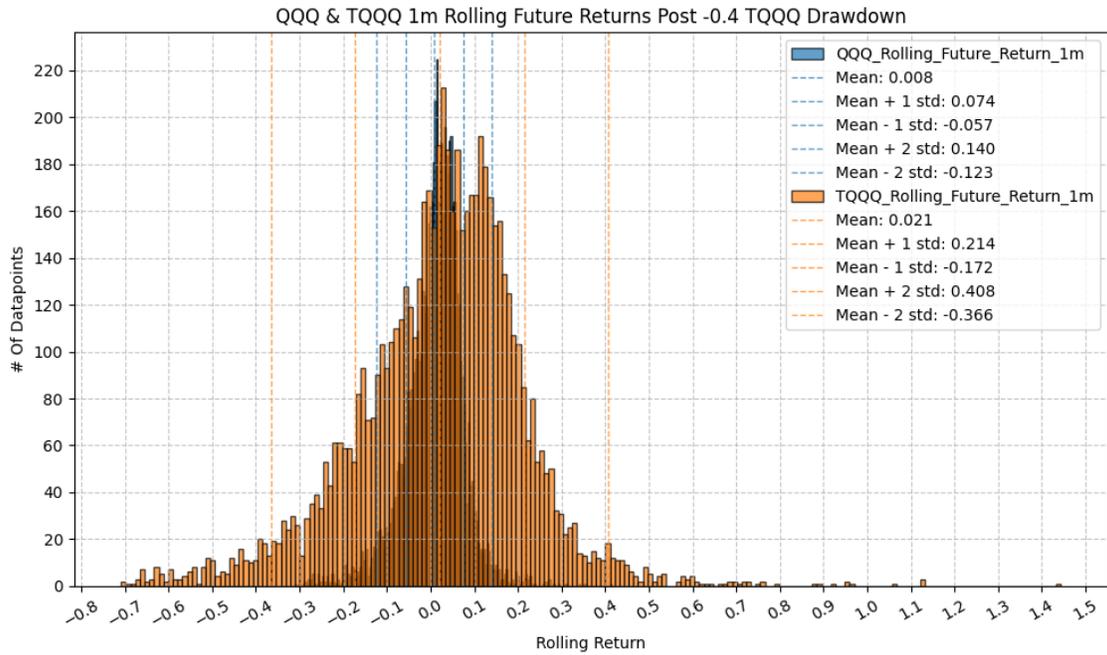
```

=====
Omnibus:                             3593.998   Durbin-Watson:                0.881
Prob(Omnibus):                        0.000   Jarque-Bera (JB):            403875.873
Skew:                                  -1.687   Prob(JB):                    0.00
Kurtosis:                              41.421   Cond. No.                    29.6
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1m R-squared:

```

0.983
Model: OLS Adj. R-squared:
0.983
Method: Least Squares F-statistic:
3.661e+05
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:53 Log-Likelihood:
14619.
No. Observations: 6500 AIC:
-2.923e+04
Df Residuals: 6498 BIC:
-2.922e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0035	0.000	-11.021	0.000
-0.004 -0.003				
QQQ_Rolling_Future_Return_1m	2.9150	0.005	605.092	0.000
2.906 2.924				

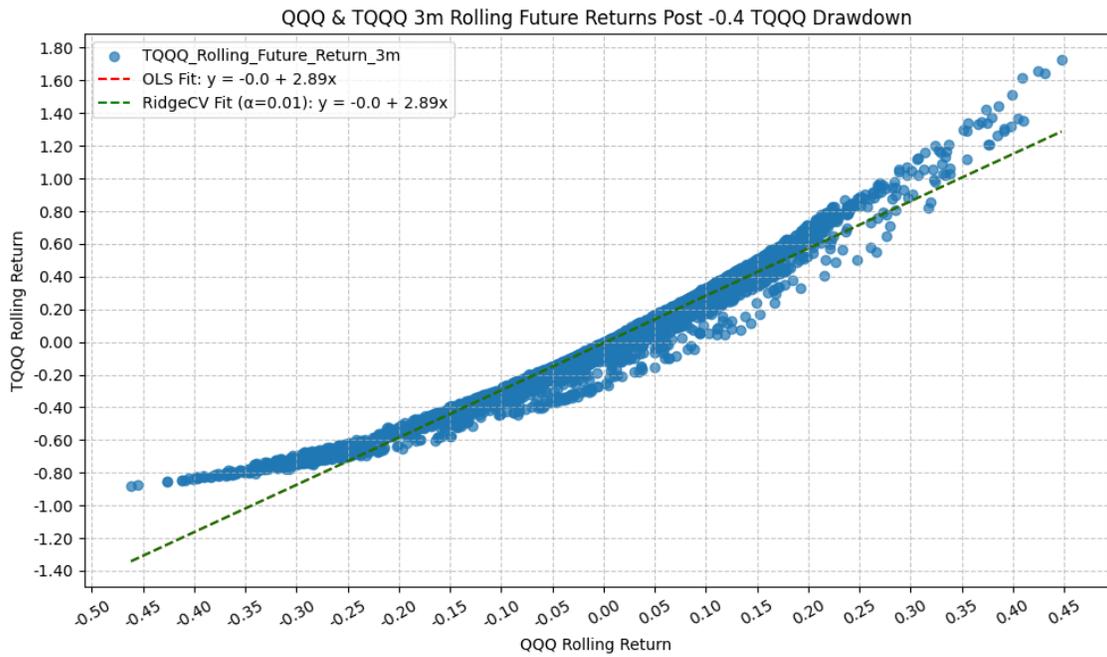
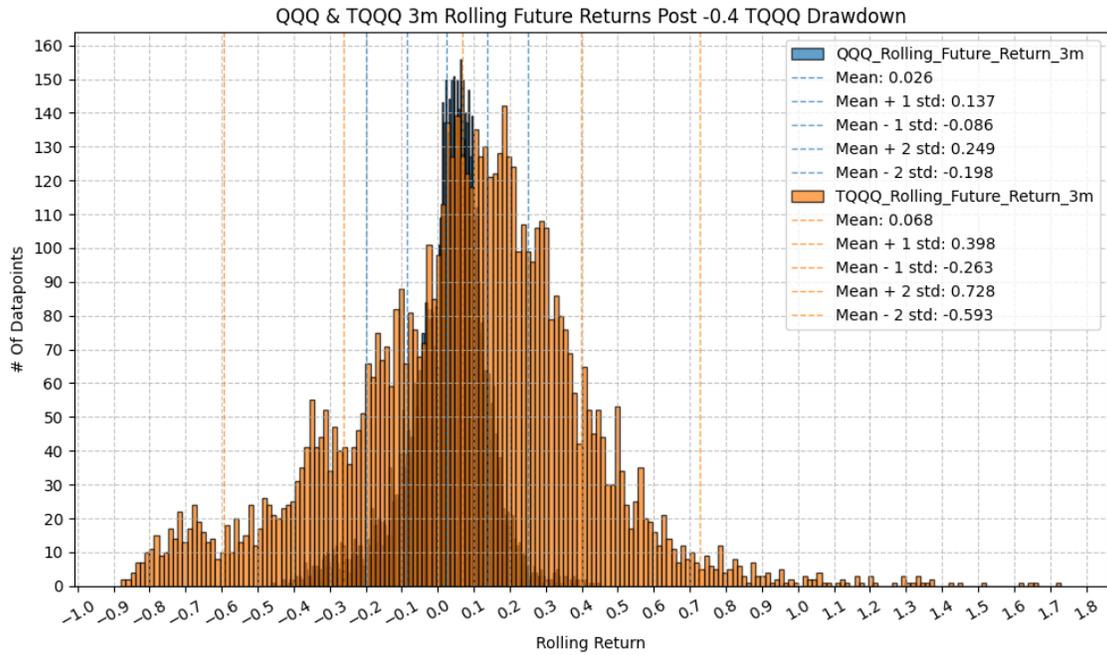
```

=====
Omnibus: 1510.573 Durbin-Watson: 0.297
Prob(Omnibus): 0.000 Jarque-Bera (JB): 82826.988
Skew: 0.062 Prob(JB): 0.00
Kurtosis: 20.487 Cond. No. 15.2
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3m R-squared:

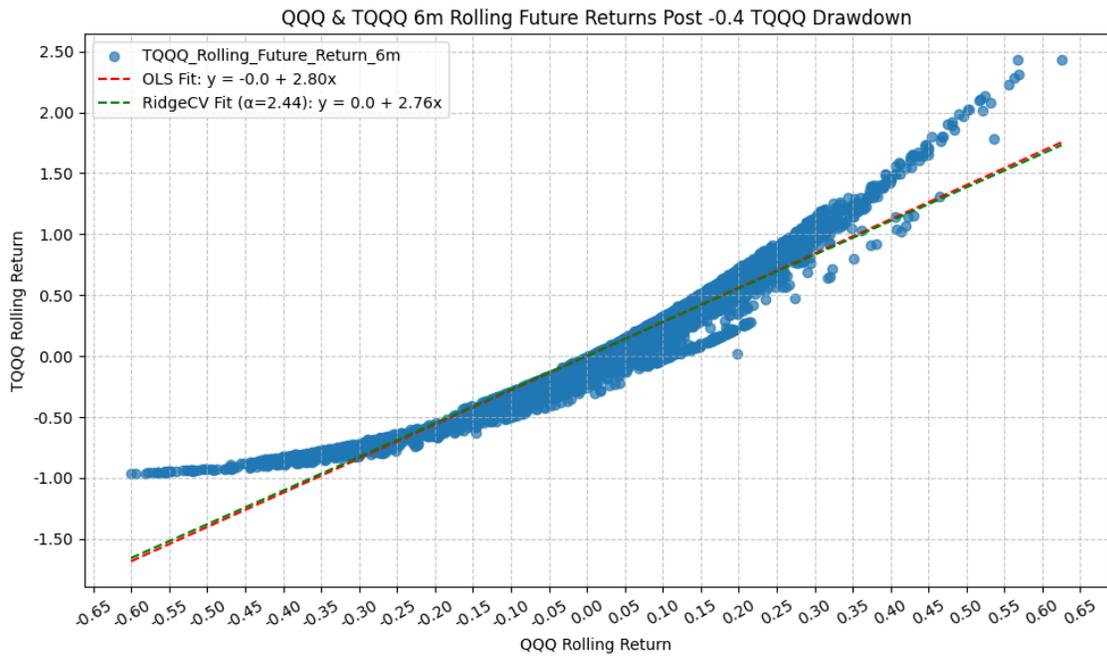
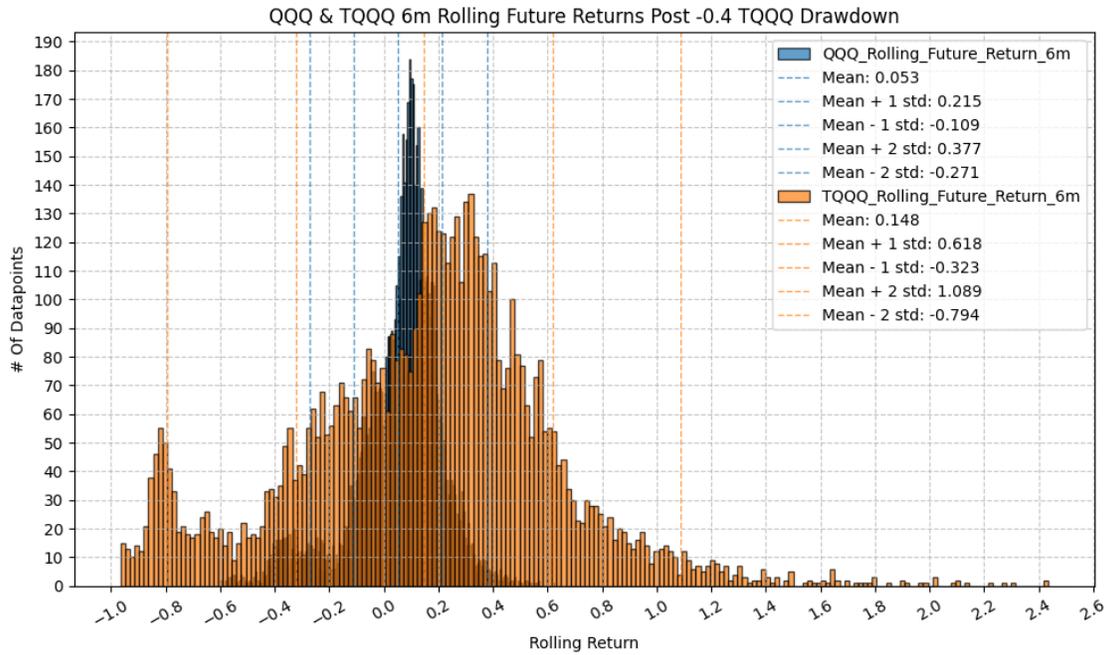
```

0.961
Model:                                OLS   Adj. R-squared:
0.961
Method:                                Least Squares   F-statistic:
1.591e+05
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:54   Log-Likelihood:
8471.5
No. Observations:                    6458   AIC:
-1.694e+04
Df Residuals:                        6456   BIC:
-1.693e+04
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                               -0.0065   0.001   -7.870   0.000
-0.008   -0.005
QQQ_Rolling_Future_Return_3m       2.8924   0.007   398.870   0.000
2.878   2.907
=====
Omnibus:                            1376.418   Durbin-Watson:           0.101
Prob(Omnibus):                       0.000   Jarque-Bera (JB):       15591.855
Skew:                                 0.692   Prob(JB):                0.00
Kurtosis:                             10.485   Cond. No.                8.95
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_6m R-squared:

```

0.931
Model:                               OLS   Adj. R-squared:
0.931
Method:                               Least Squares   F-statistic:
8.656e+04
Date:                               Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                               14:26:55   Log-Likelihood:
4305.0
No. Observations:                   6395   AIC:
-8606.
Df Residuals:                       6393   BIC:
-8593.
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-4.855e-06	0.002	-0.003	0.998
-0.003 0.003				
QQQ_Rolling_Future_Return_6m	2.8036	0.010	294.207	0.000
2.785 2.822				
=====				

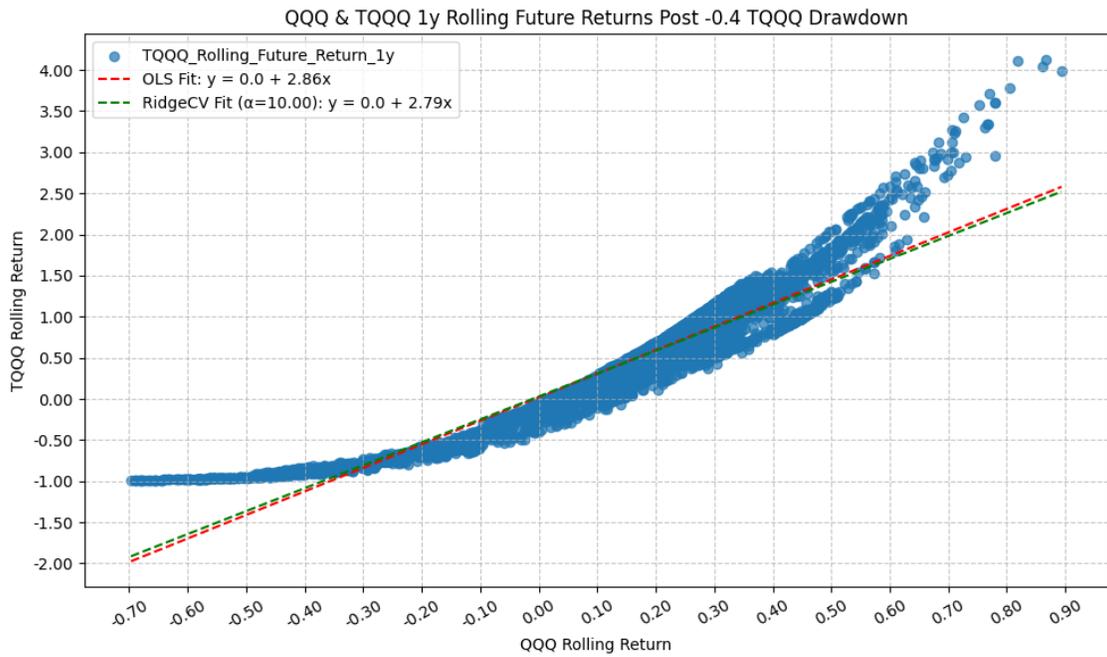
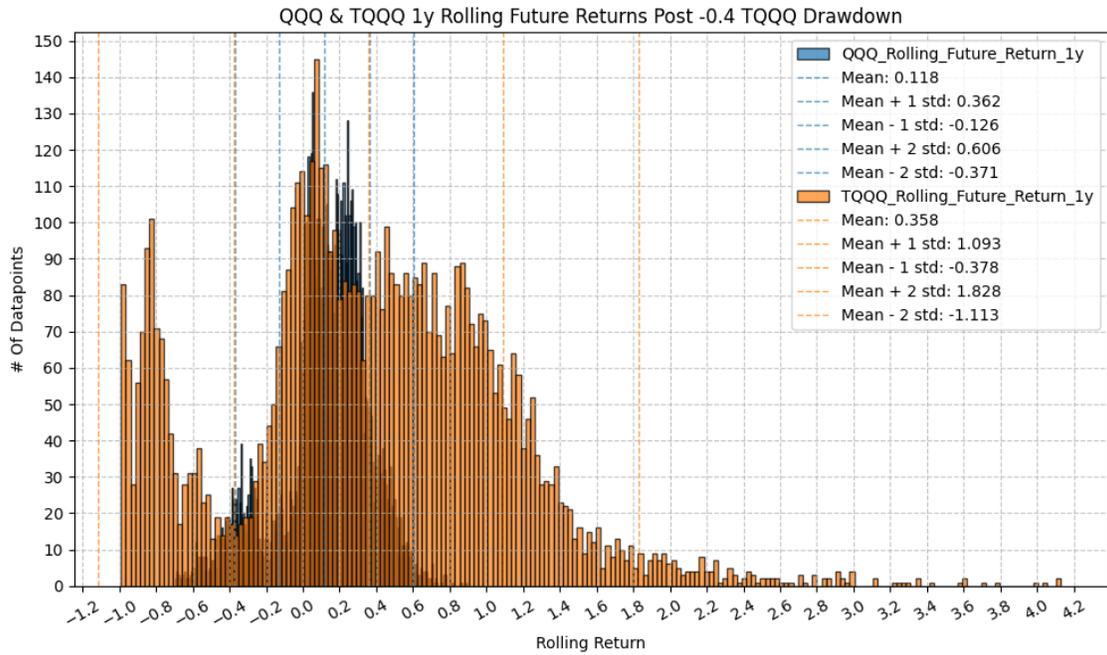
```

Omnibus:                            1637.994   Durbin-Watson:                0.057
Prob(Omnibus):                      0.000   Jarque-Bera (JB):            8138.991
Skew:                                1.146   Prob(JB):                    0.00
Kurtosis:                            8.029   Cond. No.:                   6.19
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1y R-squared:

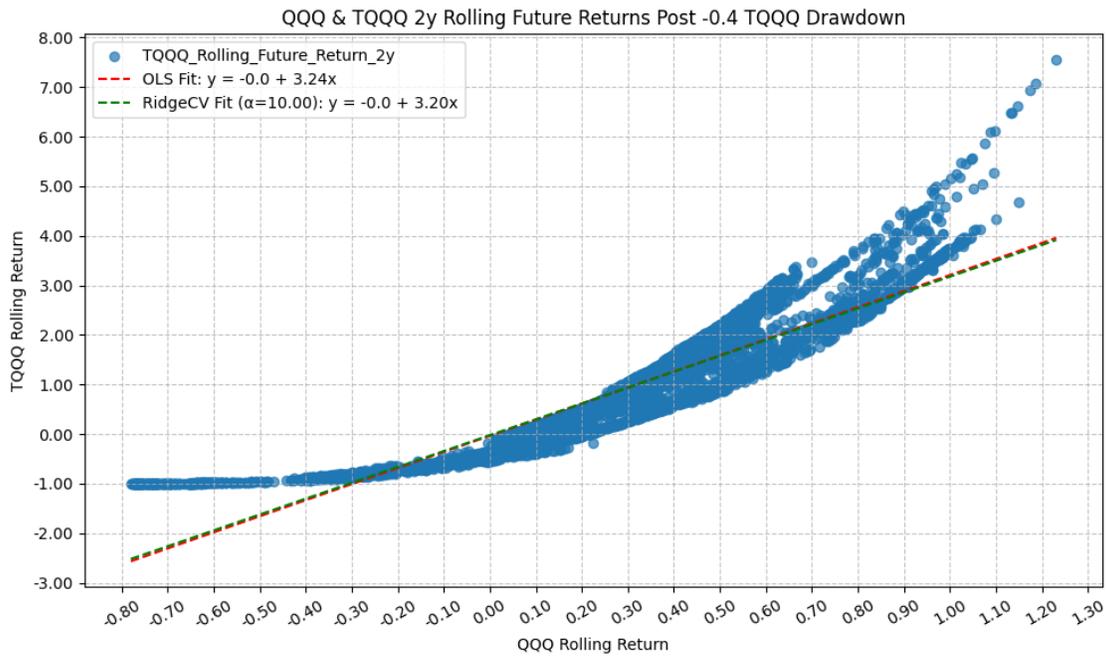
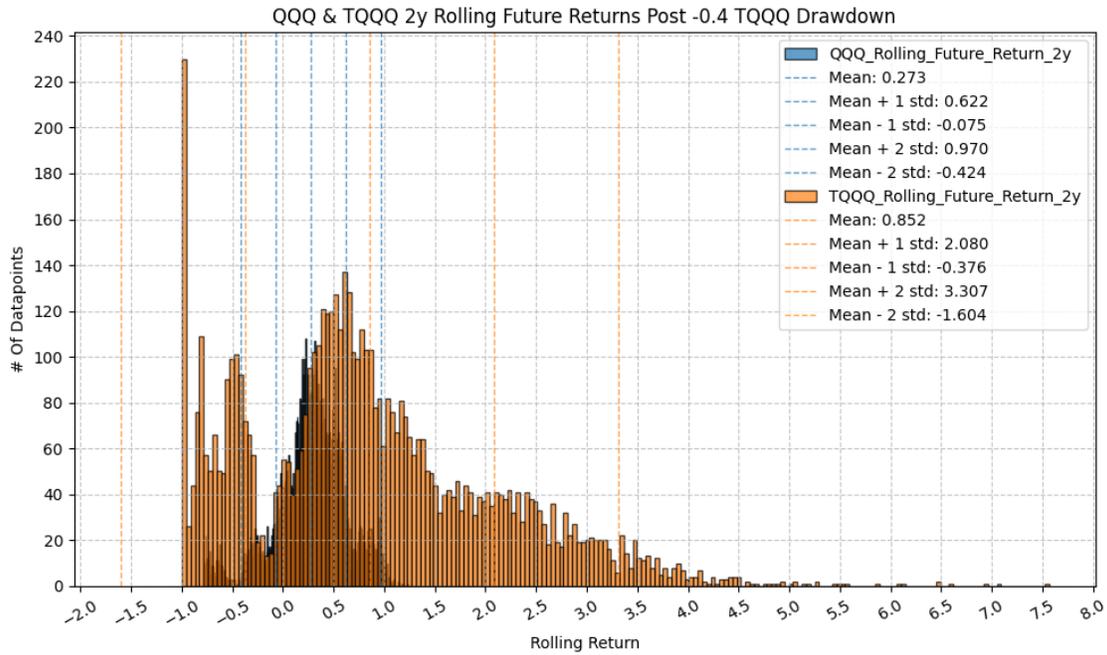
```

0.902
Model:                                OLS   Adj. R-squared:
0.902
Method:                                Least Squares   F-statistic:
5.795e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:57   Log-Likelihood:
326.09
No. Observations:                    6269   AIC:
-648.2
Df Residuals:                        6267   BIC:
-634.7
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            0.0211   0.003   6.535   0.000
0.015   0.027
QQQ_Rolling_Future_Return_1y    2.8618   0.012  240.727   0.000
2.838   2.885
=====
Omnibus:                          1984.175   Durbin-Watson:                0.039
Prob(Omnibus):                     0.000   Jarque-Bera (JB):            8573.296
Skew:                              1.494   Prob(JB):                    0.00
Kurtosis:                          7.888   Cond. No.                     4.16
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_2y R-squared:

```

0.847
Model: OLS Adj. R-squared:
0.847
Method: Least Squares F-statistic:
3.333e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:26:58 Log-Likelihood:
-4121.6
No. Observations: 6017 AIC:
8247.
Df Residuals: 6015 BIC:
8261.
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

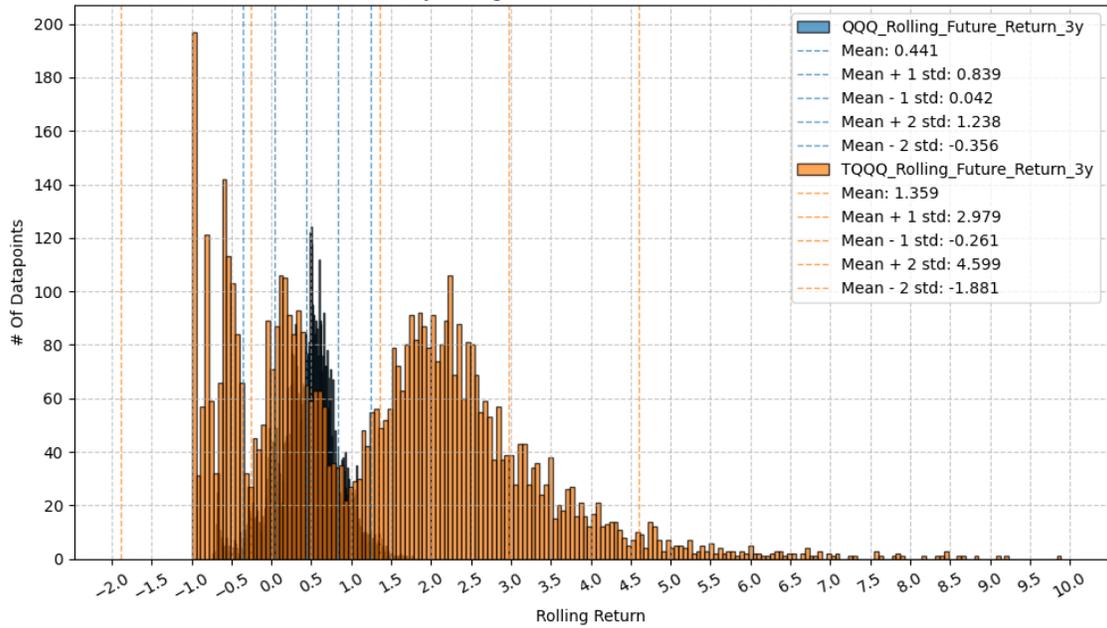
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0345	0.008	-4.386	0.000
-0.050 -0.019				
QQQ_Rolling_Future_Return_2y	3.2439	0.018	182.575	0.000
3.209 3.279				
=====				
Omnibus:	1712.301	Durbin-Watson:		0.019
Prob(Omnibus):	0.000	Jarque-Bera (JB):		5037.509
Skew:	1.480	Prob(JB):		0.00
Kurtosis:	6.367	Cond. No.		3.11
=====				

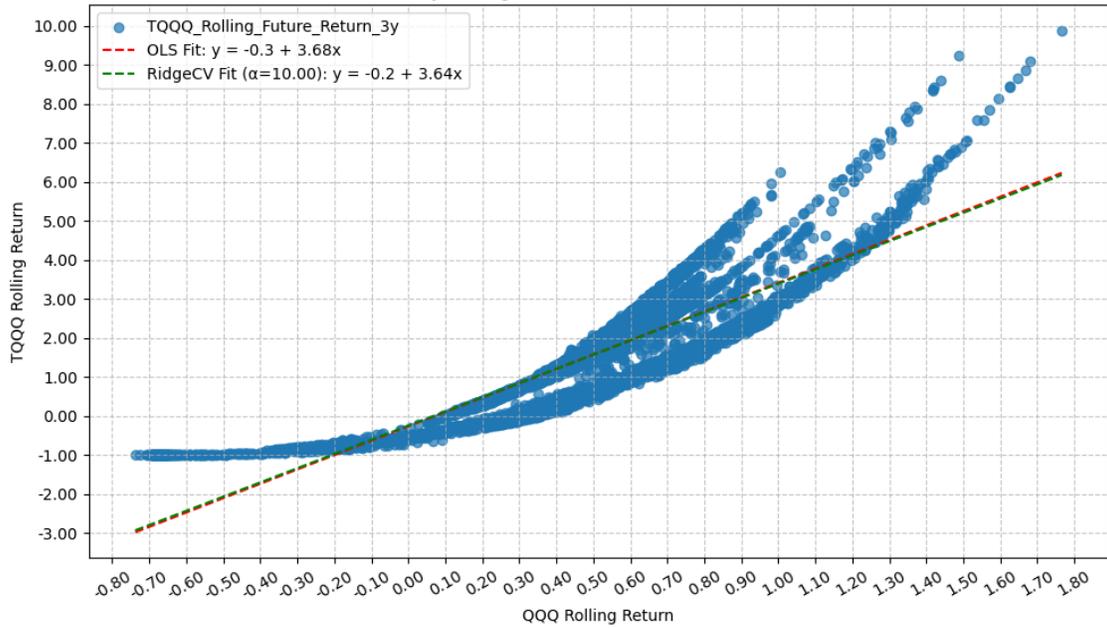
Notes:

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

QQQ & TQQQ 3y Rolling Future Returns Post -0.4 TQQQ Drawdown



QQQ & TQQQ 3y Rolling Future Returns Post -0.4 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3y R-squared:

```

0.817
Model:                                OLS   Adj. R-squared:
0.817
Method:                                Least Squares   F-statistic:
2.581e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:26:59   Log-Likelihood:
-6058.9
No. Observations:                    5765   AIC:
1.212e+04
Df Residuals:                        5763   BIC:
1.214e+04
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====

```

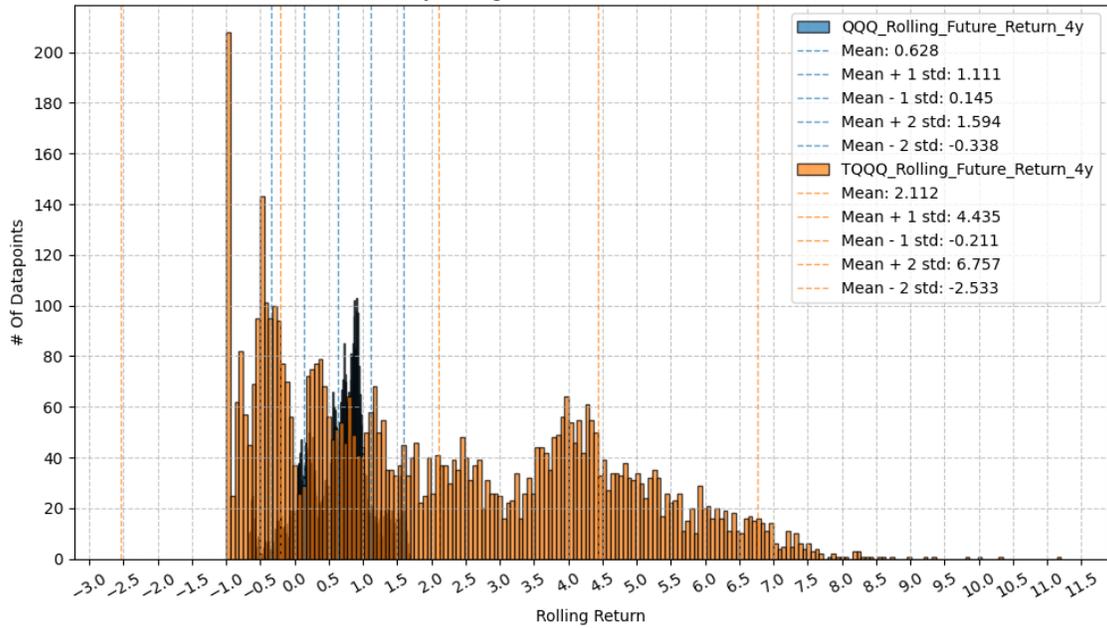
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.2618	0.014	-19.253	0.000
-0.288 -0.235				
QQQ_Rolling_Future_Return_3y	3.6767	0.023	160.644	0.000
3.632 3.722				
=====				
Omnibus:	869.452	Durbin-Watson:		0.015
Prob(Omnibus):	0.000	Jarque-Bera (JB):		1585.916
Skew:	0.962	Prob(JB):		0.00
Kurtosis:	4.703	Cond. No.		3.07
=====				

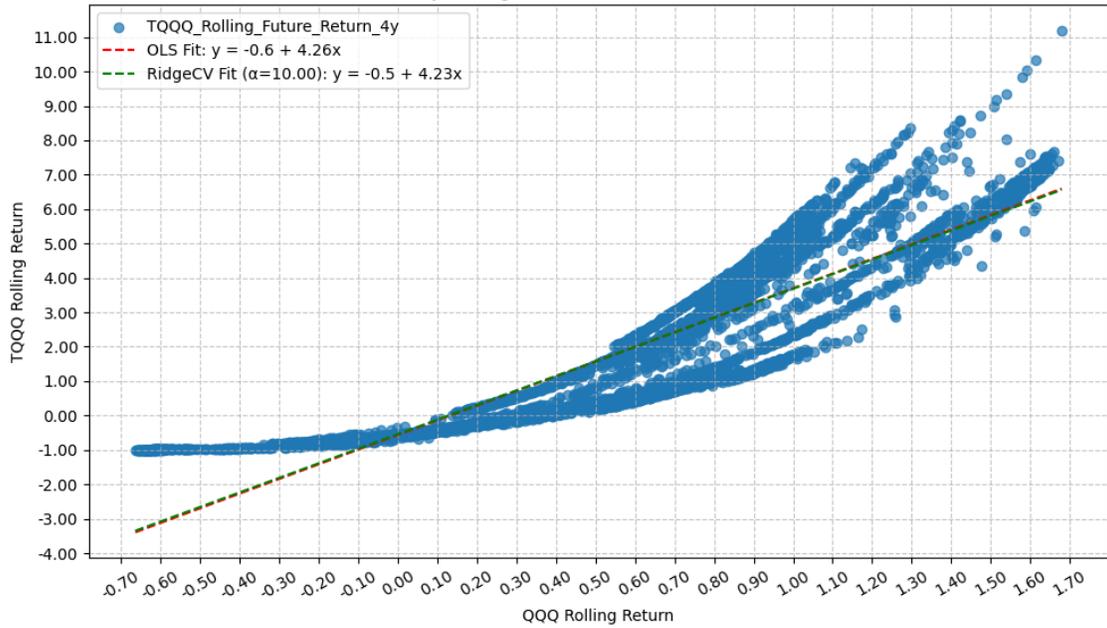
Notes:

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

QQQ & TQQQ 4y Rolling Future Returns Post -0.4 TQQQ Drawdown



QQQ & TQQQ 4y Rolling Future Returns Post -0.4 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_4y R-squared:

```

0.786
Model: OLS Adj. R-squared:
0.786
Method: Least Squares F-statistic:
2.019e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:00 Log-Likelihood:
-8223.4
No. Observations: 5513 AIC:
1.645e+04
Df Residuals: 5511 BIC:
1.646e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

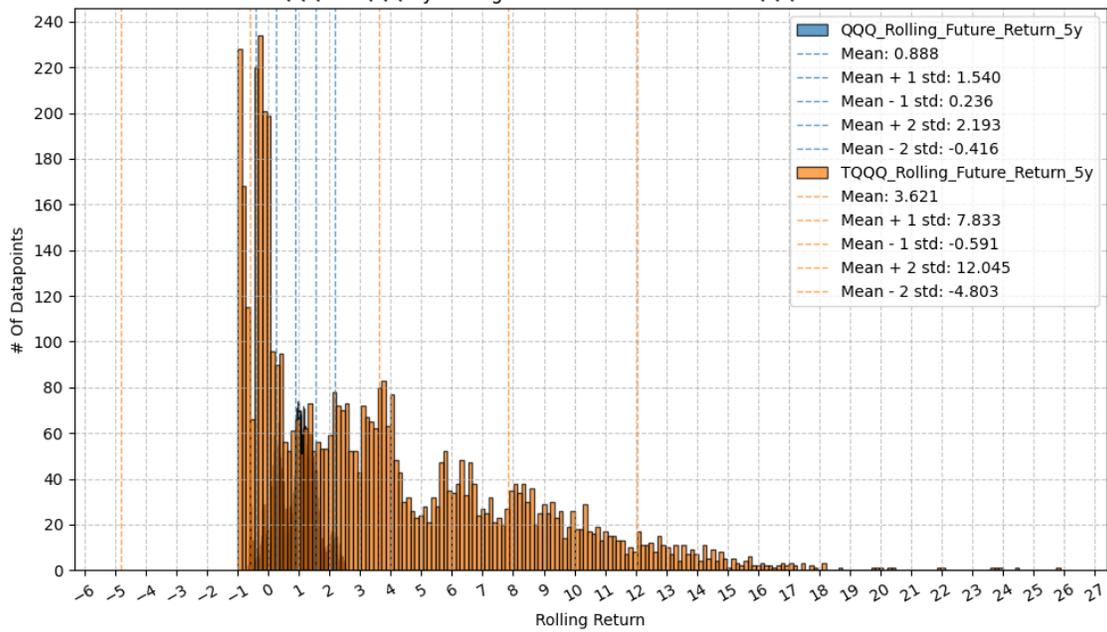
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.5646	0.024	-23.758	0.000
-0.611 -0.518				
QQQ_Rolling_Future_Return_4y	4.2630	0.030	142.094	0.000
4.204 4.322				
=====				
Omnibus:	67.431	Durbin-Watson:		0.010
Prob(Omnibus):	0.000	Jarque-Bera (JB):		52.172
Skew:	0.153	Prob(JB):		4.69e-12
Kurtosis:	2.634	Cond. No.		3.04
=====				

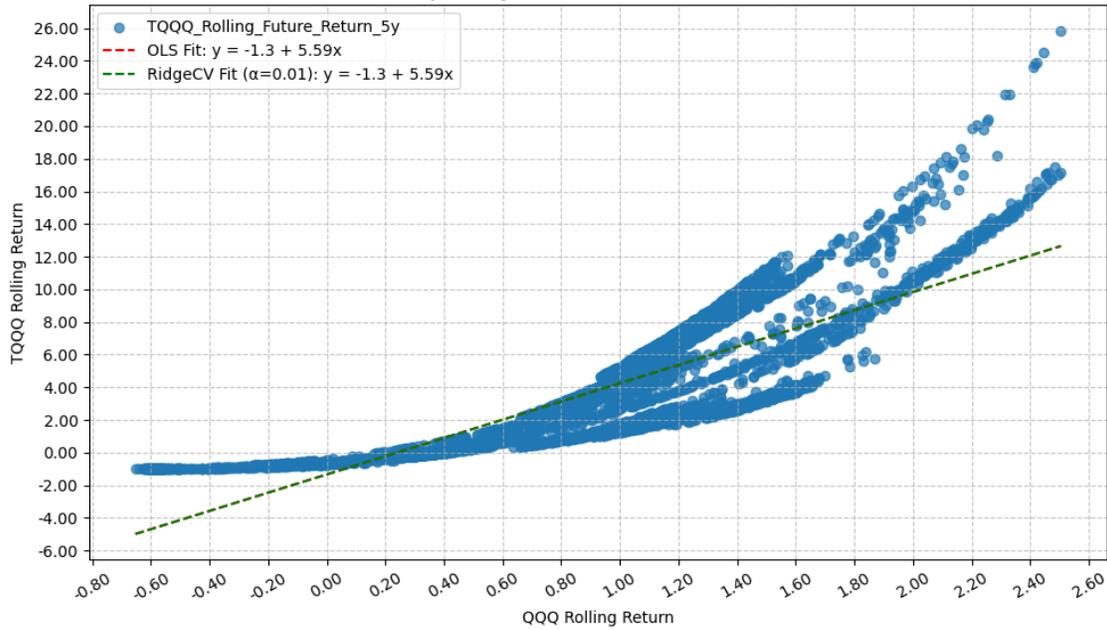
Notes:

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

QQQ & TQQQ 5y Rolling Future Returns Post -0.4 TQQQ Drawdown



QQQ & TQQQ 5y Rolling Future Returns Post -0.4 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_5y R-squared:

```

0.748
Model:                                OLS   Adj. R-squared:
0.748
Method:                                Least Squares   F-statistic:
1.562e+04
Date:                                  Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                  14:27:01   Log-Likelihood:
-11403.
No. Observations:                      5261   AIC:
2.281e+04
Df Residuals:                          5259   BIC:
2.282e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====

```

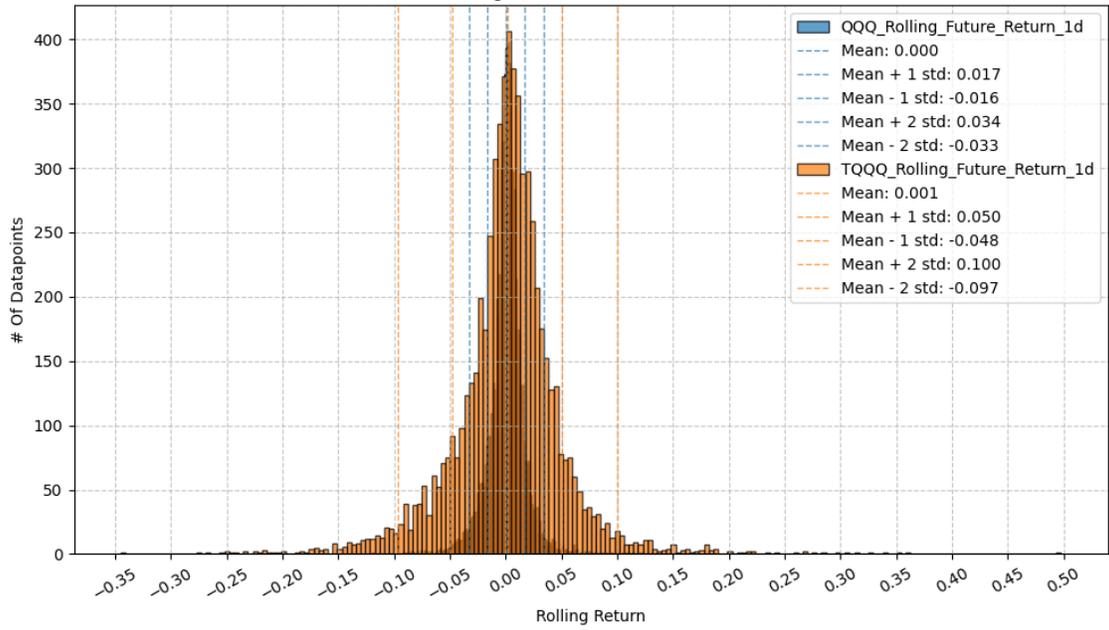
	coef	std err	t	P> t
[0.025 0.975]				

const	-1.3405	0.049	-27.216	0.000
-1.437 -1.244				
QQQ_Rolling_Future_Return_5y	5.5855	0.045	124.962	0.000
5.498 5.673				
=====				
Omnibus:	241.818	Durbin-Watson:		0.009
Prob(Omnibus):	0.000	Jarque-Bera (JB):		363.534
Skew:	0.417	Prob(JB):		1.15e-79
Kurtosis:	3.981	Cond. No.		3.07
=====				

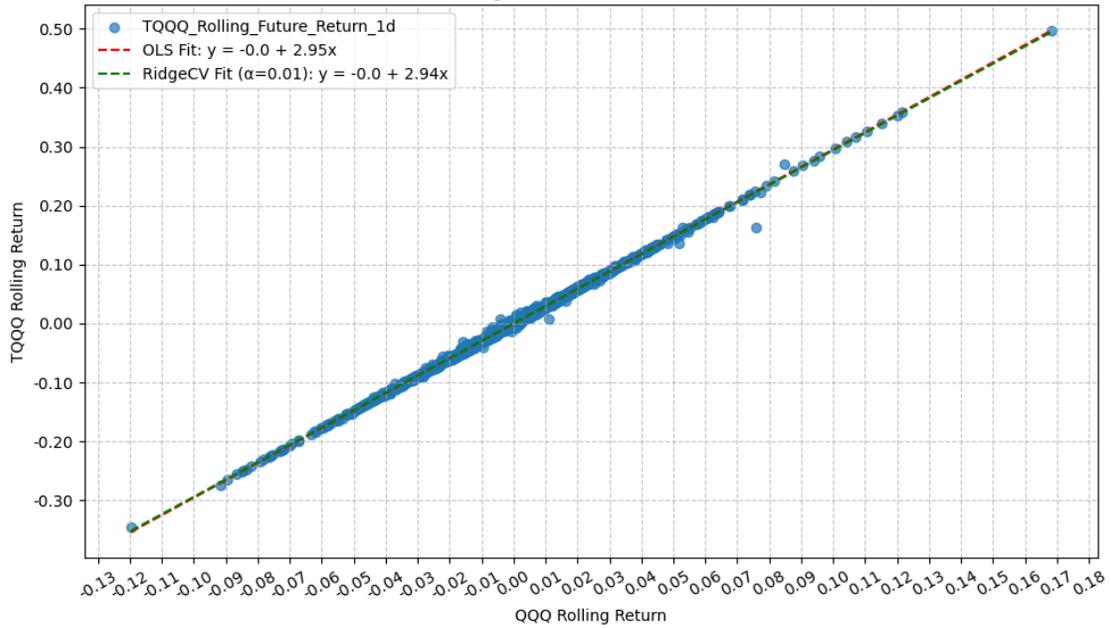
Notes:

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

QQQ & TQQQ 1d Rolling Future Returns Post -0.5 TQQQ Drawdown



QQQ & TQQQ 1d Rolling Future Returns Post -0.5 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1d R-squared:

```

0.999
Model: OLS Adj. R-squared:
0.999
Method: Least Squares F-statistic:
6.255e+06
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:03 Log-Likelihood:
32495.
No. Observations: 6457 AIC:
-6.499e+04
Df Residuals: 6455 BIC:
-6.497e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

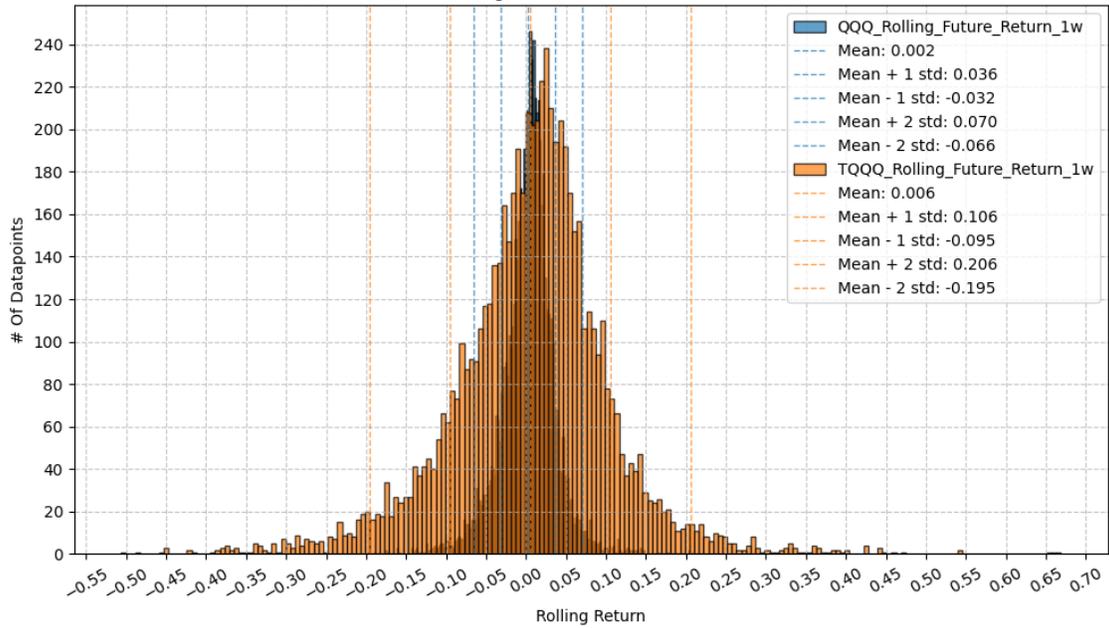
	coef	std err	t	P> t
[0.025 0.975]				

const	-4.913e-05	1.97e-05	-2.500	0.012
-8.77e-05 -1.06e-05				
QQQ_Rolling_Future_Return_1d	2.9549	0.001	2501.003	0.000
2.953 2.957				
=====				
Omnibus:	9580.111	Durbin-Watson:		2.567
Prob(Omnibus):	0.000	Jarque-Bera (JB):		38114515.631
Skew:	-8.108	Prob(JB):		0.00
Kurtosis:	379.038	Cond. No.		60.1
=====				

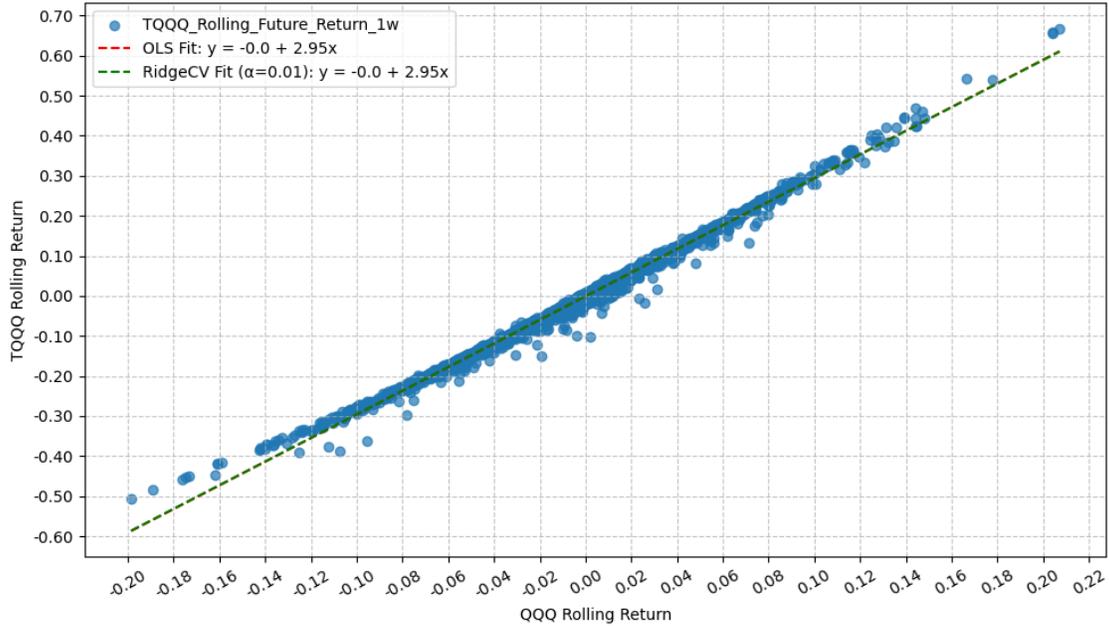
Notes:

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

QQQ & TQQQ 1w Rolling Future Returns Post -0.5 TQQQ Drawdown



QQQ & TQQQ 1w Rolling Future Returns Post -0.5 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1w R-squared:

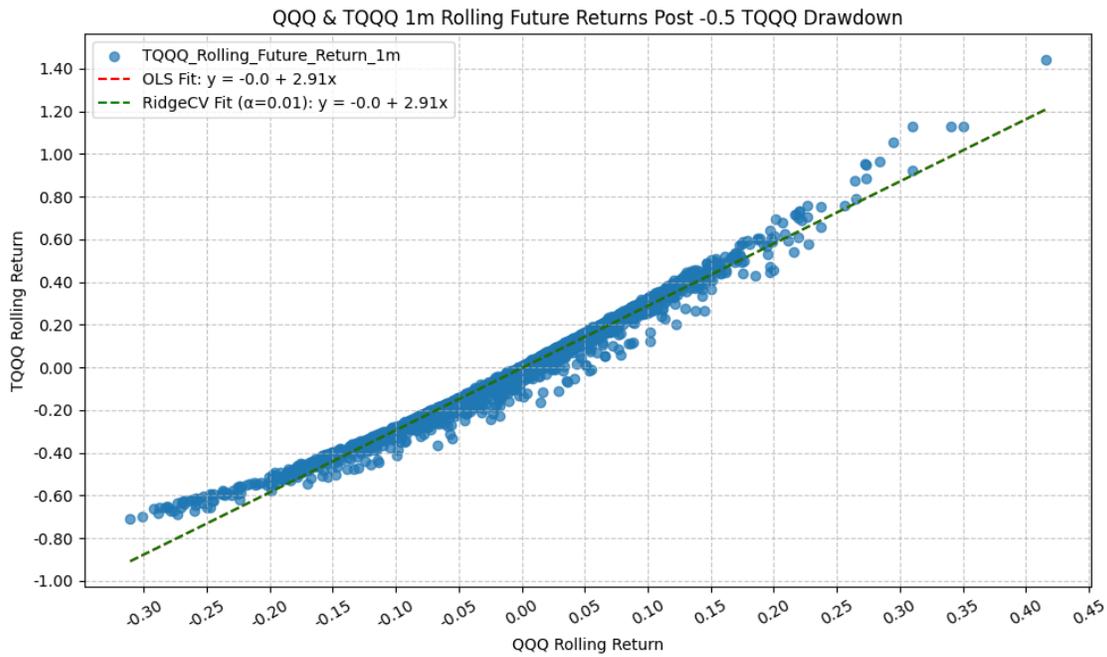
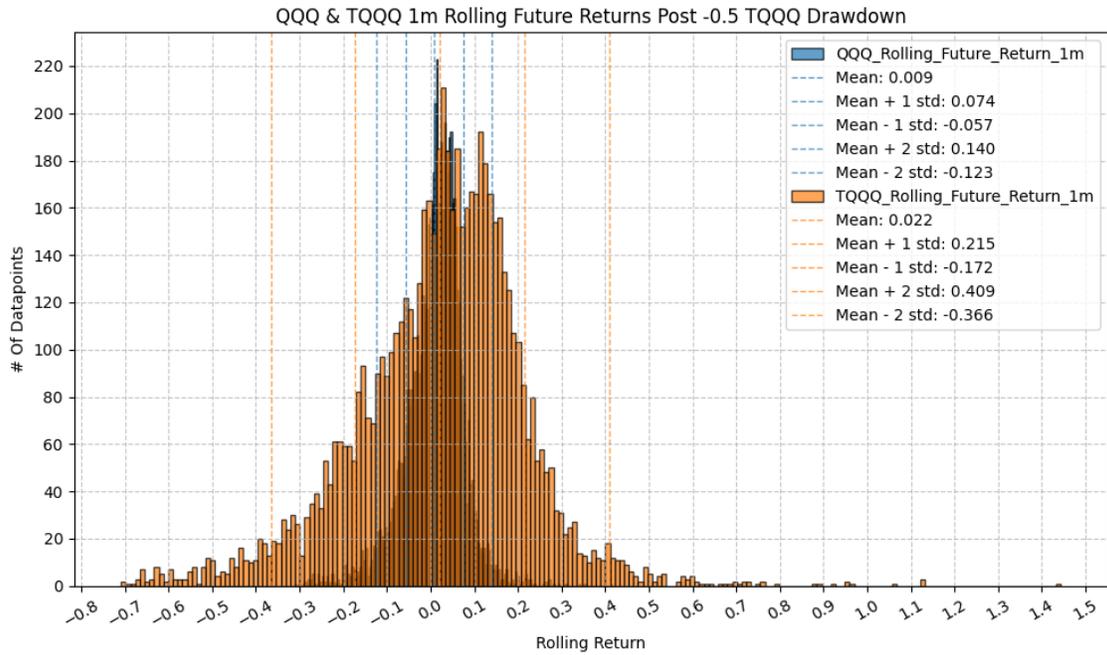
```

0.994
Model:                                OLS   Adj. R-squared:
0.994
Method:                               Least Squares   F-statistic:
1.109e+06
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:27:04   Log-Likelihood:
22311.
No. Observations:                    6453   AIC:
-4.462e+04
Df Residuals:                        6451   BIC:
-4.461e+04
Df Model:                             1
Covariance Type:                    nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0008   9.51e-05   -8.169   0.000
-0.001   -0.001
QQQ_Rolling_Future_Return_1w     2.9529    0.003   1053.321   0.000
2.947   2.958
=====
Omnibus:                          3540.518   Durbin-Watson:                0.887
Prob(Omnibus):                     0.000   Jarque-Bera (JB):             402393.065
Skew:                               -1.669   Prob(JB):                     0.00
Kurtosis:                          41.541   Cond. No.                     29.5
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1m R-squared:

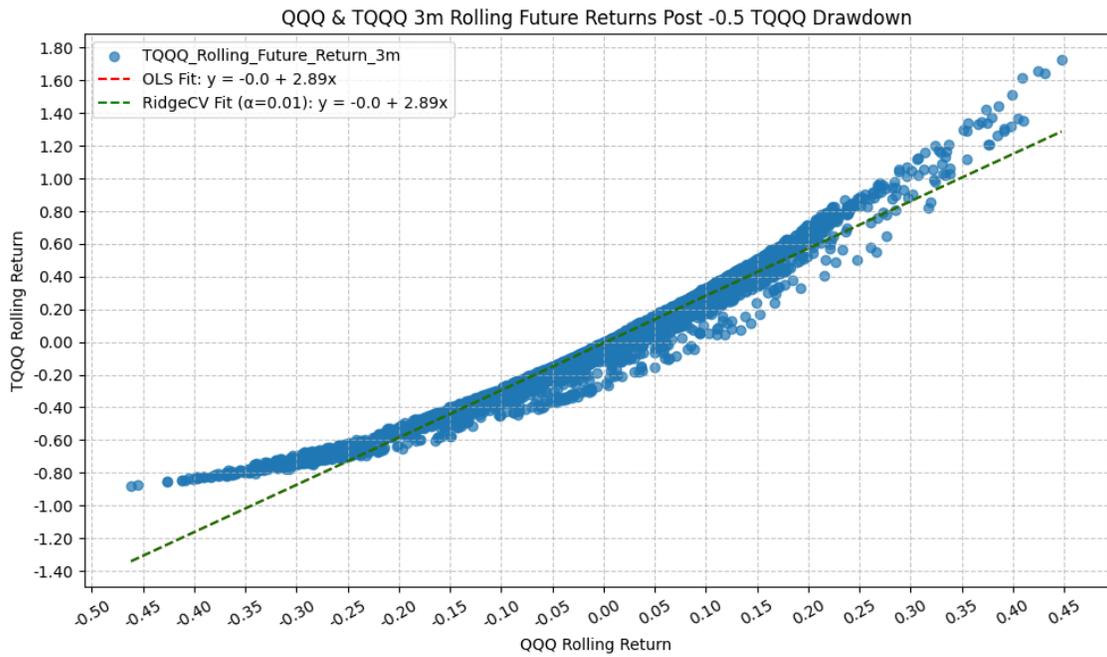
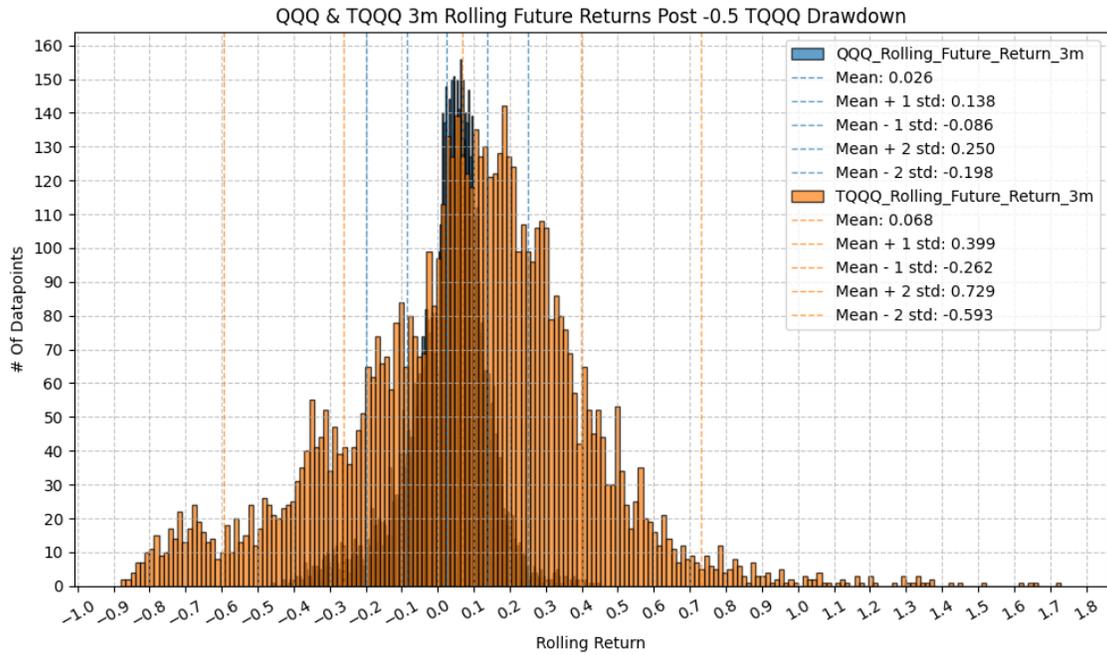
```

0.983
Model:                               OLS   Adj. R-squared:
0.983
Method:                               Least Squares   F-statistic:
3.615e+05
Date:                               Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                               14:27:05   Log-Likelihood:
14455.
No. Observations:                   6437   AIC:
-2.891e+04
Df Residuals:                       6435   BIC:
-2.889e+04
Df Model:                           1
Covariance Type:                   nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0034   0.000   -10.594   0.000
-0.004   -0.003
QQQ_Rolling_Future_Return_1m    2.9144   0.005   601.219   0.000
2.905   2.924
=====
Omnibus:                          1490.690   Durbin-Watson:           0.295
Prob(Omnibus):                     0.000   Jarque-Bera (JB):       81043.655
Skew:                               0.049   Prob(JB):                0.00
Kurtosis:                          20.383   Cond. No.                15.2
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3m R-squared:

```

0.961
Model: OLS Adj. R-squared:
0.961
Method: Least Squares F-statistic:
1.589e+05
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:06 Log-Likelihood:
8428.1
No. Observations: 6424 AIC:
-1.685e+04
Df Residuals: 6422 BIC:
-1.684e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

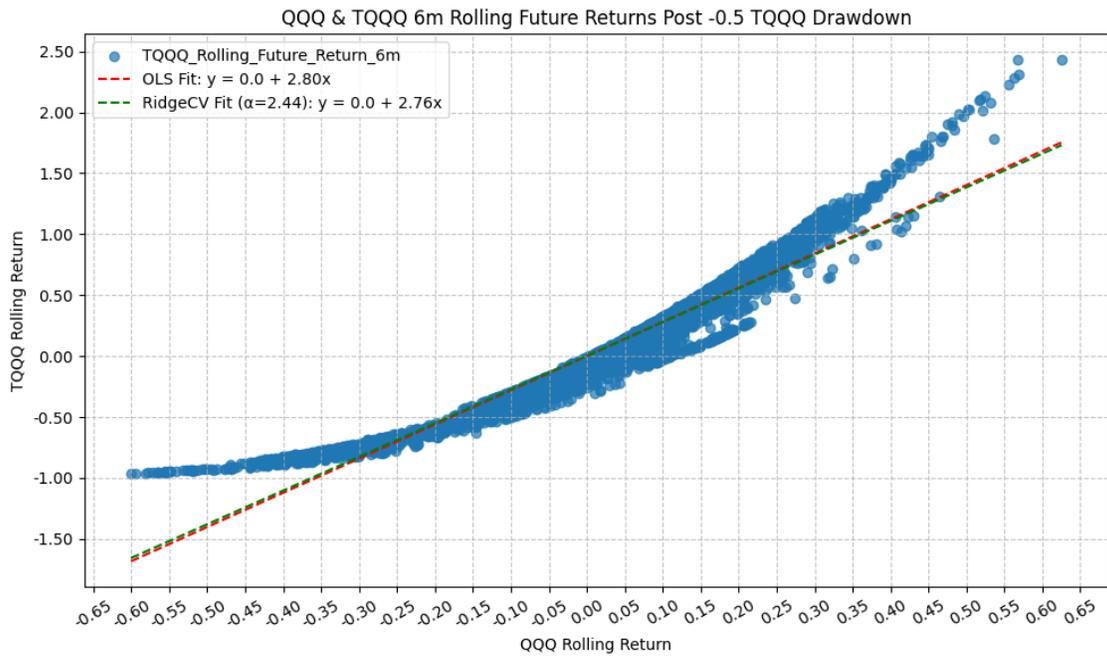
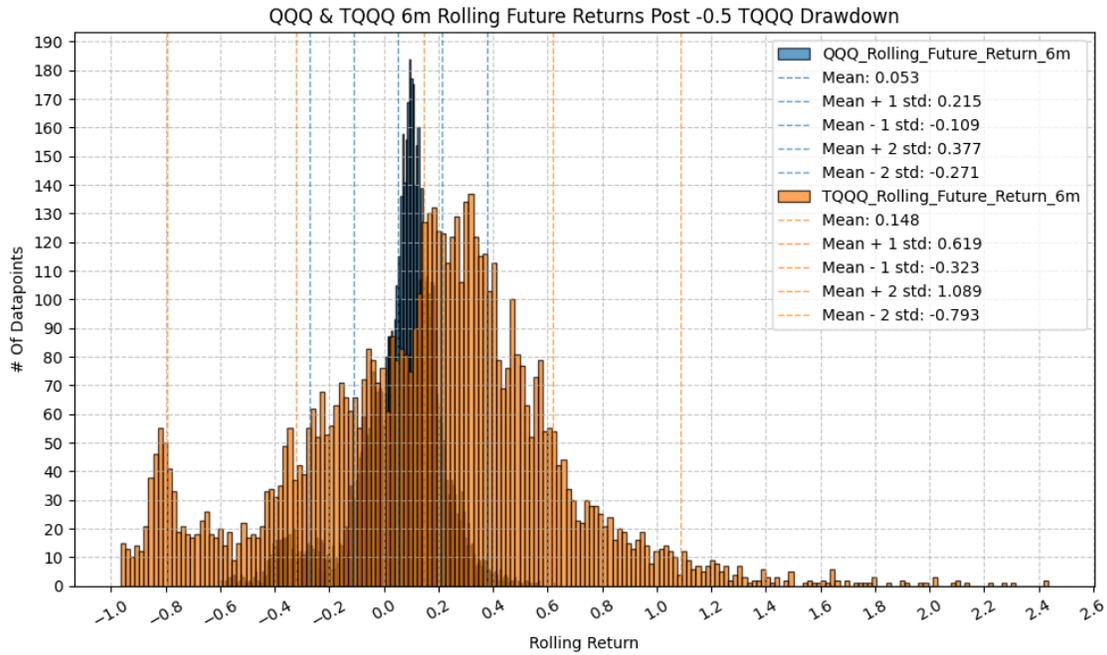
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0063	0.001	-7.529	0.000
-0.008 -0.005				
QQQ_Rolling_Future_Return_3m	2.8919	0.007	398.560	0.000
2.878 2.906				
=====				
Omnibus:	1375.718	Durbin-Watson:		0.101
Prob(Omnibus):	0.000	Jarque-Bera (JB):		15496.490
Skew:	0.698	Prob(JB):		0.00
Kurtosis:	10.480	Cond. No.		8.93
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_6m R-squared:

```

0.931
Model: OLS Adj. R-squared:
0.931
Method: Least Squares F-statistic:
8.673e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:07 Log-Likelihood:
4311.8
No. Observations: 6392 AIC:
-8620.
Df Residuals: 6390 BIC:
-8606.
Df Model: 1
Covariance Type: nonrobust
=====
=====

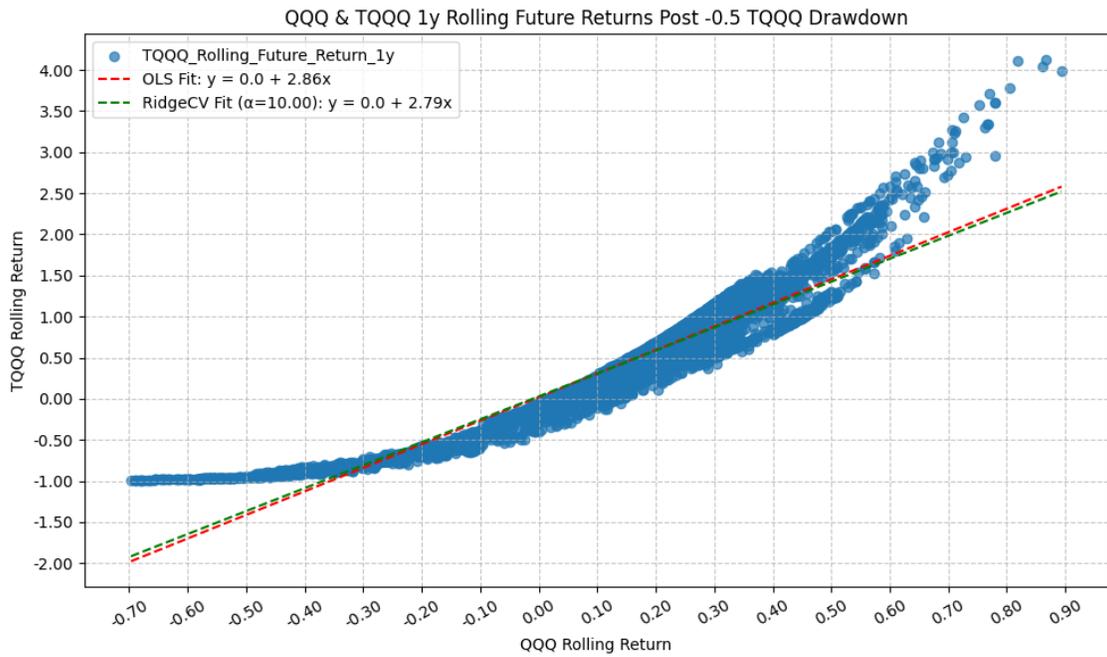
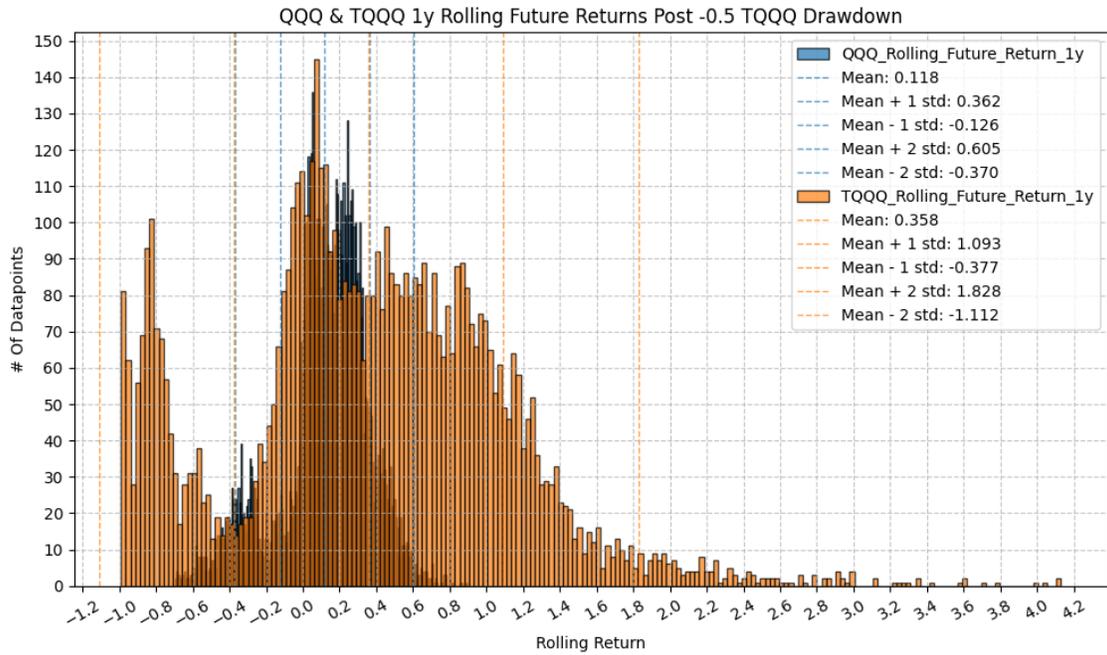
```

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0001	0.002	0.068	0.946
-0.003 0.003				
QQQ_Rolling_Future_Return_6m	2.8037	0.010	294.503	0.000
2.785 2.822				
=====				
Omnibus:	1653.772	Durbin-Watson:		0.055
Prob(Omnibus):	0.000	Jarque-Bera (JB):		8144.760
Skew:	1.162	Prob(JB):		0.00
Kurtosis:	8.018	Cond. No.		6.19
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1y R-squared:

```

0.903
Model: OLS Adj. R-squared:
0.903
Method: Least Squares F-statistic:
5.801e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:09 Log-Likelihood:
333.68
No. Observations: 6266 AIC:
-663.4
Df Residuals: 6264 BIC:
-649.9
Df Model: 1
Covariance Type: nonrobust
=====
=====

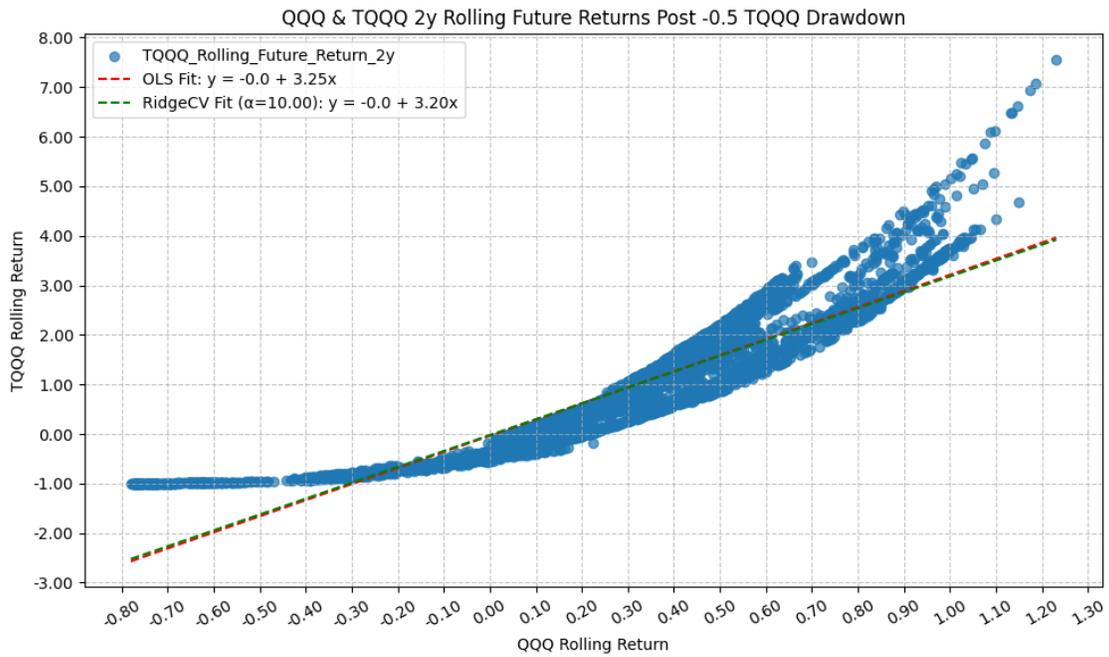
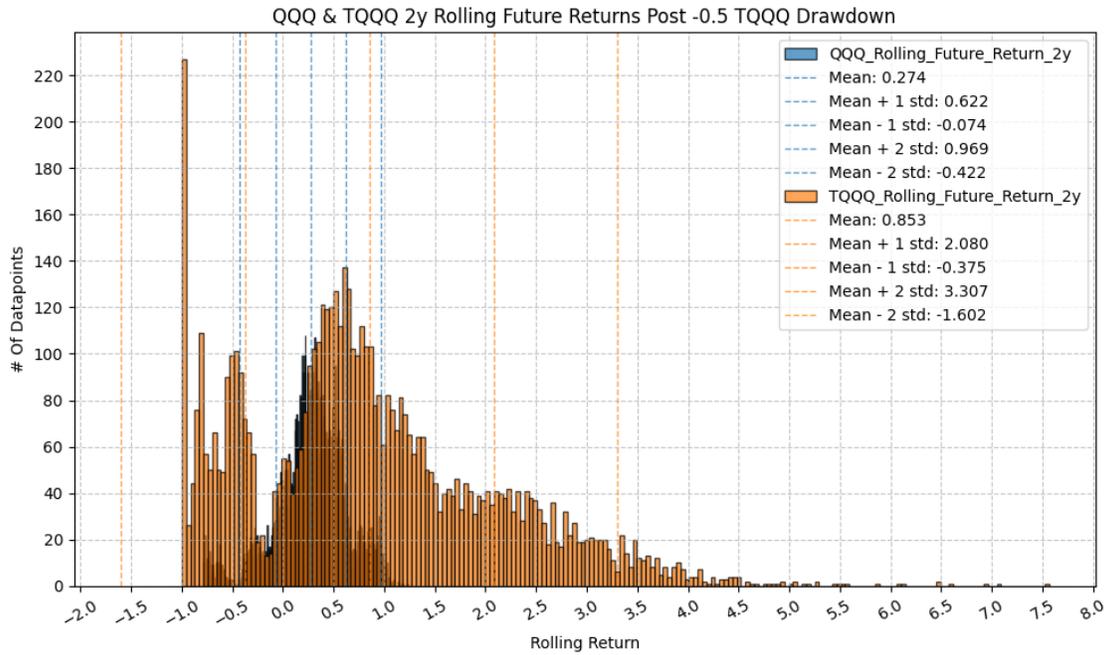
```

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0205	0.003	6.376	0.000
0.014 0.027				
QQQ_Rolling_Future_Return_1y	2.8644	0.012	240.863	0.000
2.841 2.888				
=====				
Omnibus:	1982.919	Durbin-Watson:		0.038
Prob(Omnibus):	0.000	Jarque-Bera (JB):		8590.359
Skew:	1.493	Prob(JB):		0.00
Kurtosis:	7.898	Cond. No.		4.16
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_2y R-squared:

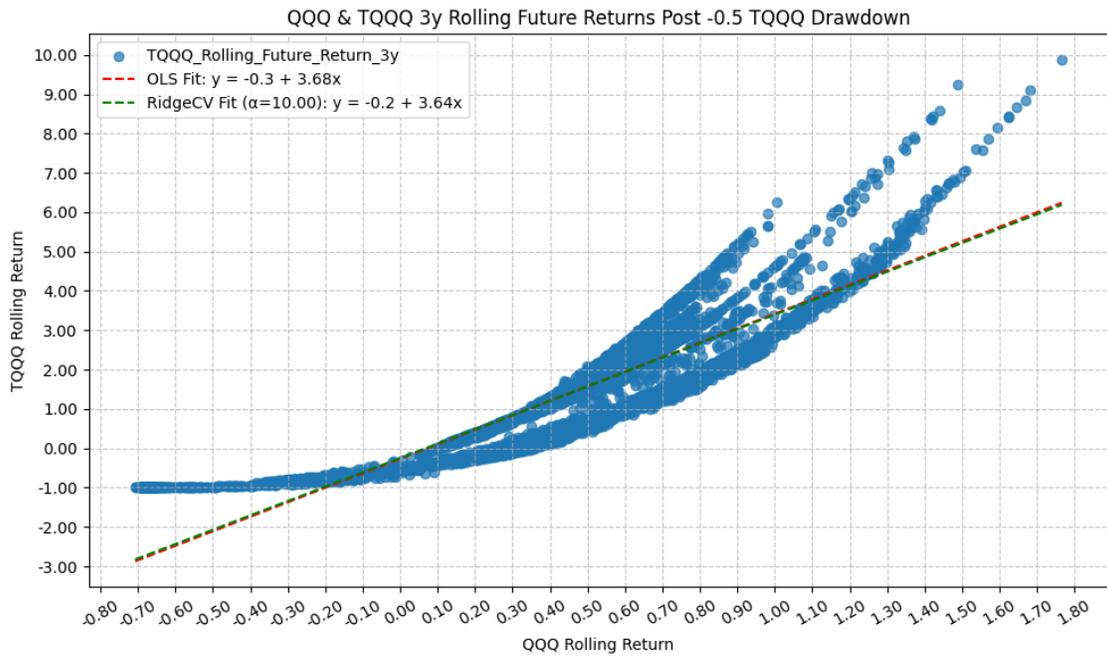
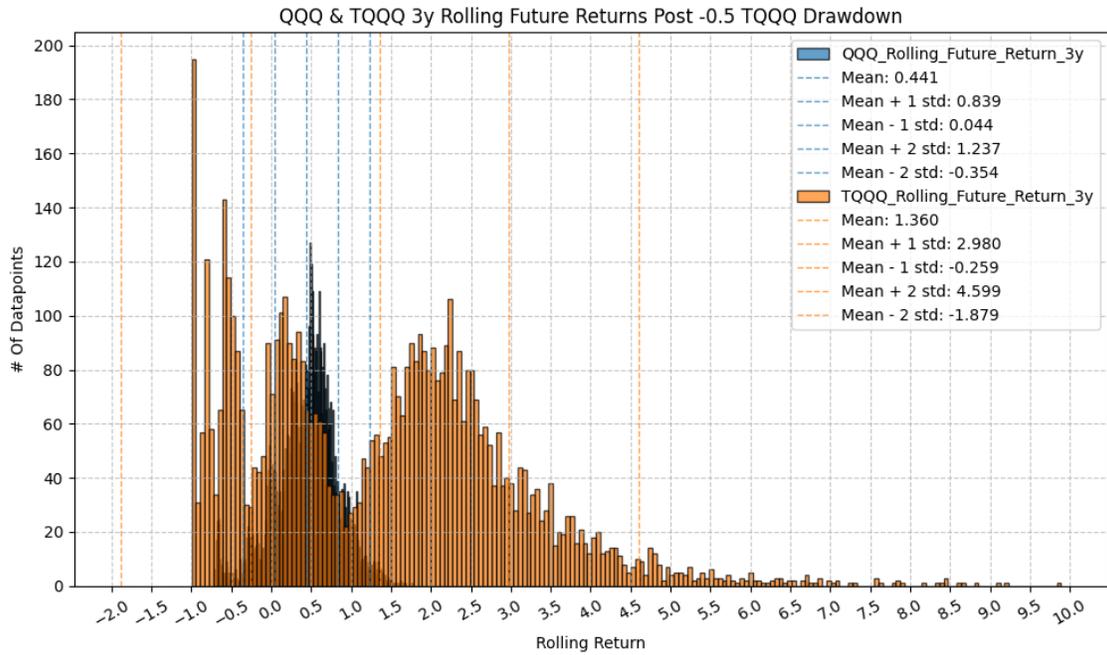
```

0.847
Model:                                OLS   Adj. R-squared:
0.847
Method:                                Least Squares   F-statistic:
3.336e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:10   Log-Likelihood:
-4114.4
No. Observations:                    6014   AIC:
8233.
Df Residuals:                        6012   BIC:
8246.
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                                -0.0360   0.008   -4.571   0.000
-0.051   -0.021
QQQ_Rolling_Future_Return_2y        3.2475   0.018   182.648   0.000
3.213   3.282
=====
Omnibus:                            1717.522   Durbin-Watson:                0.018
Prob(Omnibus):                      0.000   Jarque-Bera (JB):            5077.382
Skew:                                1.483   Prob(JB):                    0.00
Kurtosis:                           6.386   Cond. No.                    3.12
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3y R-squared:

```

0.818
Model: OLS Adj. R-squared:
0.818
Method: Least Squares F-statistic:
2.588e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:11 Log-Likelihood:
-6046.1
No. Observations: 5762 AIC:
1.210e+04
Df Residuals: 5760 BIC:
1.211e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.2659	0.014	-19.547	0.000
-0.293 -0.239				
QQQ_Rolling_Future_Return_3y	3.6838	0.023	160.873	0.000
3.639 3.729				

```

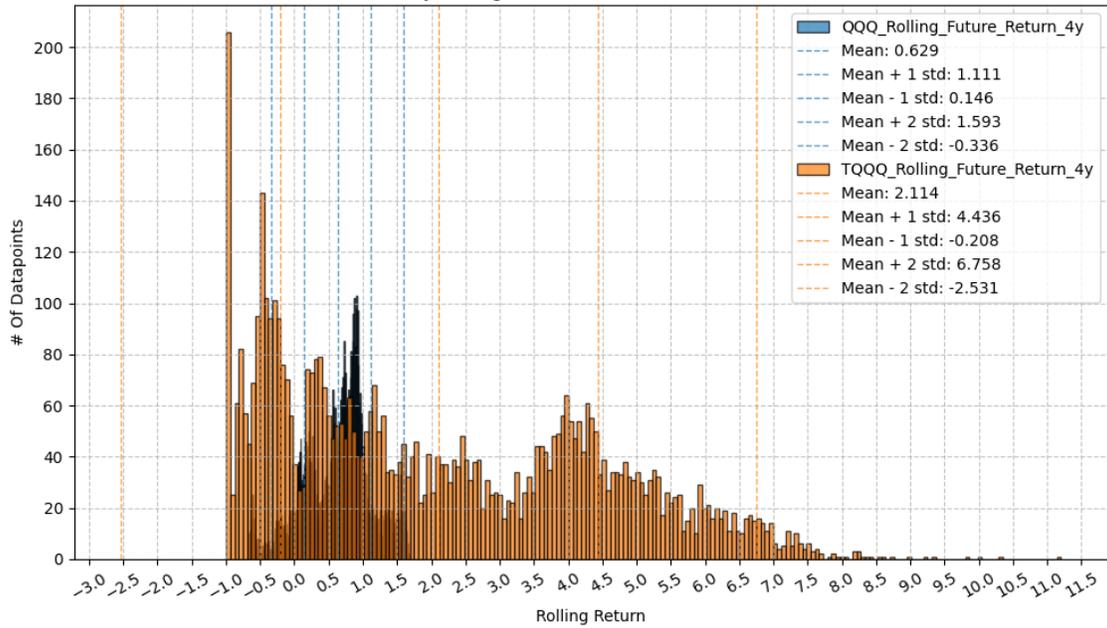
=====
Omnibus: 866.163 Durbin-Watson: 0.015
Prob(Omnibus): 0.000 Jarque-Bera (JB): 1580.248
Skew: 0.959 Prob(JB): 0.00
Kurtosis: 4.704 Cond. No. 3.08
=====

```

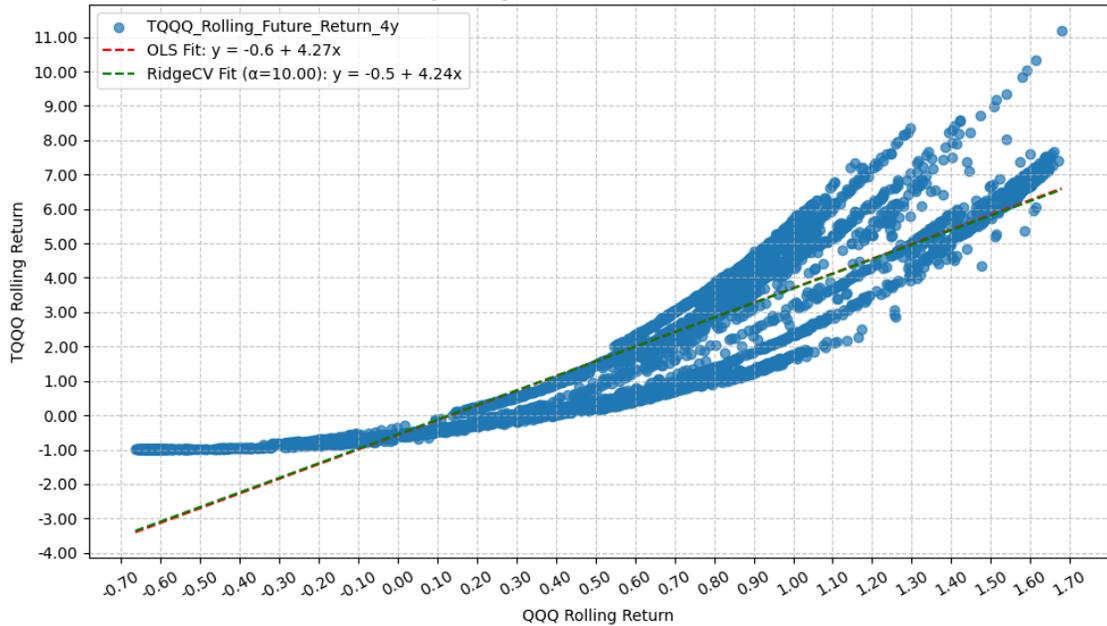
Notes:

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

QQQ & TQQQ 4y Rolling Future Returns Post -0.5 TQQQ Drawdown



QQQ & TQQQ 4y Rolling Future Returns Post -0.5 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_4y R-squared:

```

0.786
Model: OLS Adj. R-squared:
0.786
Method: Least Squares F-statistic:
2.021e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:12 Log-Likelihood:
-8214.5
No. Observations: 5510 AIC:
1.643e+04
Df Residuals: 5508 BIC:
1.645e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

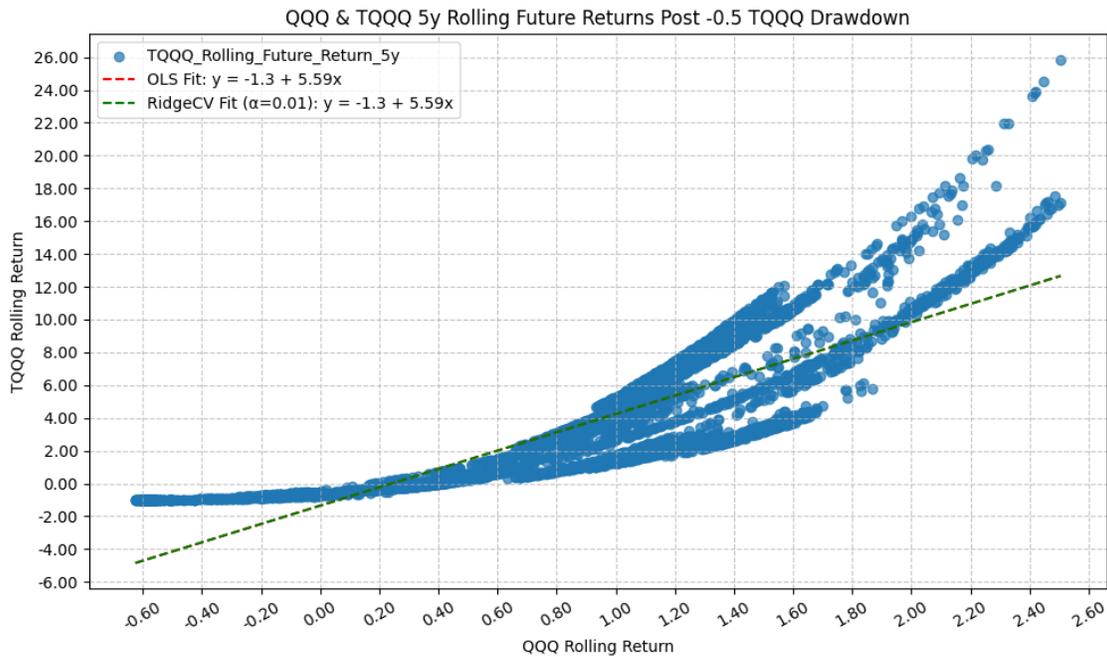
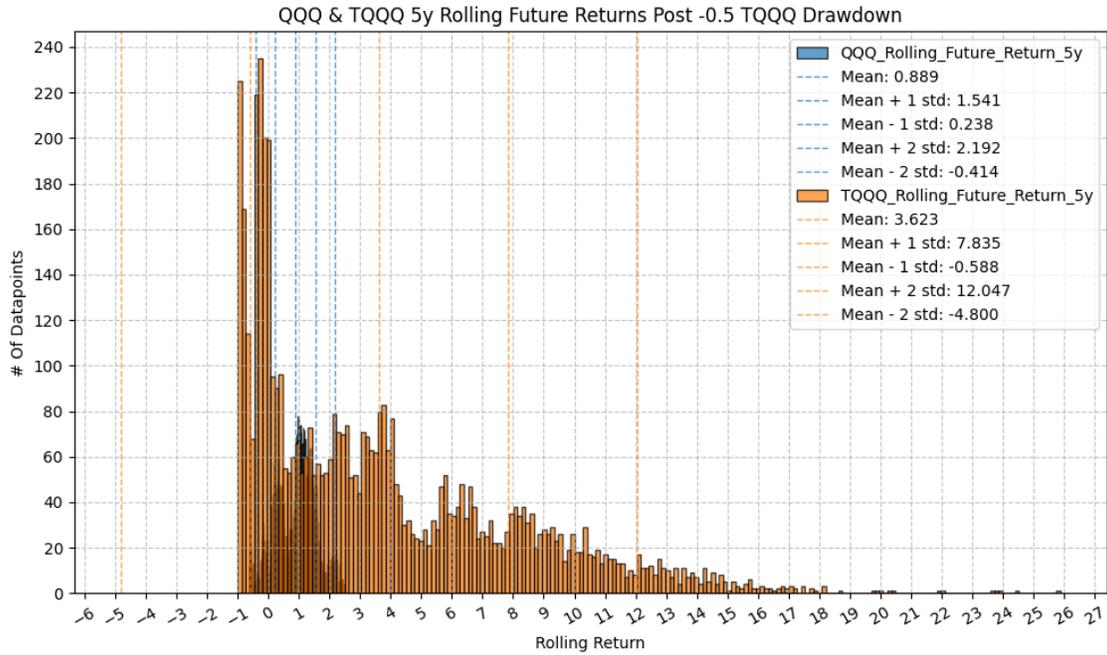
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.5696	0.024	-23.943	0.000
-0.616 -0.523				
QQQ_Rolling_Future_Return_4y	4.2692	0.030	142.161	0.000
4.210 4.328				
=====				
Omnibus:	65.711	Durbin-Watson:		0.010
Prob(Omnibus):	0.000	Jarque-Bera (JB):		51.050
Skew:	0.151	Prob(JB):		8.22e-12
Kurtosis:	2.638	Cond. No.		3.05
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_5y R-squared:

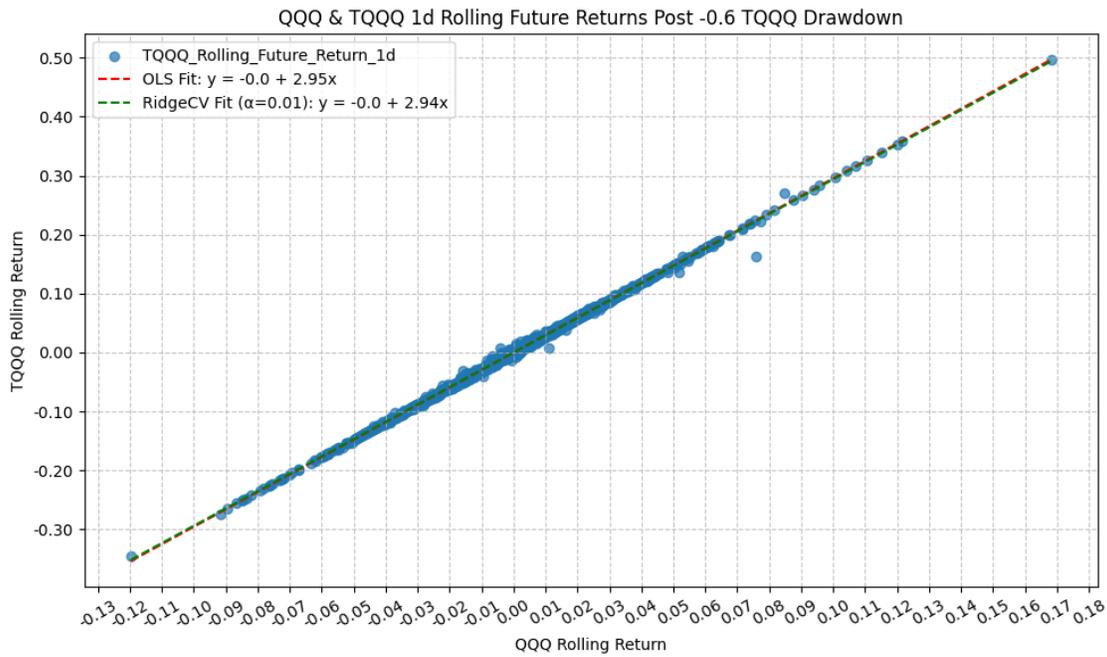
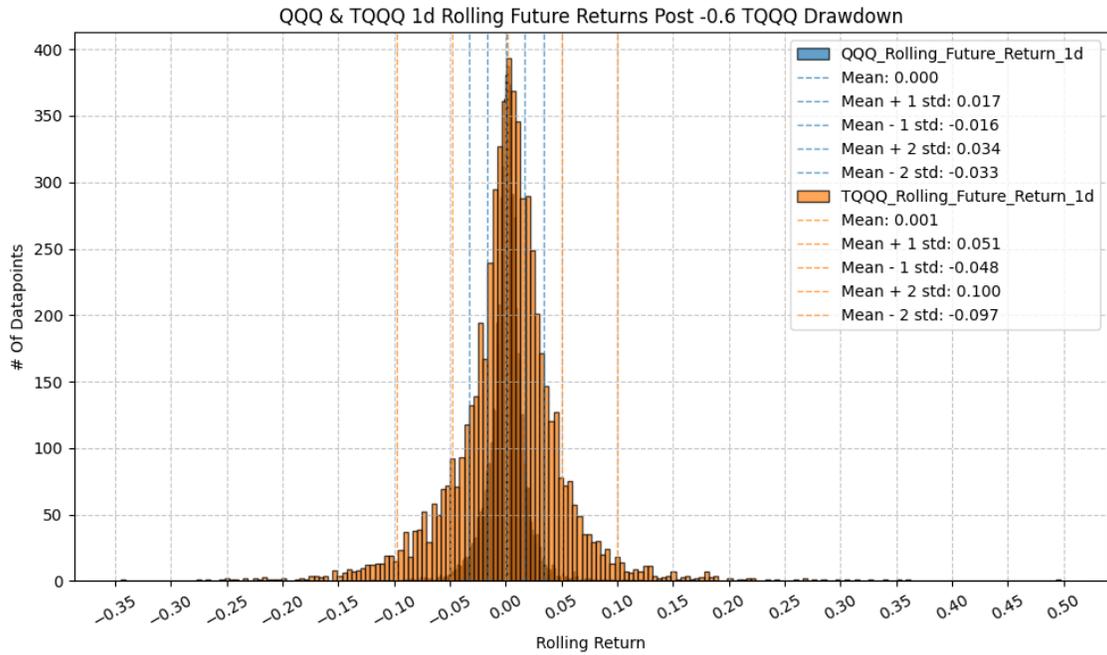
```

0.748
Model:                                OLS   Adj. R-squared:
0.748
Method:                                Least Squares   F-statistic:
1.563e+04
Date:                                    Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                    14:27:13   Log-Likelihood:
-11393.
No. Observations:                       5258   AIC:
2.279e+04
Df Residuals:                             5256   BIC:
2.280e+04
Df Model:                                  1
Covariance Type:                          nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                               -1.3493   0.049   -27.365   0.000
-1.446   -1.253
QQQ_Rolling_Future_Return_5y        5.5930   0.045   125.018   0.000
5.505   5.681
=====
Omnibus:                             239.977   Durbin-Watson:           0.009
Prob(Omnibus):                        0.000   Jarque-Bera (JB):       361.637
Skew:                                  0.414   Prob(JB):                2.96e-79
Kurtosis:                              3.982   Cond. No.                3.08
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1d R-squared:

```

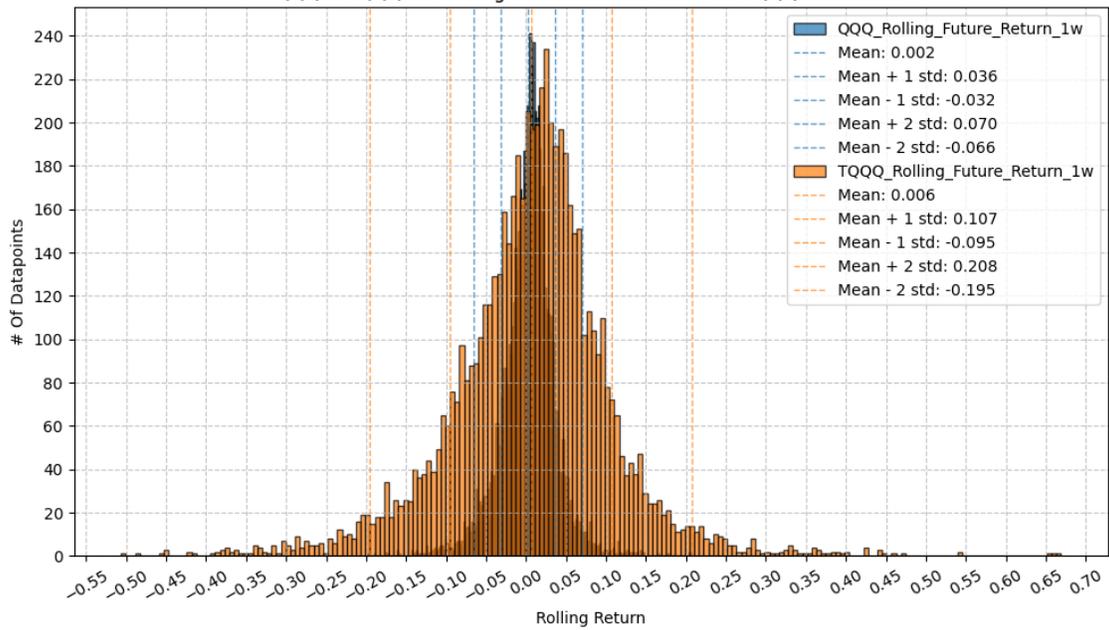
0.999
Model:                                OLS   Adj. R-squared:
0.999
Method:                               Least Squares   F-statistic:
5.999e+06
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:27:15   Log-Likelihood:
31532.
No. Observations:                    6280   AIC:
-6.306e+04
Df Residuals:                        6278   BIC:
-6.305e+04
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -4.232e-05   2.02e-05   -2.100   0.036
-8.18e-05   -2.81e-06
QQQ_Rolling_Future_Return_1d    2.9547      0.001   2449.263   0.000
2.952      2.957
=====
Omnibus:                          9286.532   Durbin-Watson:                2.569
Prob(Omnibus):                     0.000   Jarque-Bera (JB):             35696636.910
Skew:                               -8.058   Prob(JB):                     0.00
Kurtosis:                          371.999   Cond. No.                     59.9
=====

```

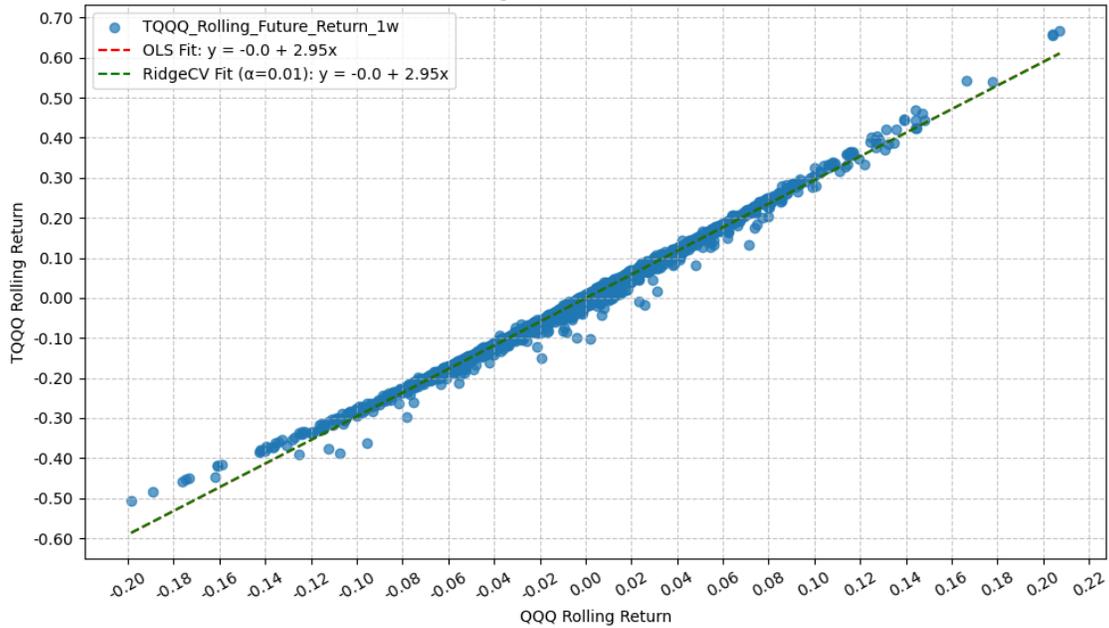
Notes:

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

QQQ & TQQQ 1w Rolling Future Returns Post -0.6 TQQQ Drawdown



QQQ & TQQQ 1w Rolling Future Returns Post -0.6 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1w R-squared:

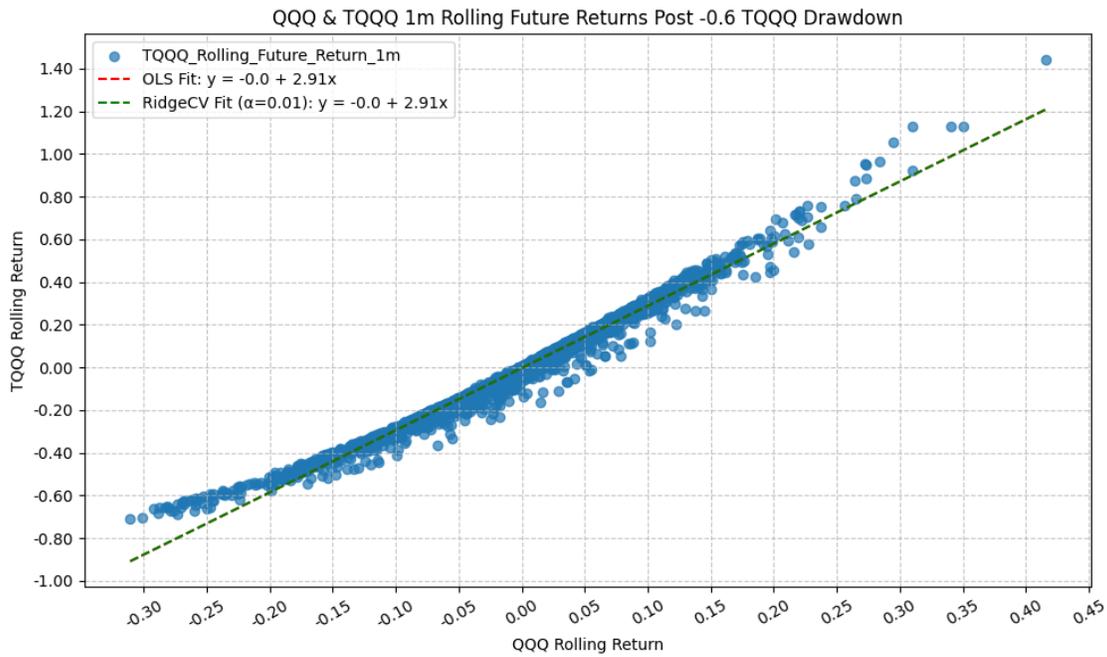
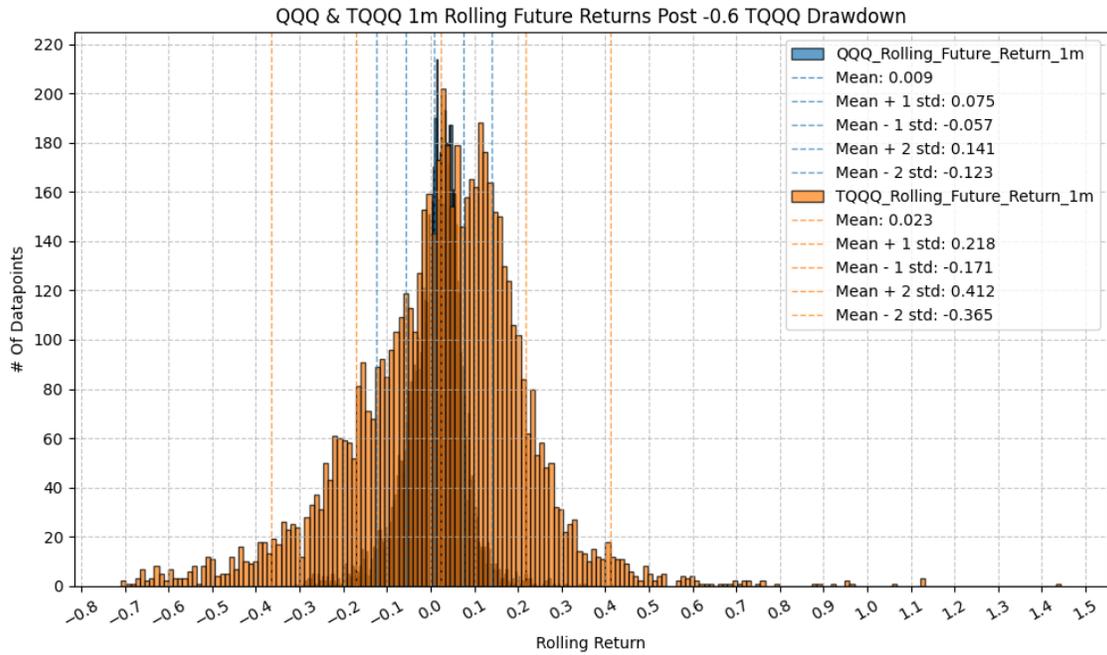
```

0.994
Model:                                OLS   Adj. R-squared:
0.994
Method:                               Least Squares   F-statistic:
1.076e+06
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:27:16   Log-Likelihood:
21675.
No. Observations:                    6280   AIC:
-4.335e+04
Df Residuals:                        6278   BIC:
-4.333e+04
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0007   9.7e-05   -7.551   0.000
-0.001   -0.001
QQQ_Rolling_Future_Return_1w     2.9525    0.003   1037.392   0.000
2.947   2.958
=====
Omnibus:                          3408.626   Durbin-Watson:           0.895
Prob(Omnibus):                     0.000   Jarque-Bera (JB):       384667.664
Skew:                              -1.639   Prob(JB):               0.00
Kurtosis:                          41.201   Cond. No.                29.4
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1m R-squared:

```

0.982
Model: OLS Adj. R-squared:
0.982
Method: Least Squares F-statistic:
3.507e+05
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:17 Log-Likelihood:
14068.
No. Observations: 6280 AIC:
-2.813e+04
Df Residuals: 6278 BIC:
-2.812e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0032	0.000	-9.790	0.000
-0.004 -0.003				
QQQ_Rolling_Future_Return_1m	2.9140	0.005	592.182	0.000
2.904 2.924				

```

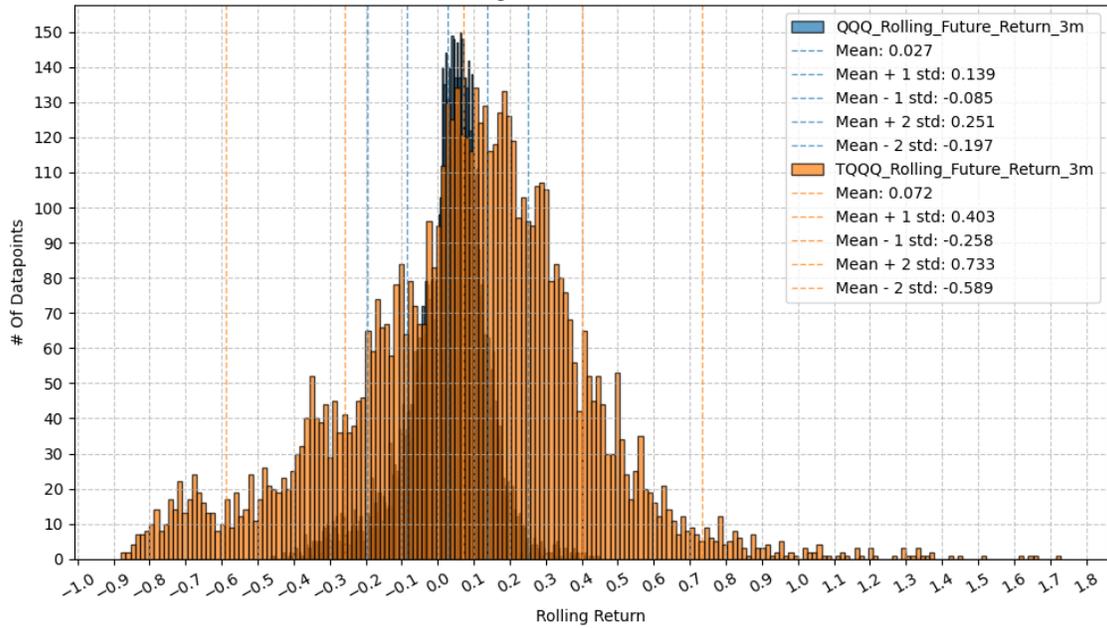
=====
Omnibus: 1452.365 Durbin-Watson: 0.296
Prob(Omnibus): 0.000 Jarque-Bera (JB): 78369.604
Skew: 0.053 Prob(JB): 0.00
Kurtosis: 20.306 Cond. No. 15.1
=====

```

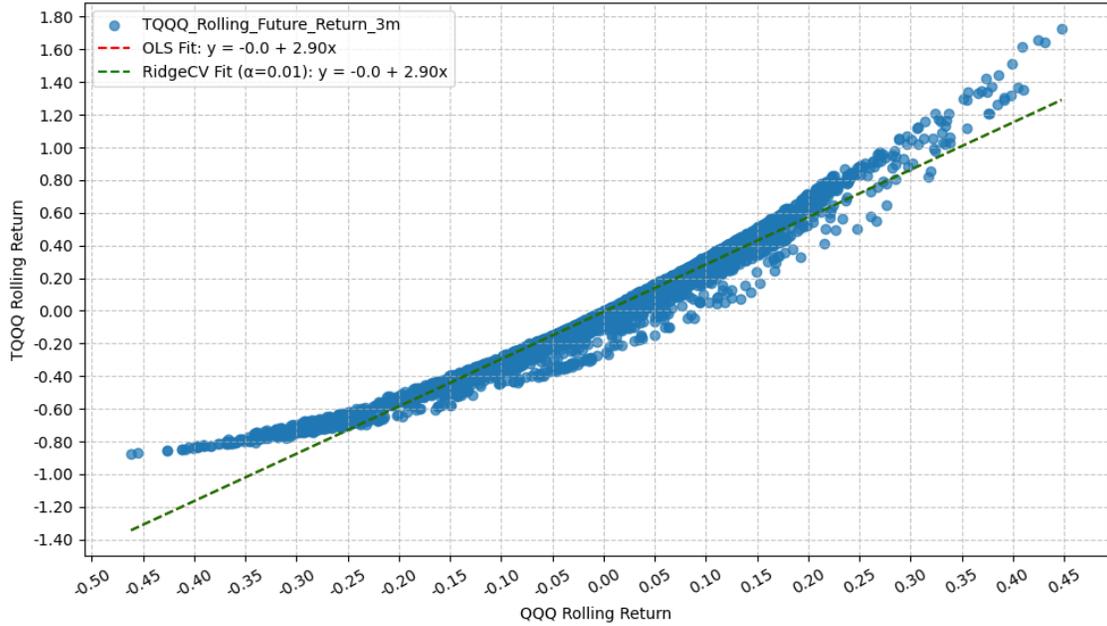
Notes:

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

QQQ & TQQQ 3m Rolling Future Returns Post -0.6 TQQQ Drawdown



QQQ & TQQQ 3m Rolling Future Returns Post -0.6 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3m R-squared:

```

0.961
Model:                                OLS   Adj. R-squared:
0.961
Method:                                Least Squares   F-statistic:
1.566e+05
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:18   Log-Likelihood:
8264.2
No. Observations:                    6280   AIC:
-1.652e+04
Df Residuals:                        6278   BIC:
-1.651e+04
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0059	0.001	-7.038	0.000
-0.008 -0.004				
QQQ_Rolling_Future_Return_3m	2.8977	0.007	395.692	0.000
2.883 2.912				
=====				

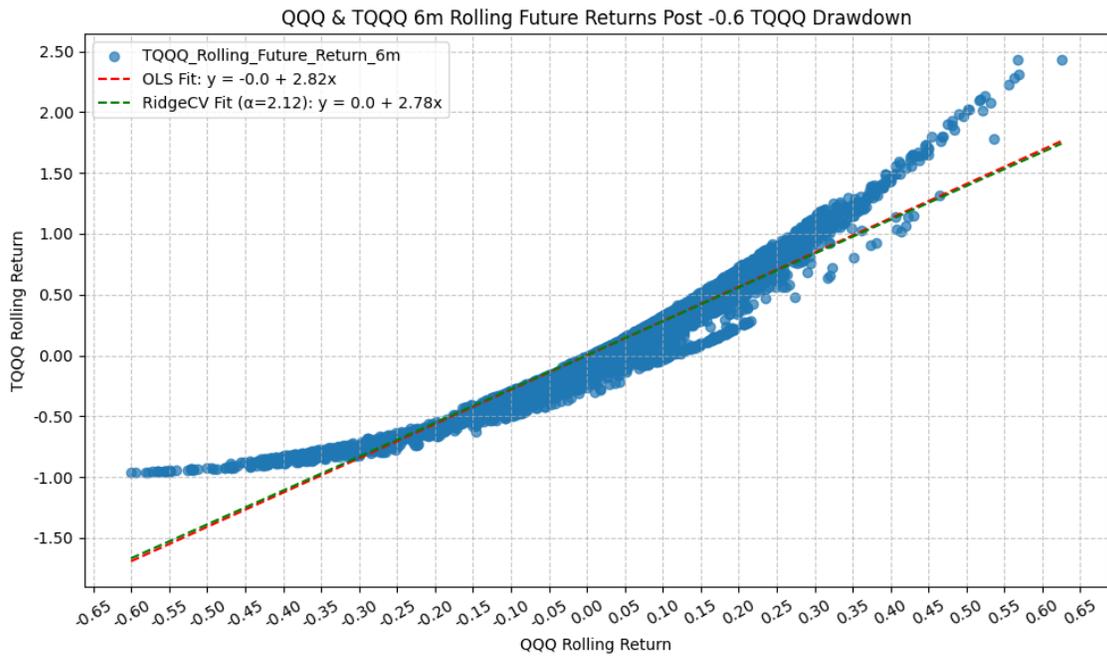
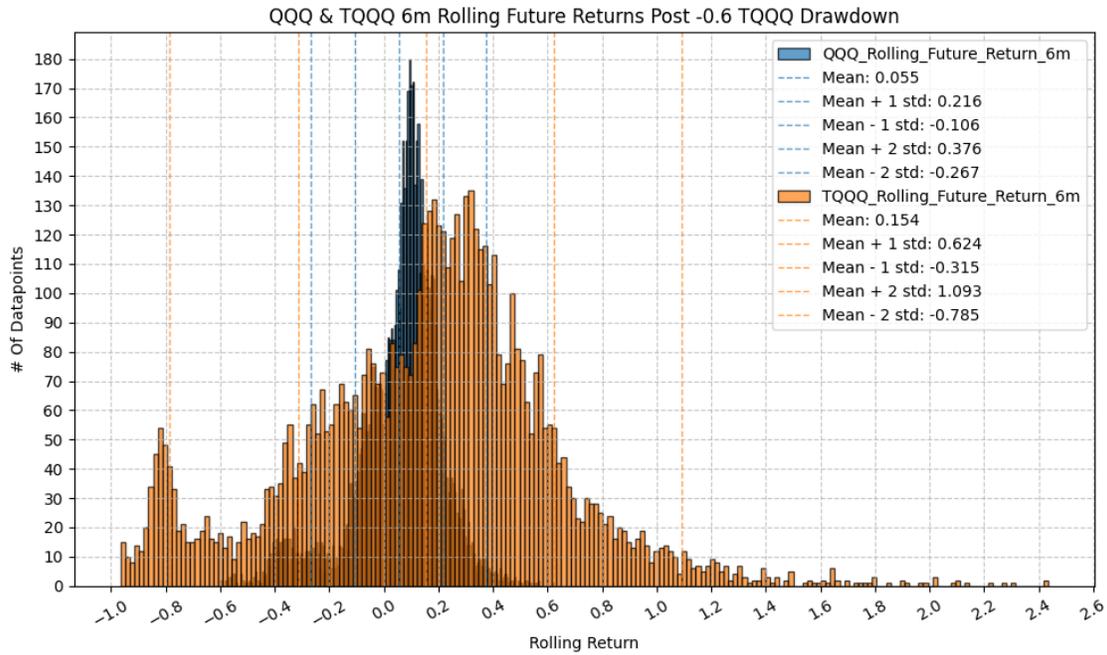
```

Omnibus:                            1352.162   Durbin-Watson:                0.102
Prob(Omnibus):                      0.000   Jarque-Bera (JB):            15599.280
Skew:                                0.696   Prob(JB):                    0.00
Kurtosis:                            10.594   Cond. No.                    8.95
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_6m R-squared:

```

0.932
Model:                                OLS   Adj. R-squared:
0.932
Method:                                Least Squares   F-statistic:
8.613e+04
Date:                                   Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                   14:27:19   Log-Likelihood:
4282.1
No. Observations:                      6280   AIC:
-8560.
Df Residuals:                          6278   BIC:
-8547.
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====

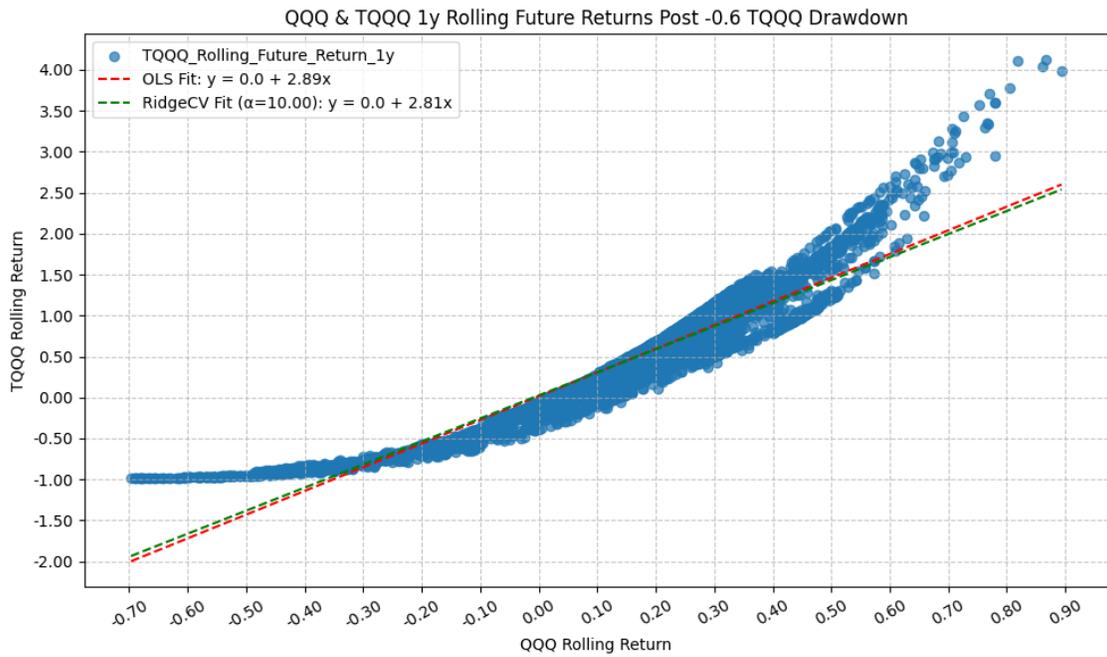
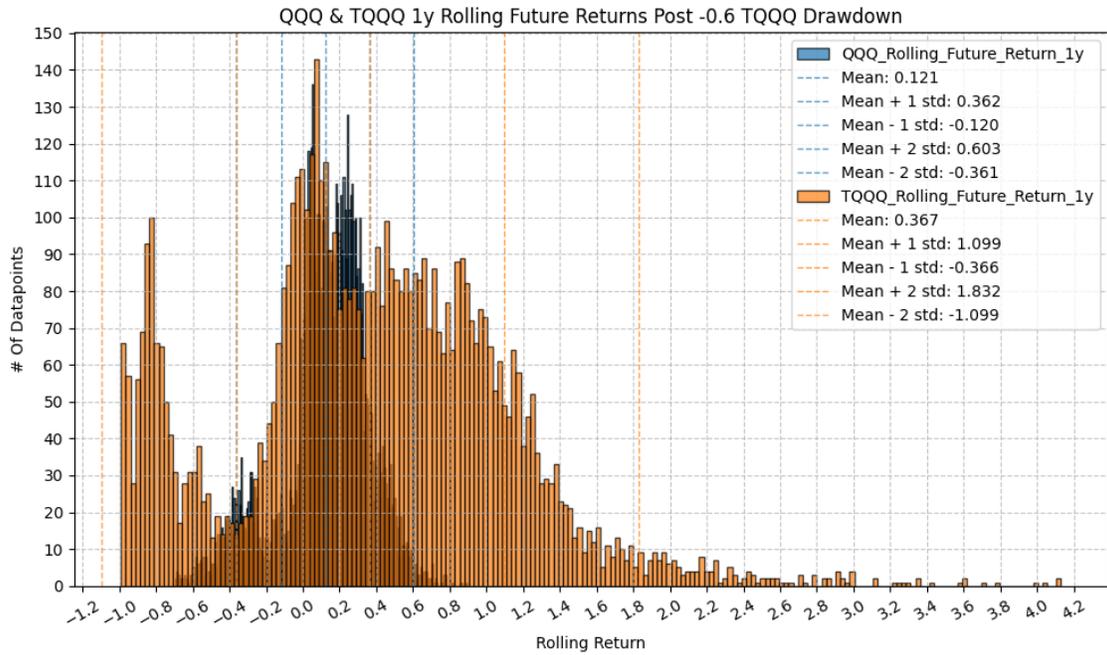
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0002	0.002	-0.127	0.899
-0.003 0.003				
QQQ_Rolling_Future_Return_6m	2.8191	0.010	293.486	0.000
2.800 2.838				
=====				
Omnibus:	1637.681	Durbin-Watson:		0.057
Prob(Omnibus):	0.000	Jarque-Bera (JB):		8395.060
Skew:	1.159	Prob(JB):		0.00
Kurtosis:	8.168	Cond. No.		6.24
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1y R-squared:

```

0.904
Model:                                OLS   Adj. R-squared:
0.904
Method:                                Least Squares   F-statistic:
5.852e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:20   Log-Likelihood:
404.91
No. Observations:                    6199   AIC:
-805.8
Df Residuals:                        6197   BIC:
-792.3
Df Model:                             1
Covariance Type:                    nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0162	0.003	5.033	0.000
0.010 0.023				
QQQ_Rolling_Future_Return_1y	2.8920	0.012	241.905	0.000
2.869 2.915				
=====				

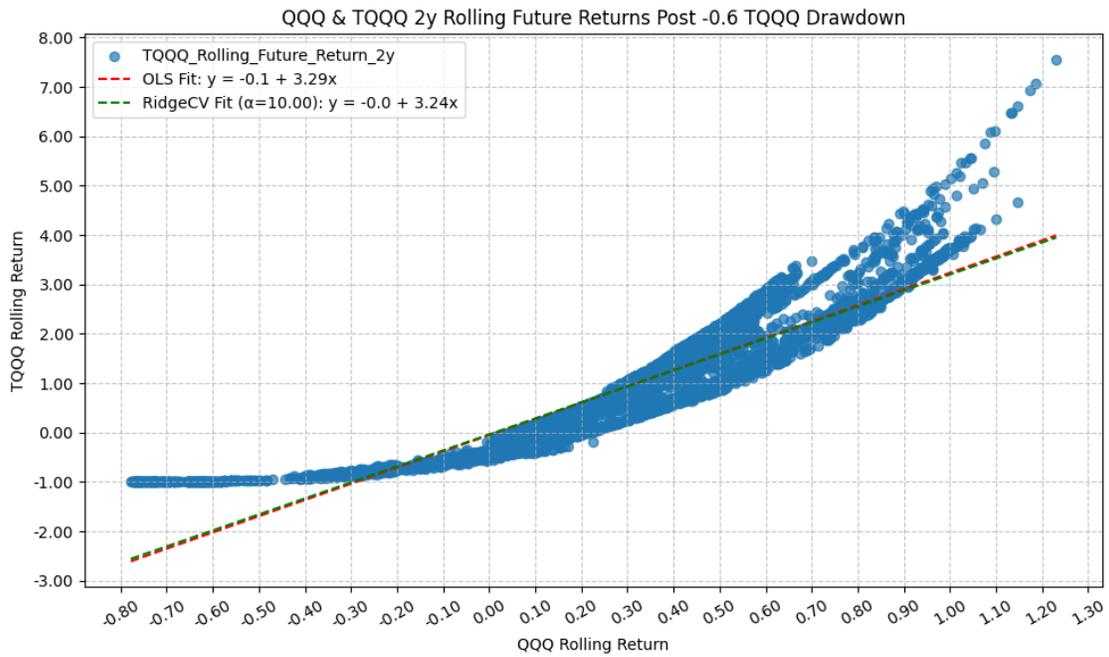
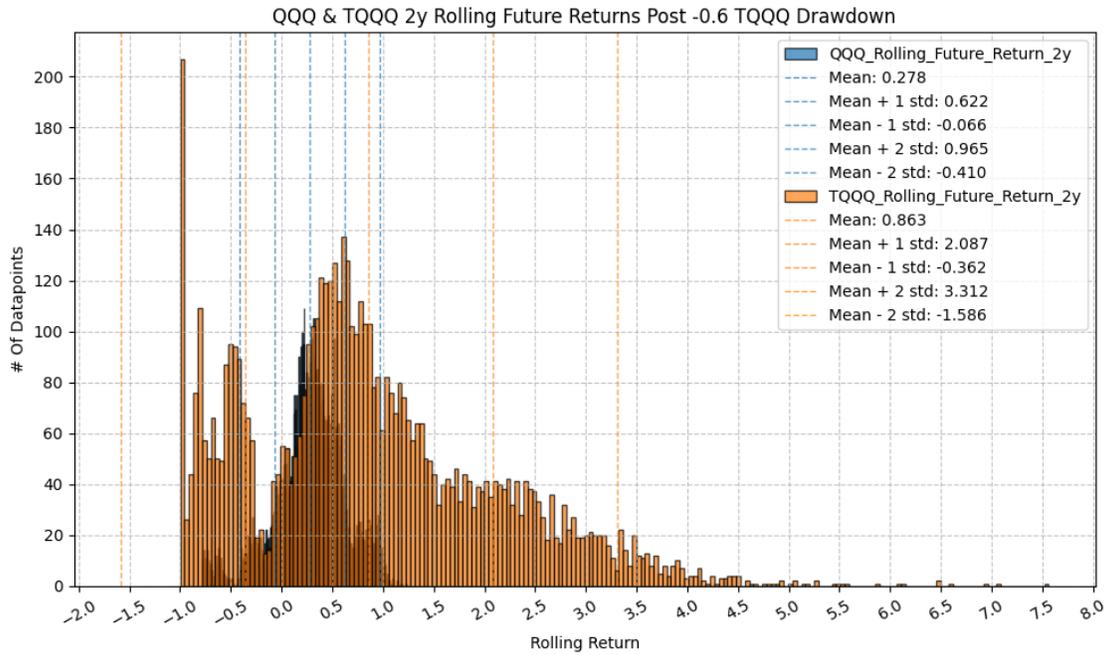
```

Omnibus:                            1966.648   Durbin-Watson:                0.038
Prob(Omnibus):                       0.000   Jarque-Bera (JB):            8739.805
Skew:                                 1.487   Prob(JB):                    0.00
Kurtosis:                             7.999   Cond. No.:                   4.22
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_2y R-squared:

```

0.851
Model: OLS Adj. R-squared:
0.851
Method: Least Squares F-statistic:
3.401e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:22 Log-Likelihood:
-4010.4
No. Observations: 5977 AIC:
8025.
Df Residuals: 5975 BIC:
8038.
Df Model: 1
Covariance Type: nonrobust
=====
=====

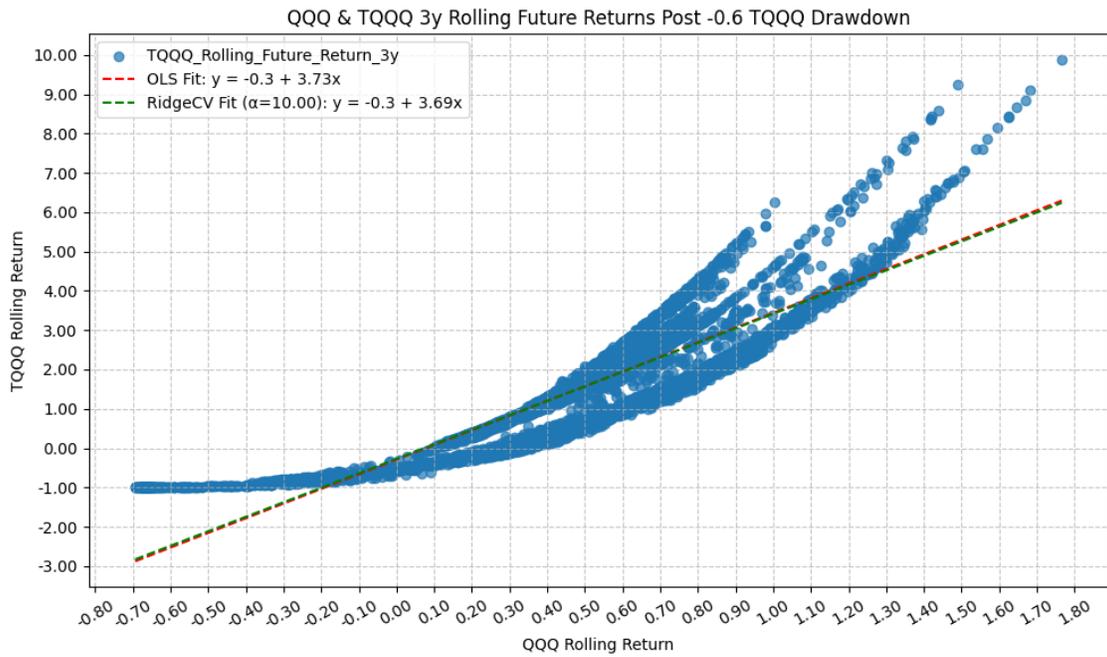
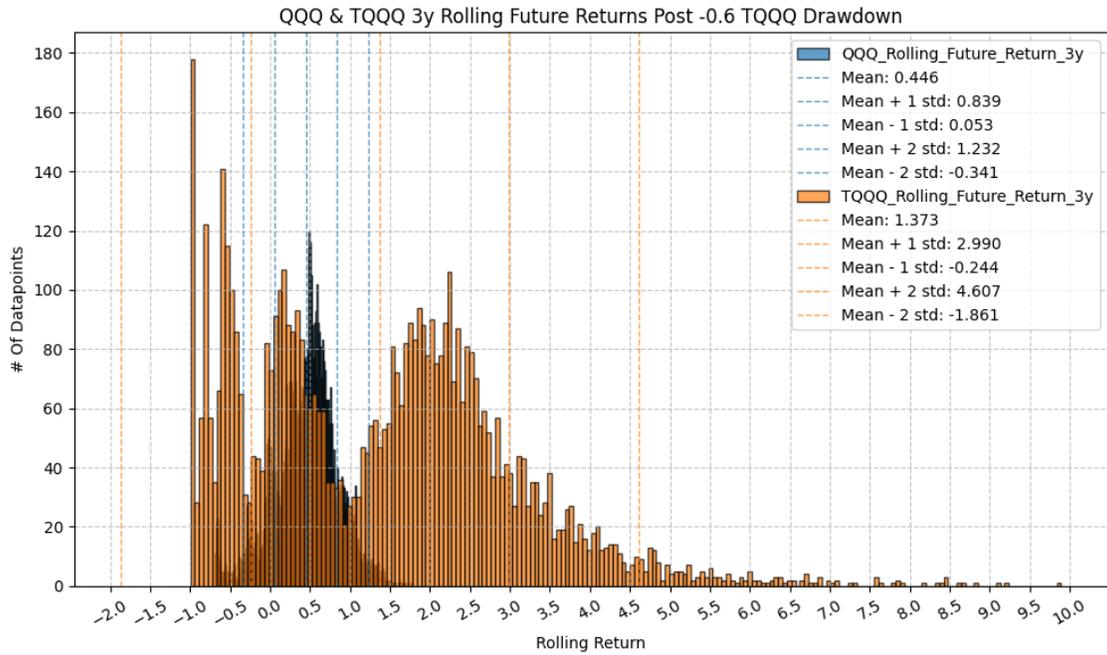
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0503	0.008	-6.388	0.000
-0.066 -0.035				
QQQ_Rolling_Future_Return_2y	3.2857	0.018	184.405	0.000
3.251 3.321				
=====				
Omnibus:	1728.061	Durbin-Watson:		0.019
Prob(Omnibus):	0.000	Jarque-Bera (JB):		5277.259
Skew:	1.488	Prob(JB):		0.00
Kurtosis:	6.512	Cond. No.		3.16
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3y R-squared:

```

0.821
Model: OLS Adj. R-squared:
0.821
Method: Least Squares F-statistic:
2.631e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:23 Log-Likelihood:
-5943.8
No. Observations: 5725 AIC:
1.189e+04
Df Residuals: 5723 BIC:
1.190e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

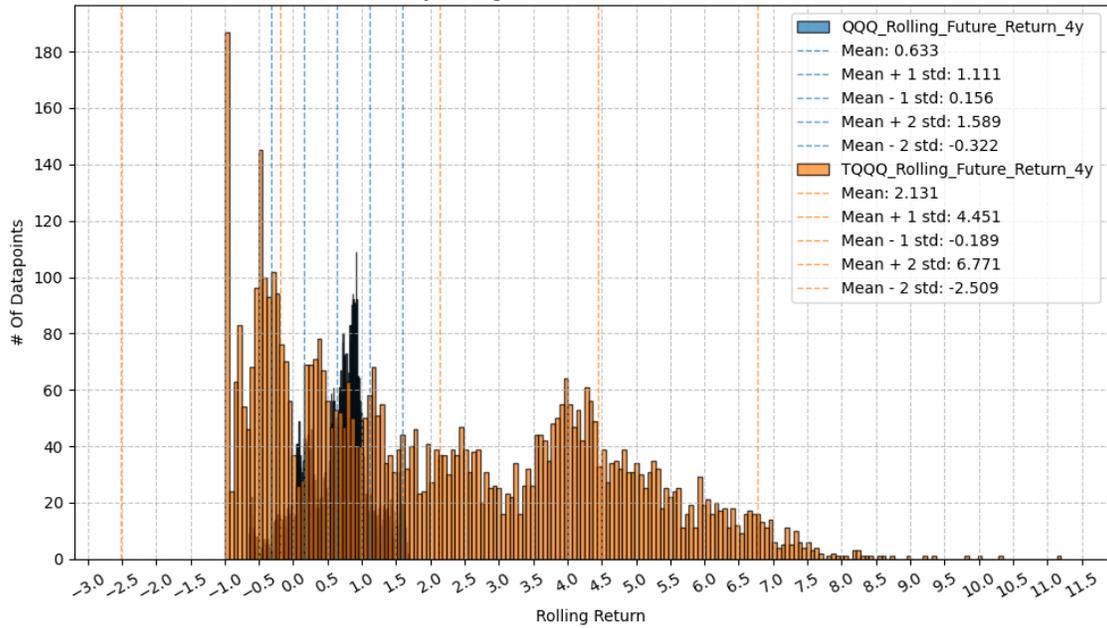
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.2891	0.014	-21.164	0.000
-0.316 -0.262				
QQQ_Rolling_Future_Return_3y	3.7271	0.023	162.217	0.000
3.682 3.772				
=====				
Omnibus:	846.190	Durbin-Watson:		0.015
Prob(Omnibus):	0.000	Jarque-Bera (JB):		1556.288
Skew:	0.941	Prob(JB):		0.00
Kurtosis:	4.726	Cond. No.		3.12
=====				

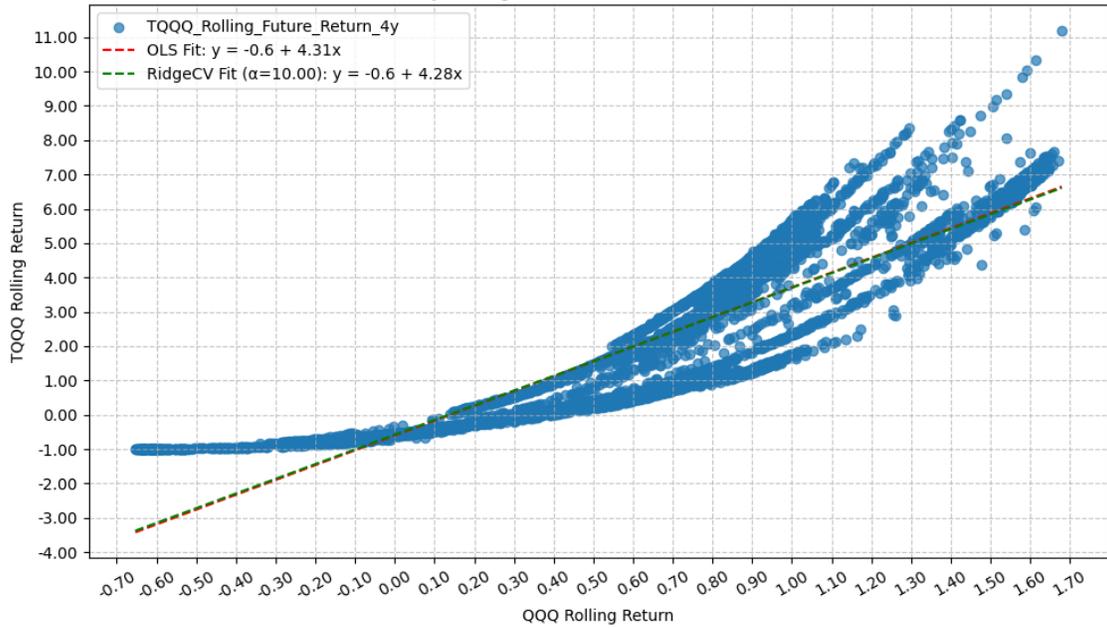
Notes:

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

QQQ & TQQQ 4y Rolling Future Returns Post -0.6 TQQQ Drawdown



QQQ & TQQQ 4y Rolling Future Returns Post -0.6 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_4y R-squared:

```

0.789
Model:                                OLS   Adj. R-squared:
0.789
Method:                                Least Squares   F-statistic:
2.045e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:24   Log-Likelihood:
-8114.6
No. Observations:                    5473   AIC:
1.623e+04
Df Residuals:                        5471   BIC:
1.625e+04
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.6018	0.024	-25.144	0.000
-0.649 -0.555				
QQQ_Rolling_Future_Return_4y	4.3140	0.030	142.997	0.000
4.255 4.373				
=====				

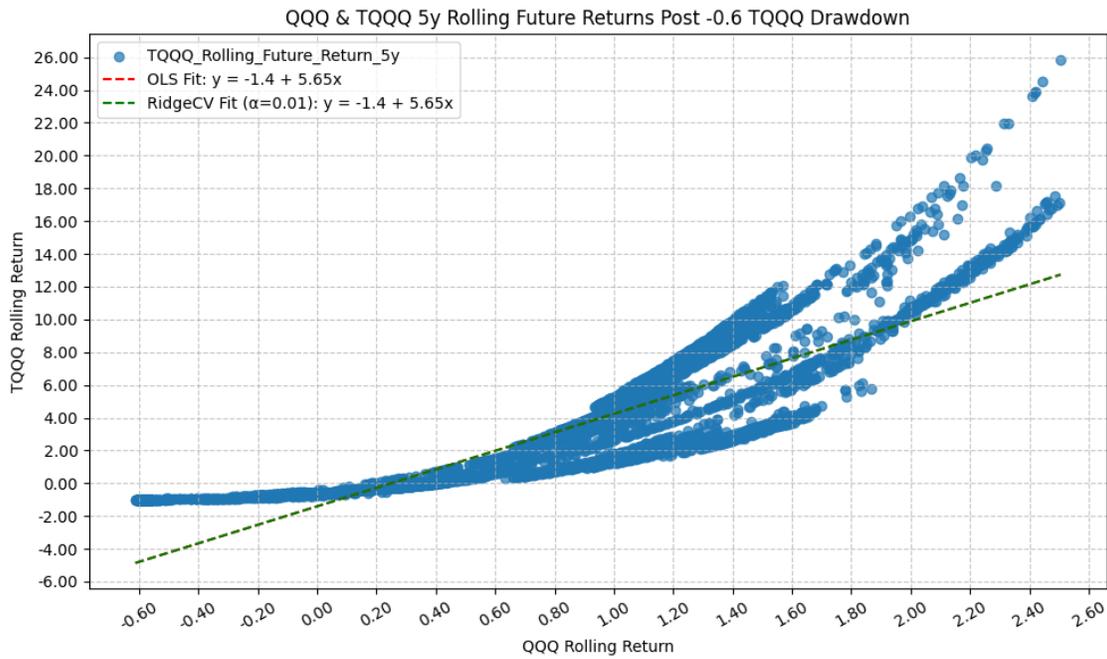
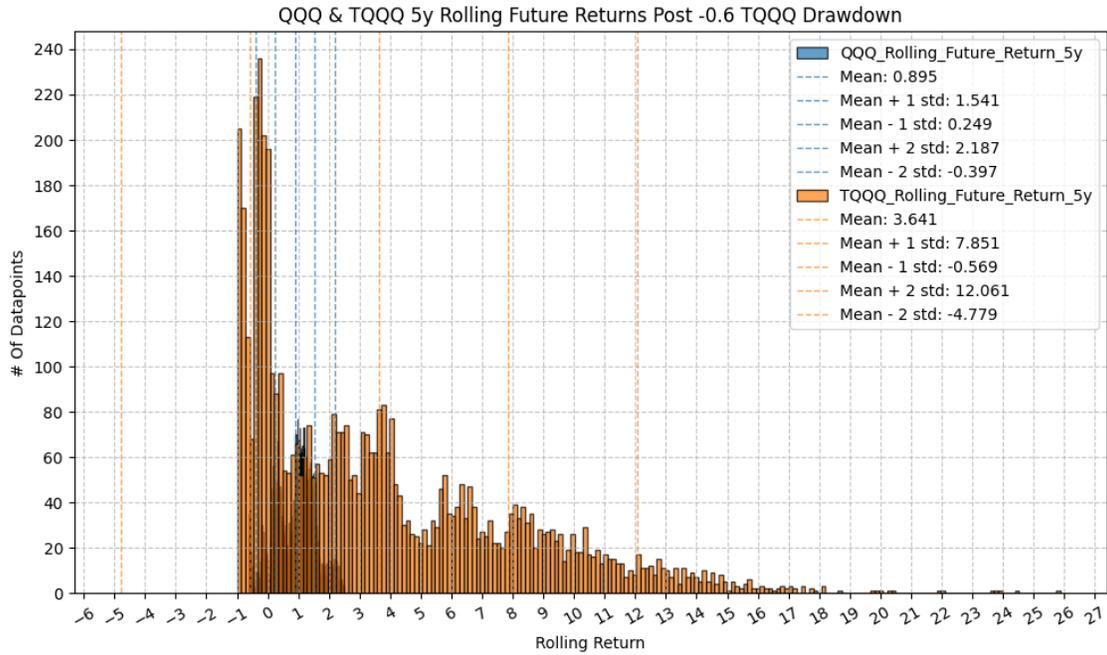
```

Omnibus:                            51.316   Durbin-Watson:                0.010
Prob(Omnibus):                       0.000   Jarque-Bera (JB):             40.579
Skew:                                 0.131   Prob(JB):                     1.54e-09
Kurtosis:                             2.669   Cond. No.                     3.09
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_5y R-squared:

```

0.750
Model: OLS Adj. R-squared:
0.750
Method: Least Squares F-statistic:
1.574e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:25 Log-Likelihood:
-11327.
No. Observations: 5238 AIC:
2.266e+04
Df Residuals: 5236 BIC:
2.267e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

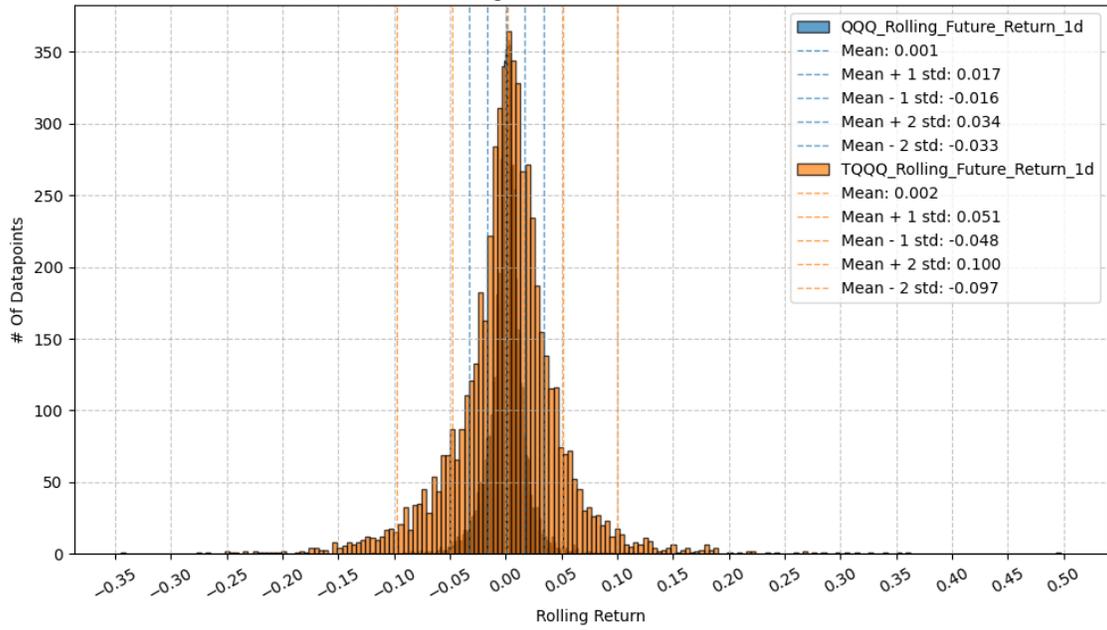
	coef	std err	t	P> t
[0.025 0.975]				

const	-1.4104	0.050	-28.398	0.000
-1.508 -1.313				
QQQ_Rolling_Future_Return_5y	5.6451	0.045	125.443	0.000
5.557 5.733				
=====				
Omnibus:	226.987	Durbin-Watson:		0.009
Prob(Omnibus):	0.000	Jarque-Bera (JB):		348.438
Skew:	0.392	Prob(JB):		2.18e-76
Kurtosis:	3.990	Cond. No.		3.11
=====				

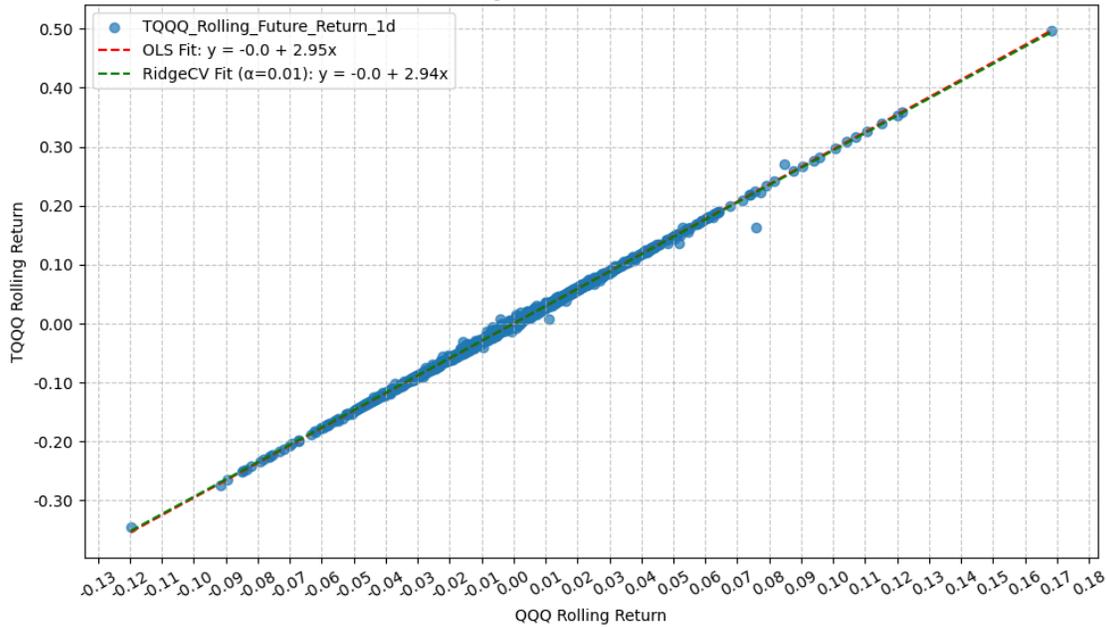
Notes:

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

QQQ & TQQQ 1d Rolling Future Returns Post -0.7 TQQQ Drawdown



QQQ & TQQQ 1d Rolling Future Returns Post -0.7 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1d R-squared:

```

0.999
Model: OLS Adj. R-squared:
0.999
Method: Least Squares F-statistic:
5.379e+06
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:26 Log-Likelihood:
29443.
No. Observations: 5890 AIC:
-5.888e+04
Df Residuals: 5888 BIC:
-5.887e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

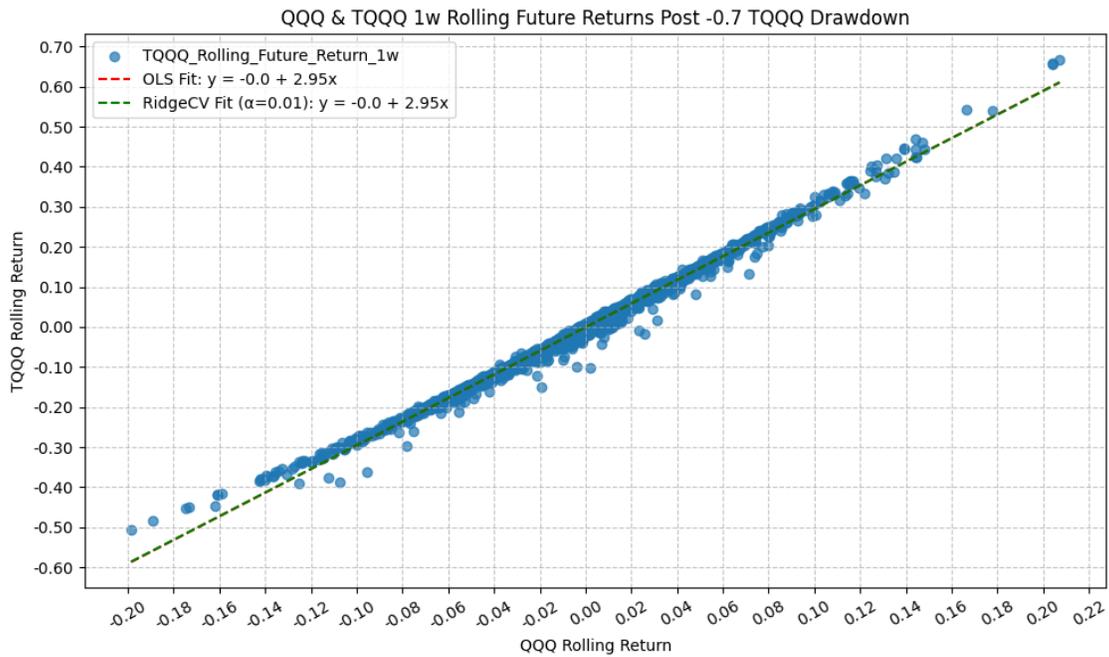
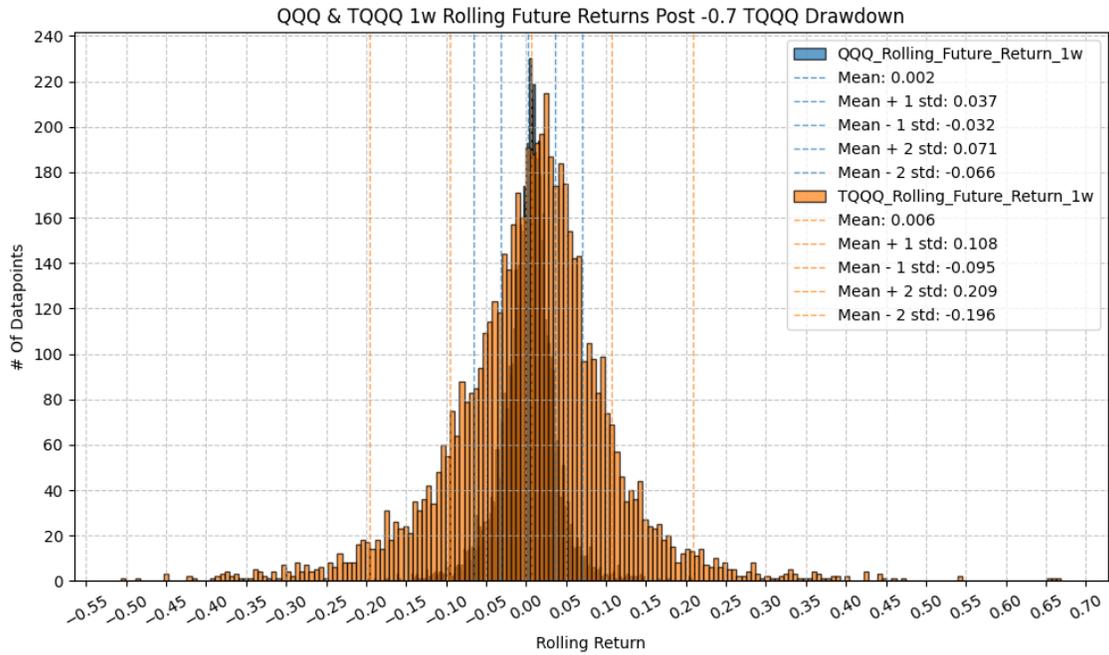
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-3.034e-05	2.13e-05	-1.426	0.154
-7.21e-05 1.14e-05				
QQQ_Rolling_Future_Return_1d	2.9544	0.001	2319.352	0.000
2.952 2.957				
=====				
Omnibus:	8697.849	Durbin-Watson:		2.575
Prob(Omnibus):	0.000	Jarque-Bera (JB):		31773160.847
Skew:	-8.043	Prob(JB):		0.00
Kurtosis:	362.454	Cond. No.		59.9
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1w R-squared:

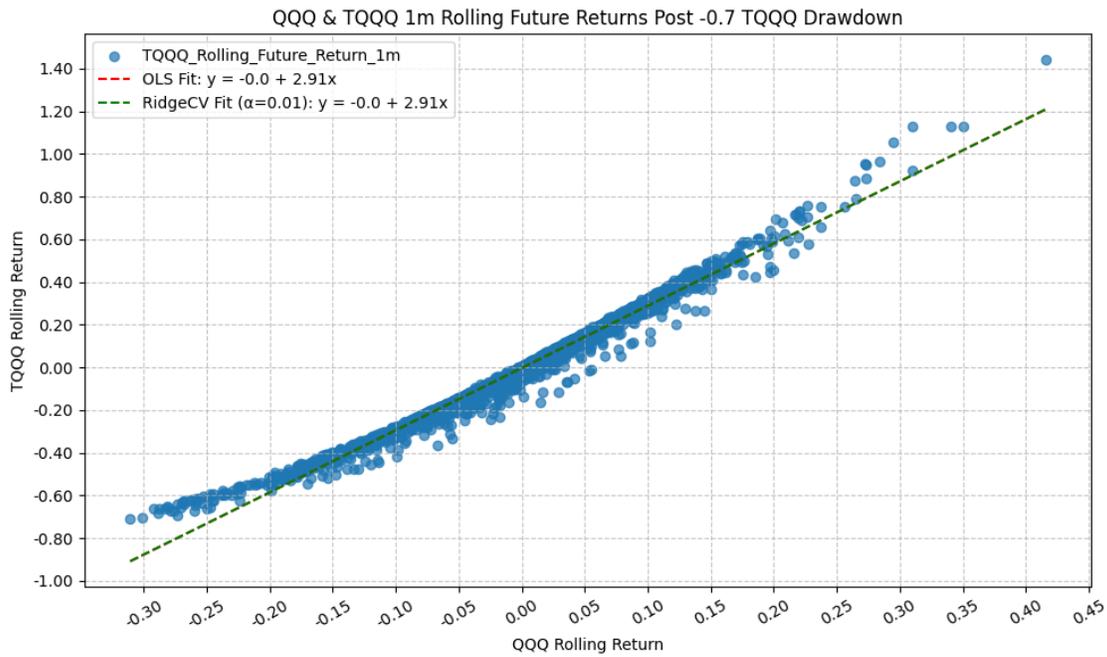
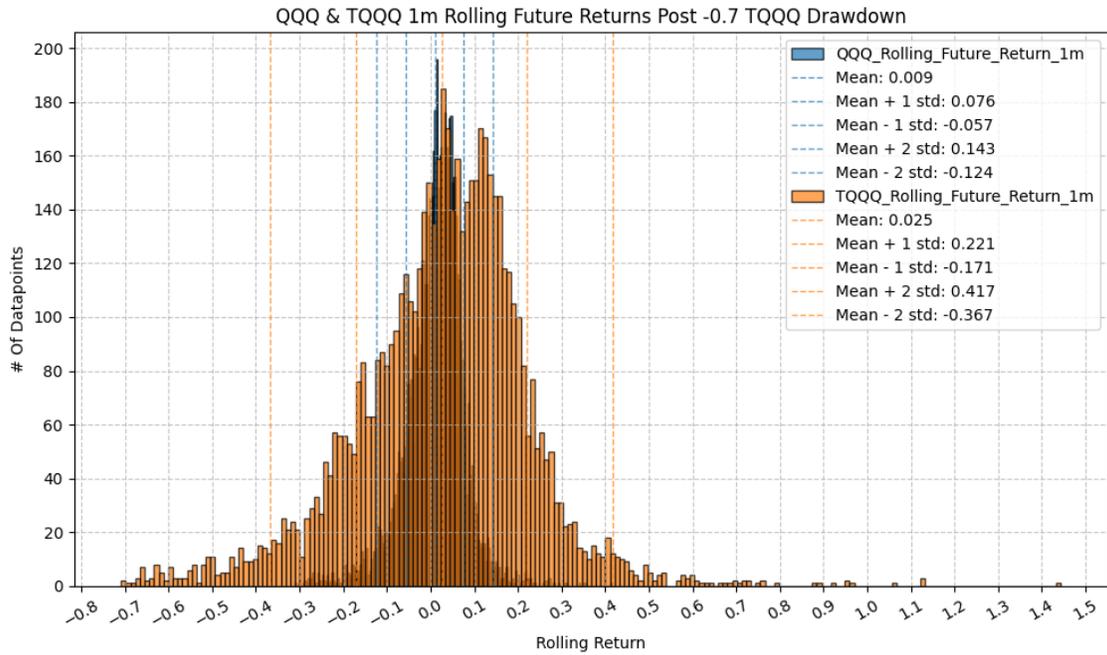
```

0.994
Model:                                OLS   Adj. R-squared:
0.994
Method:                                Least Squares   F-statistic:
1.008e+06
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:27   Log-Likelihood:
20303.
No. Observations:                    5890   AIC:
-4.060e+04
Df Residuals:                        5888   BIC:
-4.059e+04
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0006   0.000   -6.361   0.000
-0.001   -0.000
QQQ_Rolling_Future_Return_1w     2.9525   0.003   1003.867   0.000
2.947   2.958
=====
Omnibus:                          3288.157   Durbin-Watson:                0.897
Prob(Omnibus):                     0.000   Jarque-Bera (JB):            369121.603
Skew:                               -1.720   Prob(JB):                    0.00
Kurtosis:                          41.629   Cond. No.                    29.3
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1m R-squared:

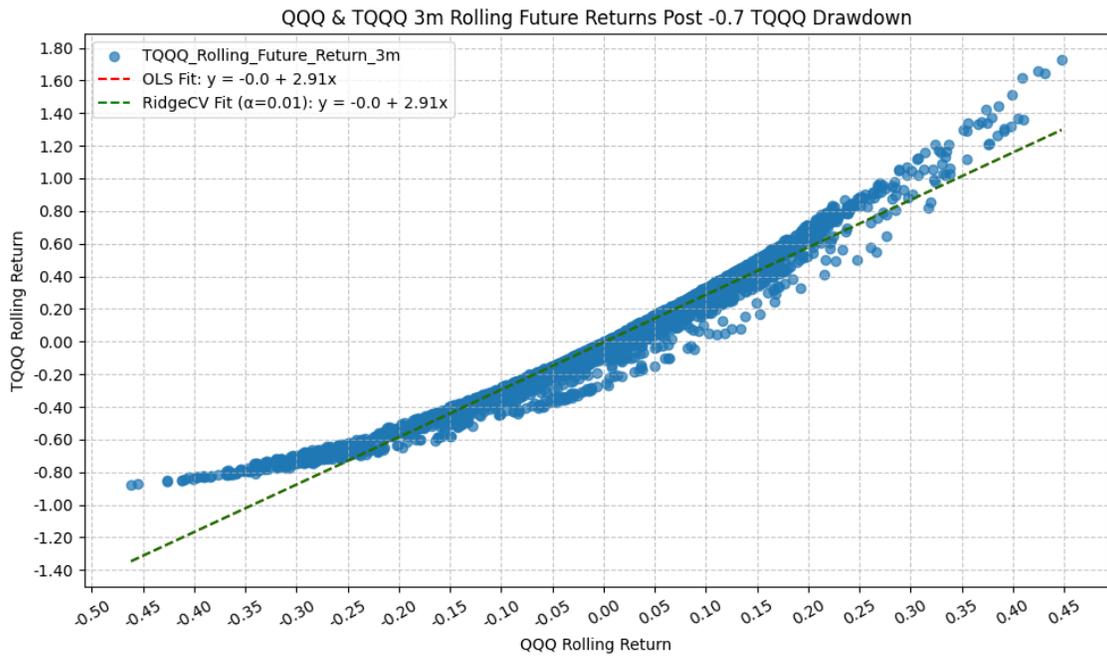
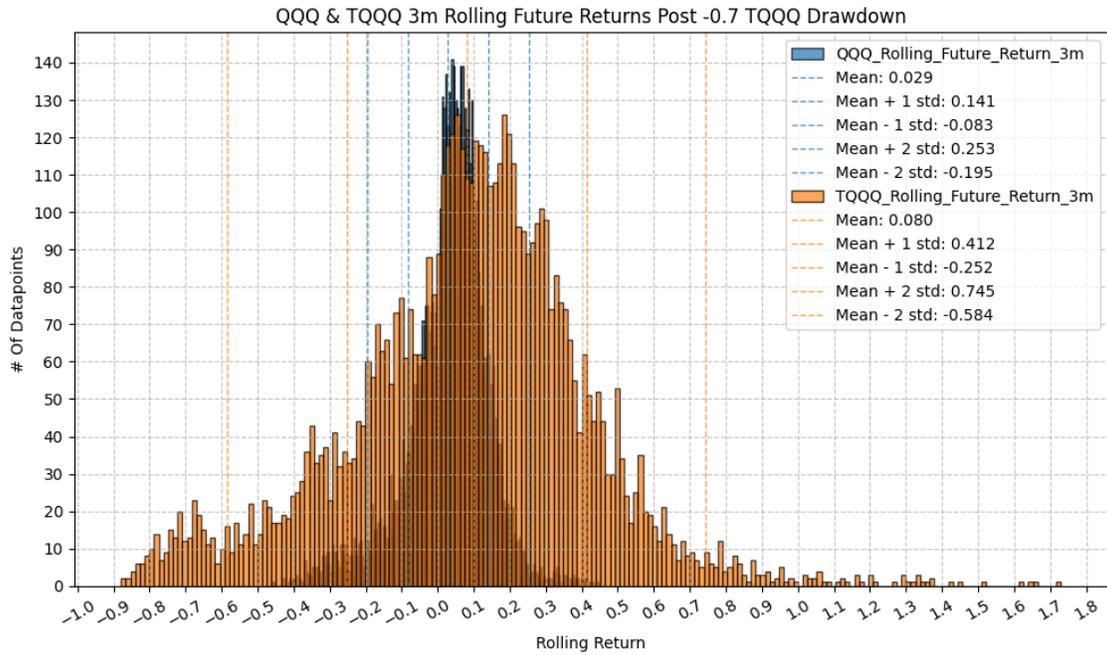
```

0.983
Model:                                OLS   Adj. R-squared:
0.983
Method:                                Least Squares   F-statistic:
3.372e+05
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:29   Log-Likelihood:
13210.
No. Observations:                    5890   AIC:
-2.642e+04
Df Residuals:                        5888   BIC:
-2.640e+04
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0025   0.000   -7.377   0.000
-0.003   -0.002
QQQ_Rolling_Future_Return_1m     2.9139   0.005   580.681   0.000
2.904   2.924
=====
Omnibus:                          1415.259   Durbin-Watson:                0.310
Prob(Omnibus):                     0.000   Jarque-Bera (JB):            78284.153
Skew:                               0.193   Prob(JB):                    0.00
Kurtosis:                          20.856   Cond. No.                    15.0
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3m R-squared:

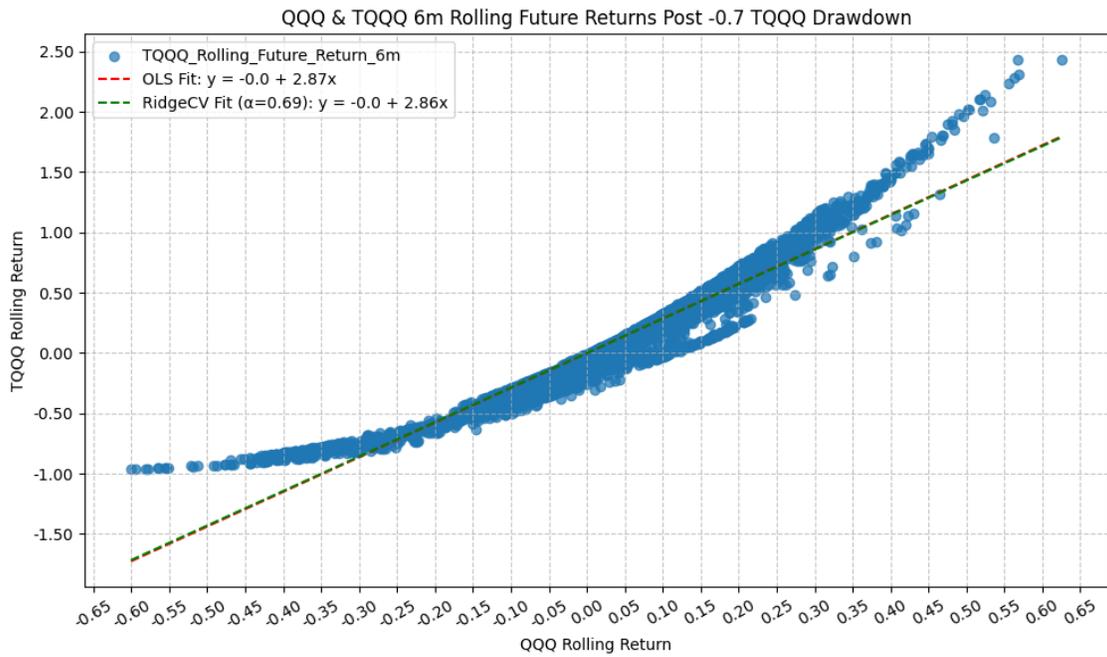
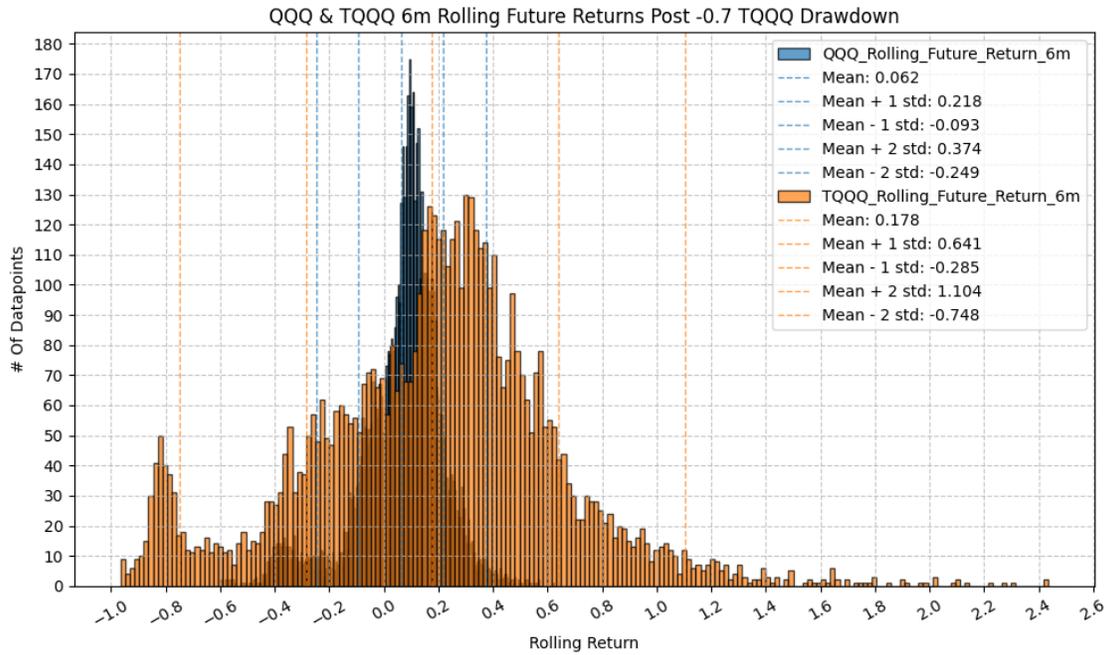
```

0.962
Model:                                OLS   Adj. R-squared:
0.962
Method:                                Least Squares   F-statistic:
1.509e+05
Date:                                  Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                  14:27:30   Log-Likelihood:
7799.9
No. Observations:                      5890   AIC:
-1.560e+04
Df Residuals:                          5888   BIC:
-1.558e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0040   0.001   -4.617   0.000
-0.006   -0.002
QQQ_Rolling_Future_Return_3m    2.9067   0.007   388.462   0.000
2.892   2.921
=====
Omnibus:                          1368.515   Durbin-Watson:                0.107
Prob(Omnibus):                     0.000   Jarque-Bera (JB):            16450.659
Skew:                               0.766   Prob(JB):                    0.00
Kurtosis:                          11.043   Cond. No.                     8.93
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_6m R-squared:

```

0.934
Model:                                OLS   Adj. R-squared:
0.934
Method:                               Least Squares   F-statistic:
8.379e+04
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:27:31   Log-Likelihood:
4198.9
No. Observations:                    5890   AIC:
-8394.
Df Residuals:                        5888   BIC:
-8380.
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0017	0.002	-1.050	0.294
-0.005 0.002				
QQQ_Rolling_Future_Return_6m	2.8731	0.010	289.464	0.000
2.854 2.893				
=====				

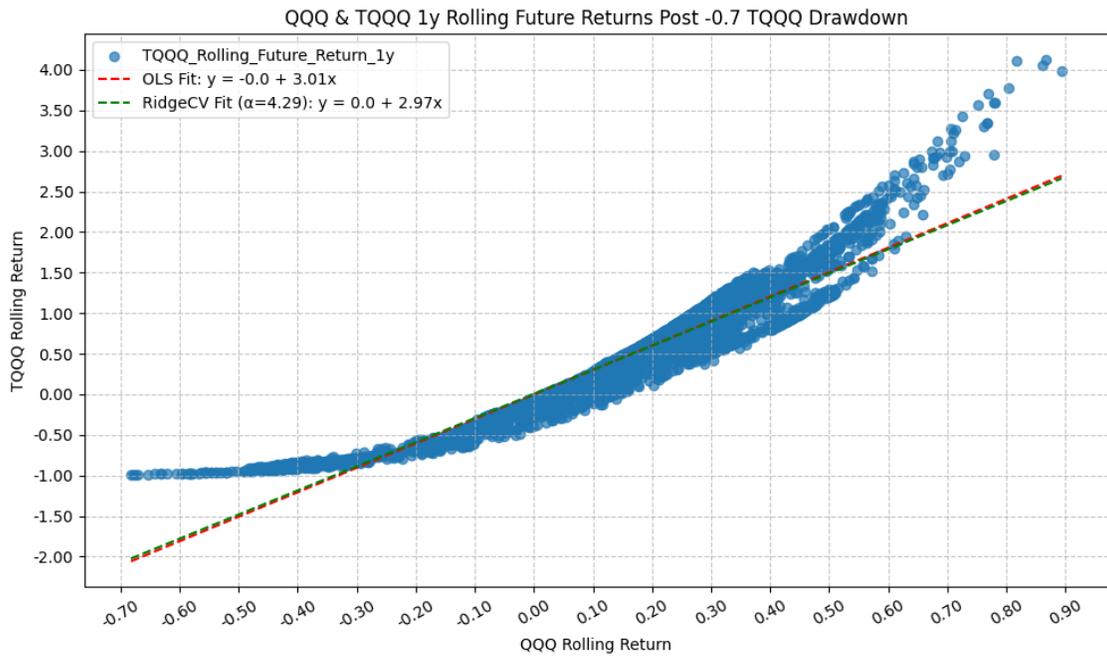
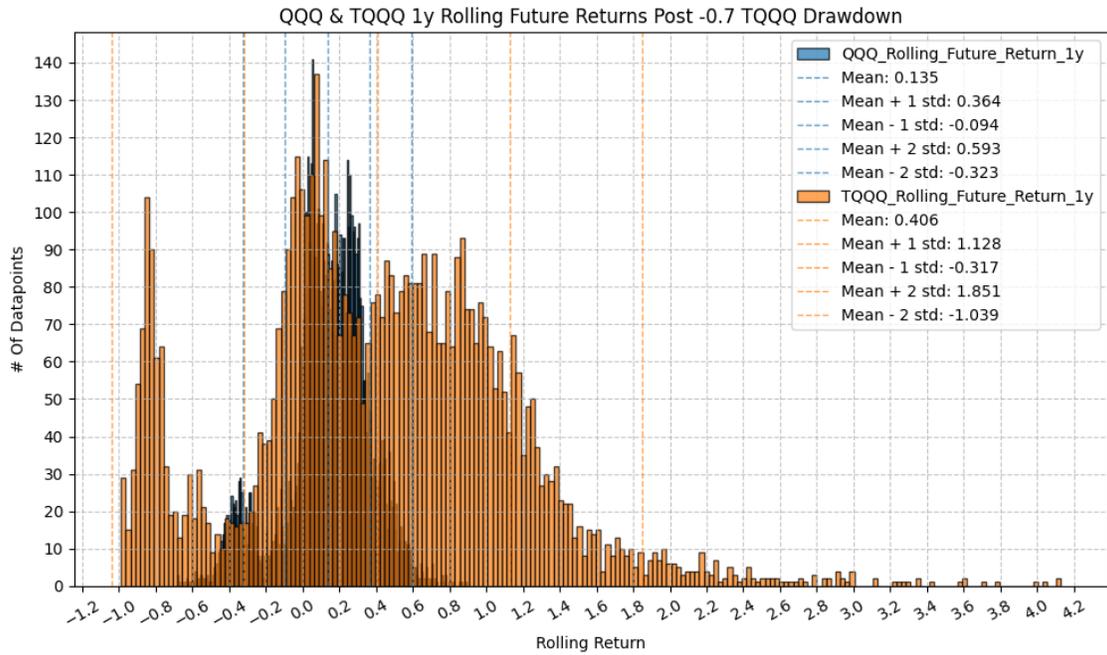
```

Omnibus:                            1462.300   Durbin-Watson:                0.063
Prob(Omnibus):                       0.000   Jarque-Bera (JB):             8111.743
Skew:                                 1.074   Prob(JB):                     0.00
Kurtosis:                             8.333   Cond. No.                     6.45
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1y R-squared:

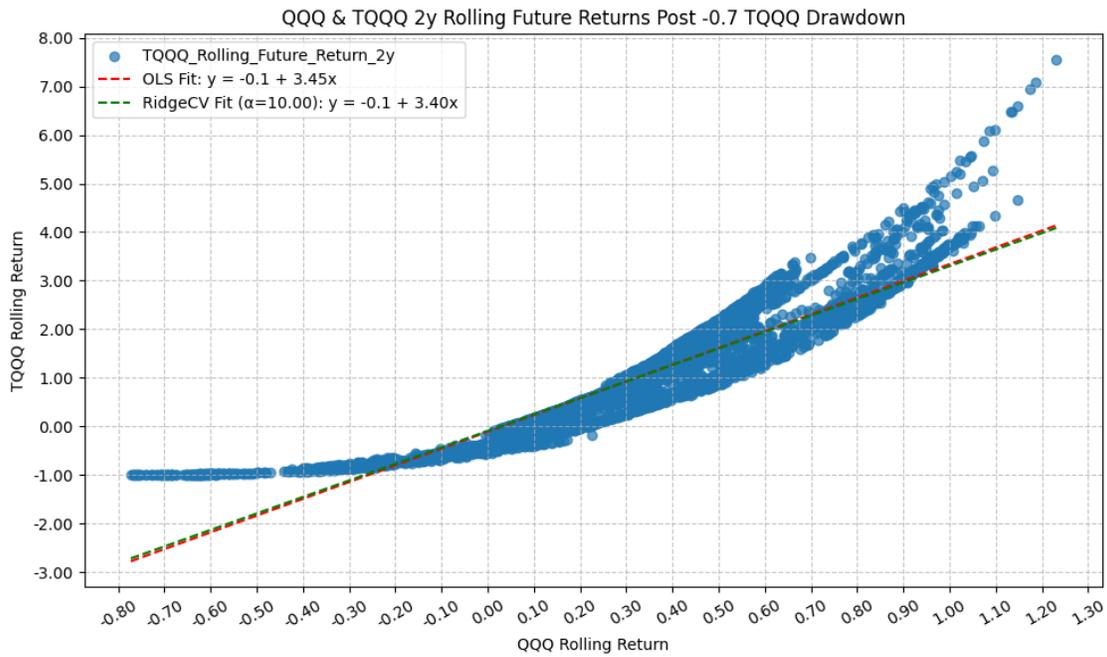
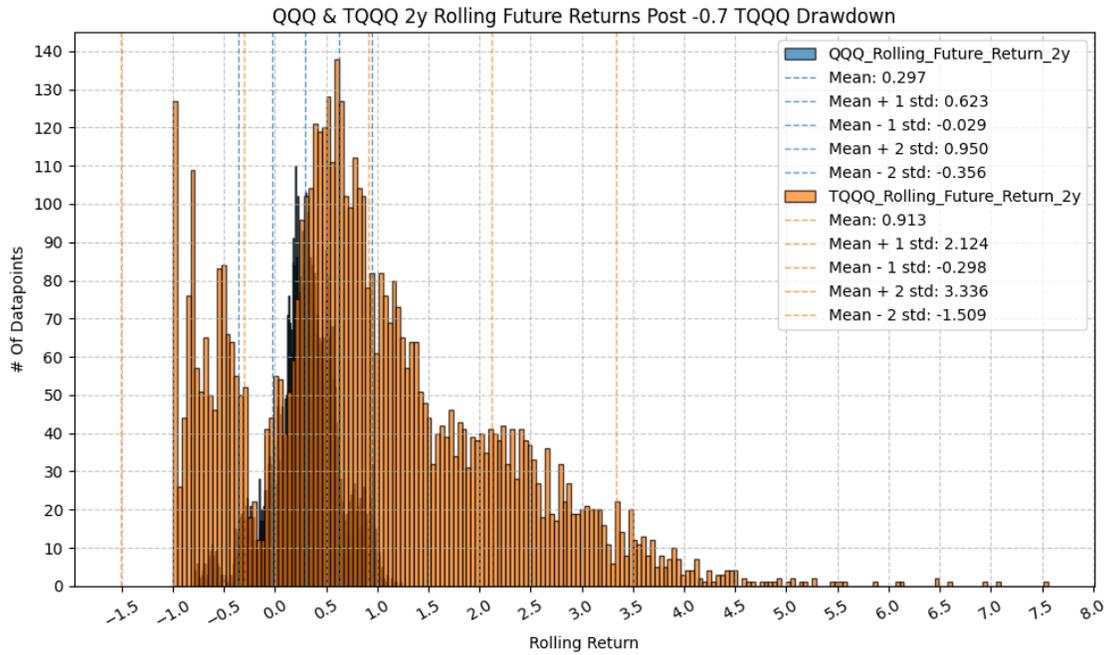
```

0.912
Model:                                OLS   Adj. R-squared:
0.912
Method:                               Least Squares   F-statistic:
6.073e+04
Date:                                  Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                  14:27:32   Log-Likelihood:
715.33
No. Observations:                     5852   AIC:
-1427.
Df Residuals:                         5850   BIC:
-1413.
Df Model:                              1
Covariance Type:                      nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.0009   0.003   -0.283   0.777
-0.007   0.005
QQQ_Rolling_Future_Return_1y    3.0133   0.012   246.430   0.000
2.989   3.037
=====
Omnibus:                         1763.446   Durbin-Watson:                0.043
Prob(Omnibus):                    0.000   Jarque-Bera (JB):            8317.030
Skew:                             1.385   Prob(JB):                    0.00
Kurtosis:                         8.142   Cond. No.                     4.45
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_2y R-squared:

```

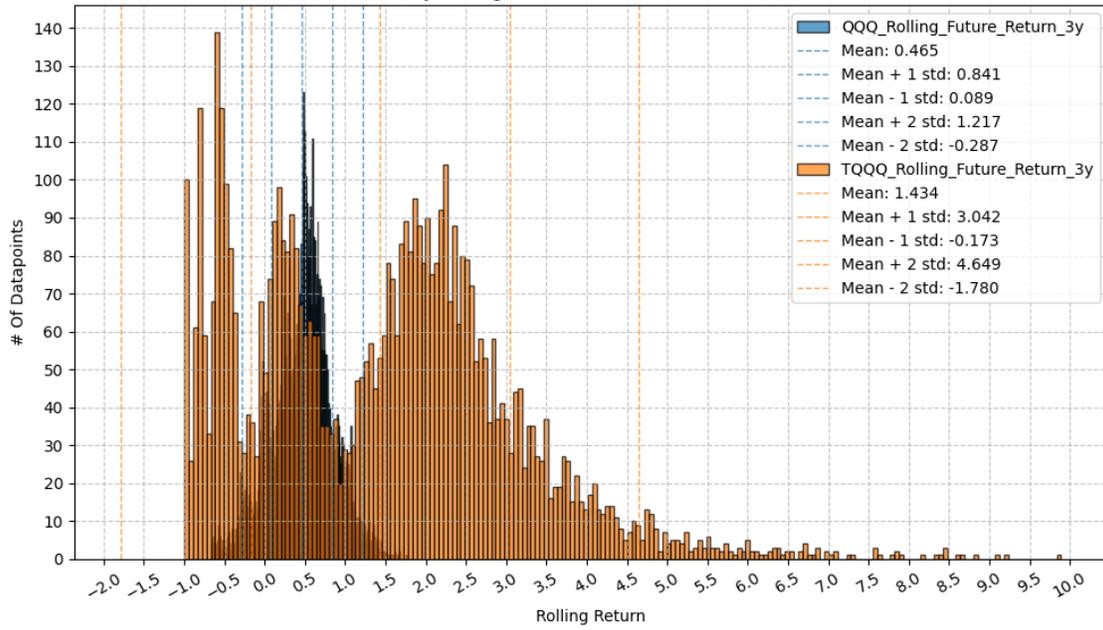
0.865
Model:                                OLS   Adj. R-squared:
0.865
Method:                                Least Squares   F-statistic:
3.714e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:33   Log-Likelihood:
-3517.9
No. Observations:                    5784   AIC:
7040.
Df Residuals:                        5782   BIC:
7053.
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.1117   0.008   -14.133   0.000
-0.127   -0.096
QQQ_Rolling_Future_Return_2y    3.4522   0.018   192.714   0.000
3.417   3.487
=====
Omnibus:                          1654.899   Durbin-Watson:                0.020
Prob(Omnibus):                     0.000   Jarque-Bera (JB):             5619.104
Skew:                               1.427   Prob(JB):                     0.00
Kurtosis:                          6.895   Cond. No.                     3.36
=====

```

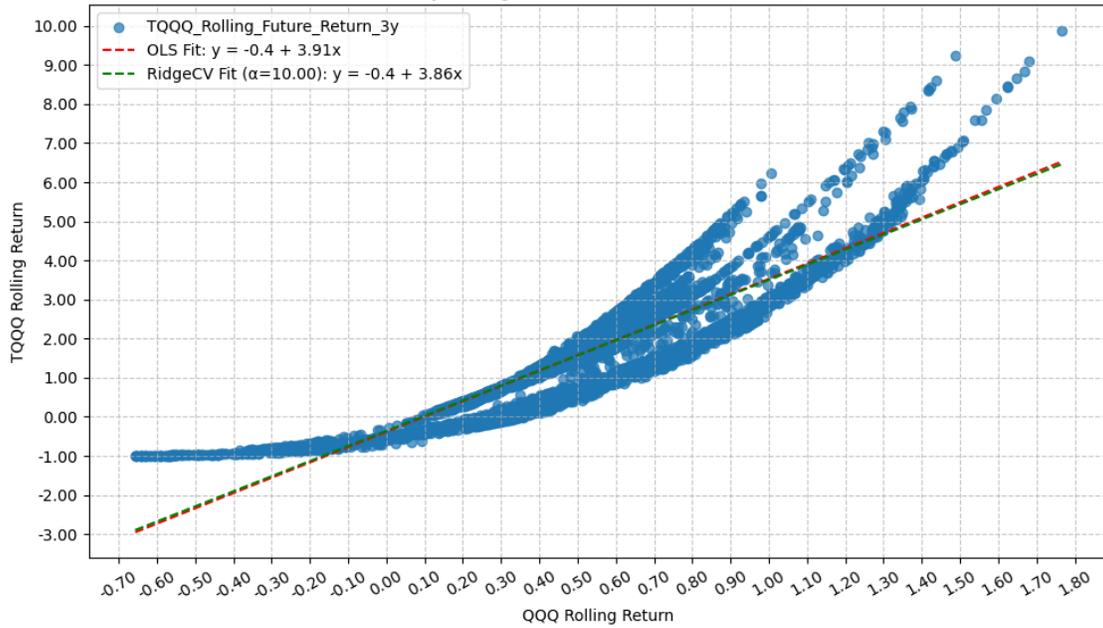
Notes:

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

QQQ & TQQQ 3y Rolling Future Returns Post -0.7 TQQQ Drawdown



QQQ & TQQQ 3y Rolling Future Returns Post -0.7 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3y R-squared:

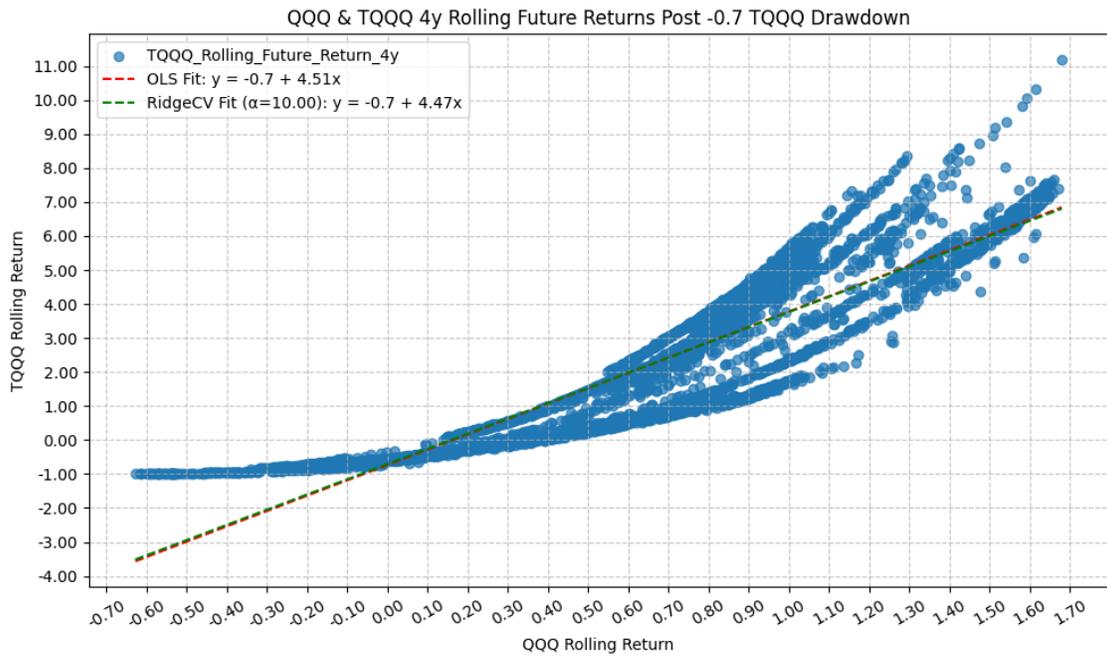
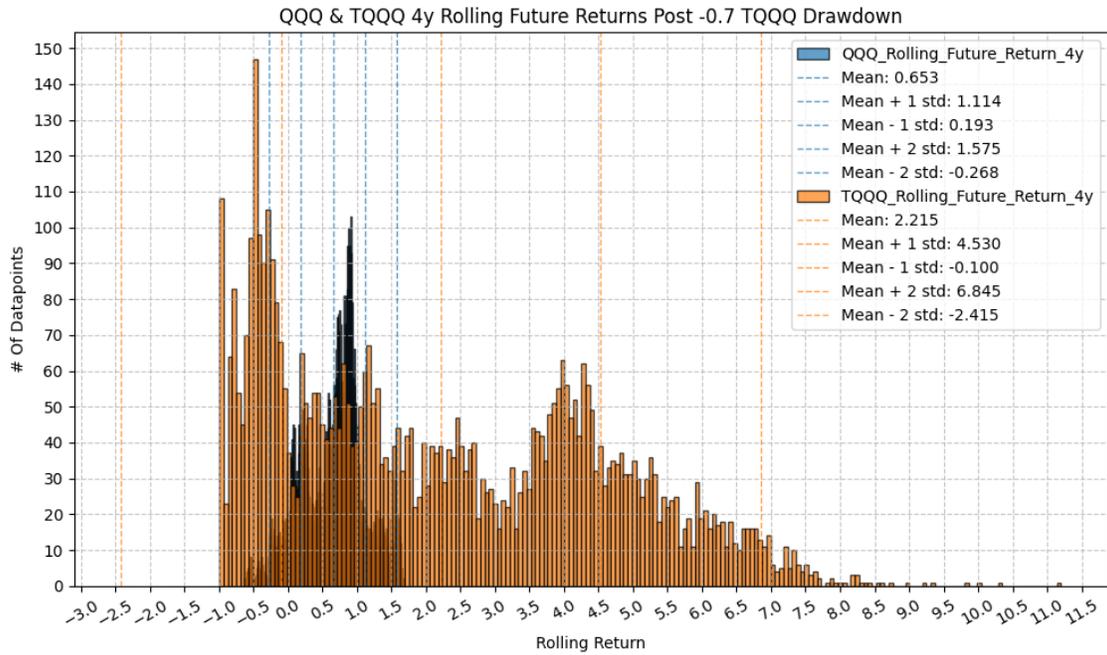
```

0.838
Model:                                OLS   Adj. R-squared:
0.838
Method:                                Least Squares   F-statistic:
2.855e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:34   Log-Likelihood:
-5444.7
No. Observations:                    5532   AIC:
1.089e+04
Df Residuals:                        5530   BIC:
1.091e+04
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.3845   0.014   -27.769   0.000
-0.412   -0.357
QQQ_Rolling_Future_Return_3y     3.9132   0.023   168.966   0.000
3.868   3.959
=====
Omnibus:                          670.448   Durbin-Watson:                0.016
Prob(Omnibus):                     0.000   Jarque-Bera (JB):             1243.454
Skew:                              0.791   Prob(JB):                     9.71e-271
Kurtosis:                          4.700   Cond. No.                     3.31
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_4y R-squared:

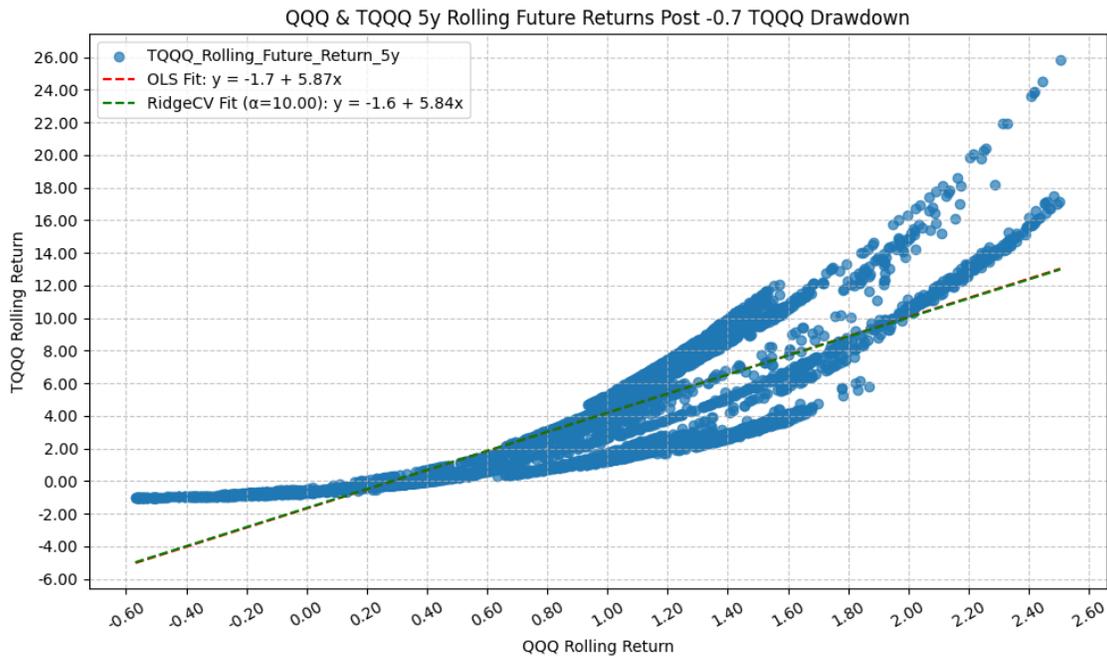
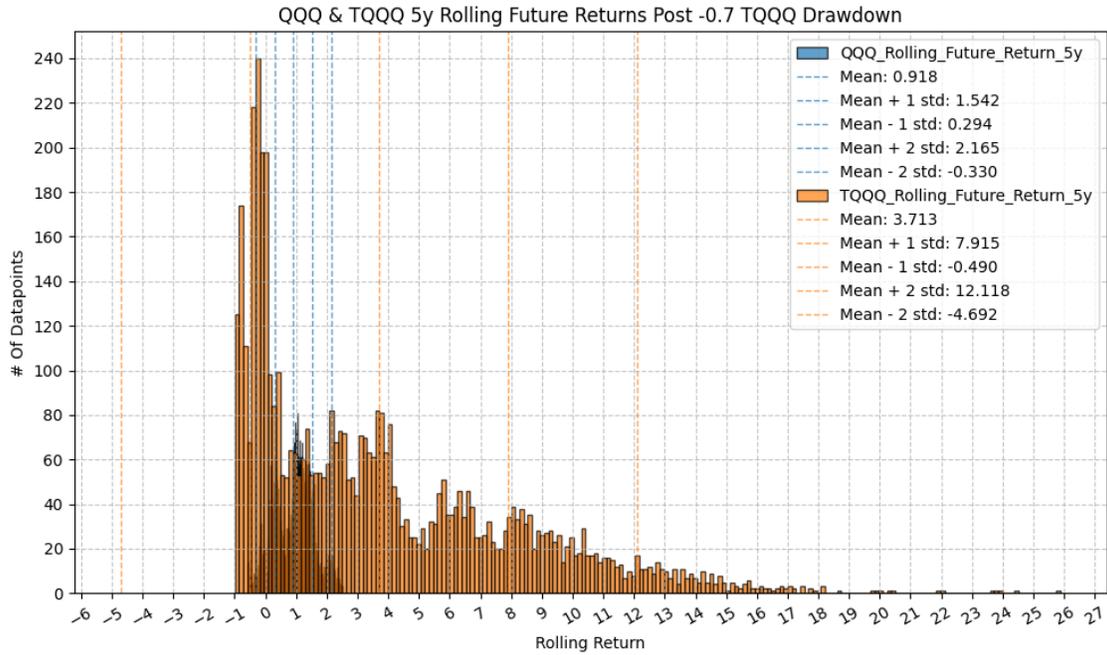
```

0.806
Model:                                OLS   Adj. R-squared:
0.806
Method:                               Least Squares   F-statistic:
2.190e+04
Date:                                  Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                  14:27:36   Log-Likelihood:
-7596.8
No. Observations:                     5280   AIC:
1.520e+04
Df Residuals:                          5278   BIC:
1.521e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.7323   0.024   -30.052   0.000
-0.780   -0.685
QQQ_Rolling_Future_Return_4y     4.5109   0.030   147.996   0.000
4.451   4.571
=====
Omnibus:                          12.319   Durbin-Watson:                0.011
Prob(Omnibus):                      0.002   Jarque-Bera (JB):             10.050
Skew:                                -0.007   Prob(JB):                      0.00657
Kurtosis:                            2.787   Cond. No.                      3.25
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_5y R-squared:

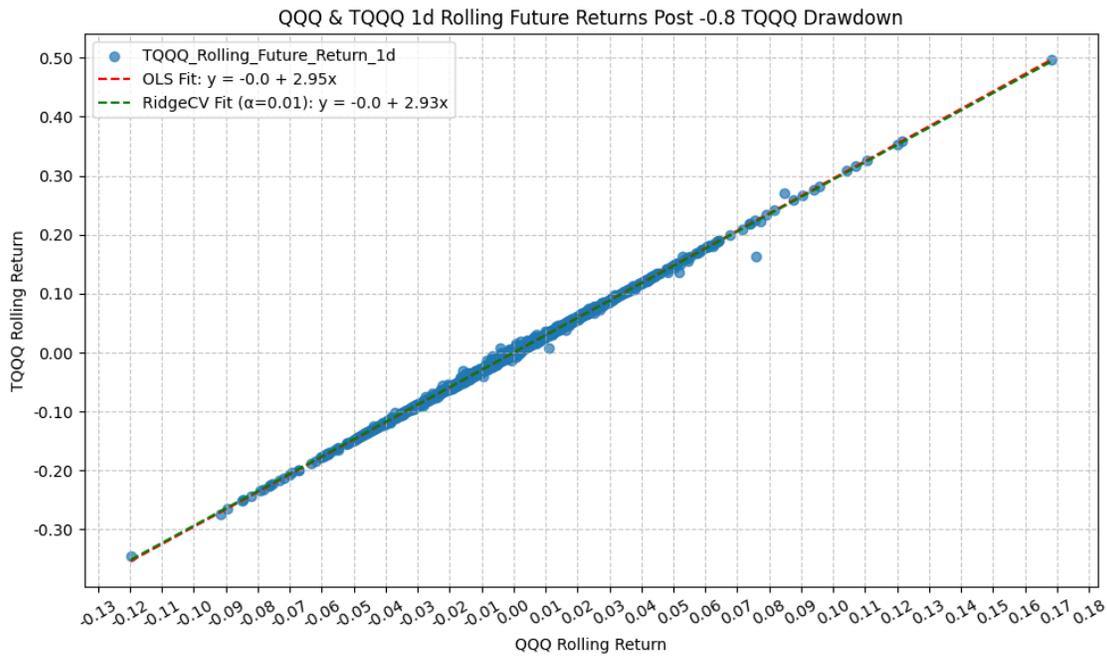
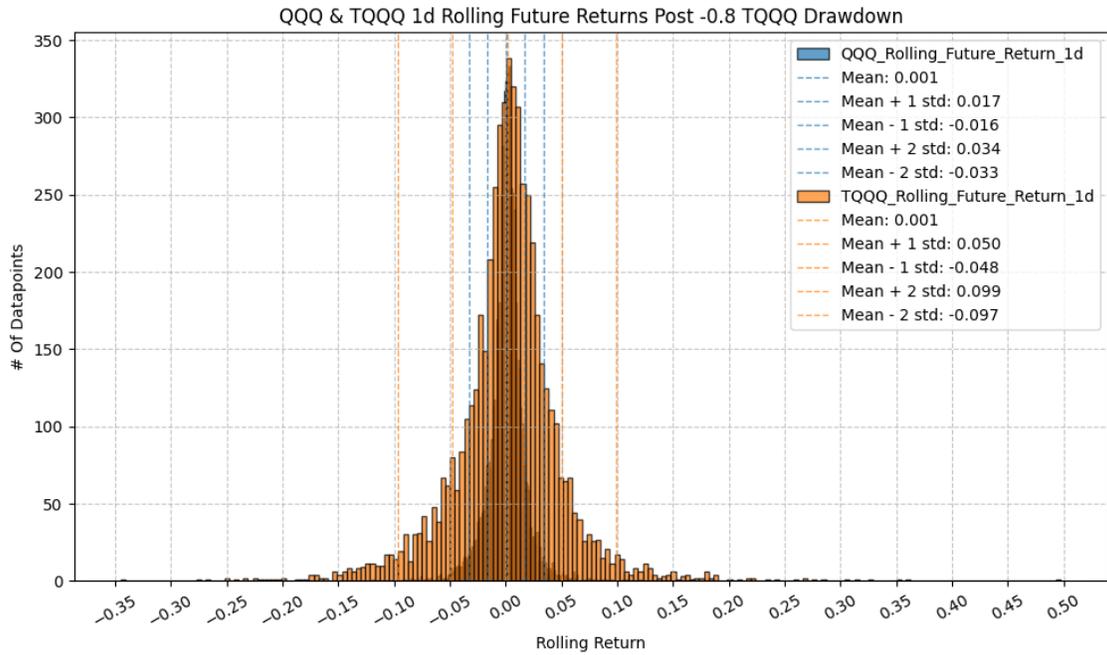
```

0.759
Model:                                OLS   Adj. R-squared:
0.759
Method:                                Least Squares   F-statistic:
1.625e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:37   Log-Likelihood:
-11052.
No. Observations:                    5158   AIC:
2.211e+04
Df Residuals:                        5156   BIC:
2.212e+04
Df Model:                             1
Covariance Type:                      nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -1.6745   0.051   -32.771   0.000
-1.775   -1.574
QQQ_Rolling_Future_Return_5y     5.8696   0.046   127.481   0.000
5.779   5.960
=====
Omnibus:                          168.503   Durbin-Watson:                0.010
Prob(Omnibus):                     0.000   Jarque-Bera (JB):             287.431
Skew:                              0.281   Prob(JB):                     3.85e-63
Kurtosis:                          4.010   Cond. No.                     3.27
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1d R-squared:

```

0.999
Model: OLS Adj. R-squared:
0.999
Method: Least Squares F-statistic:
4.764e+06
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:38 Log-Likelihood:
27156.
No. Observations: 5448 AIC:
-5.431e+04
Df Residuals: 5446 BIC:
-5.429e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

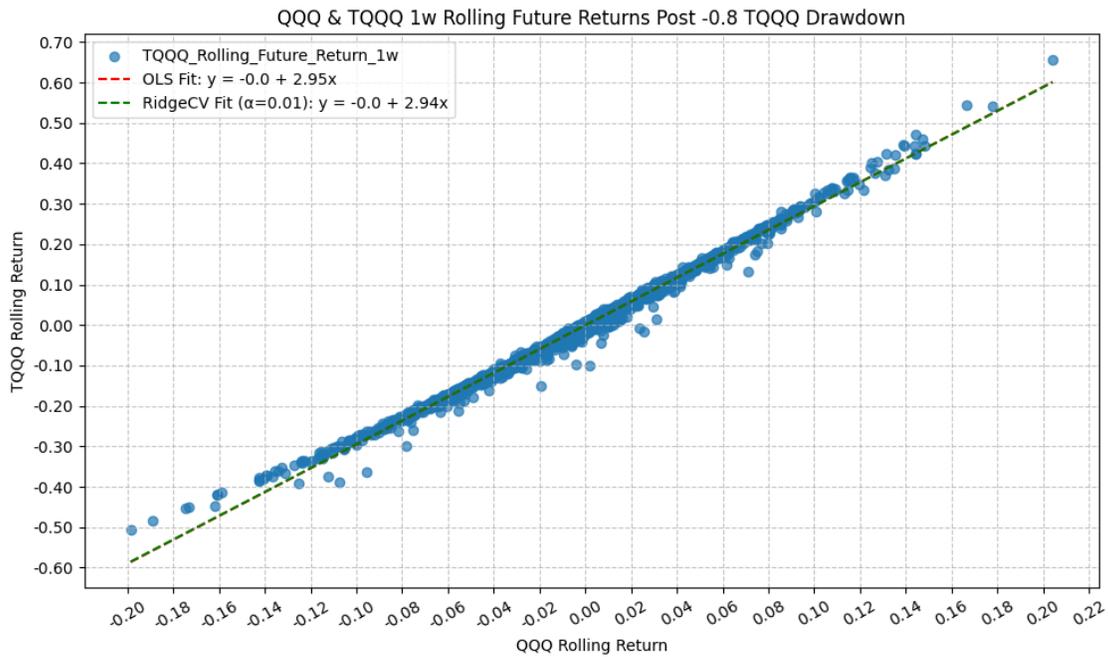
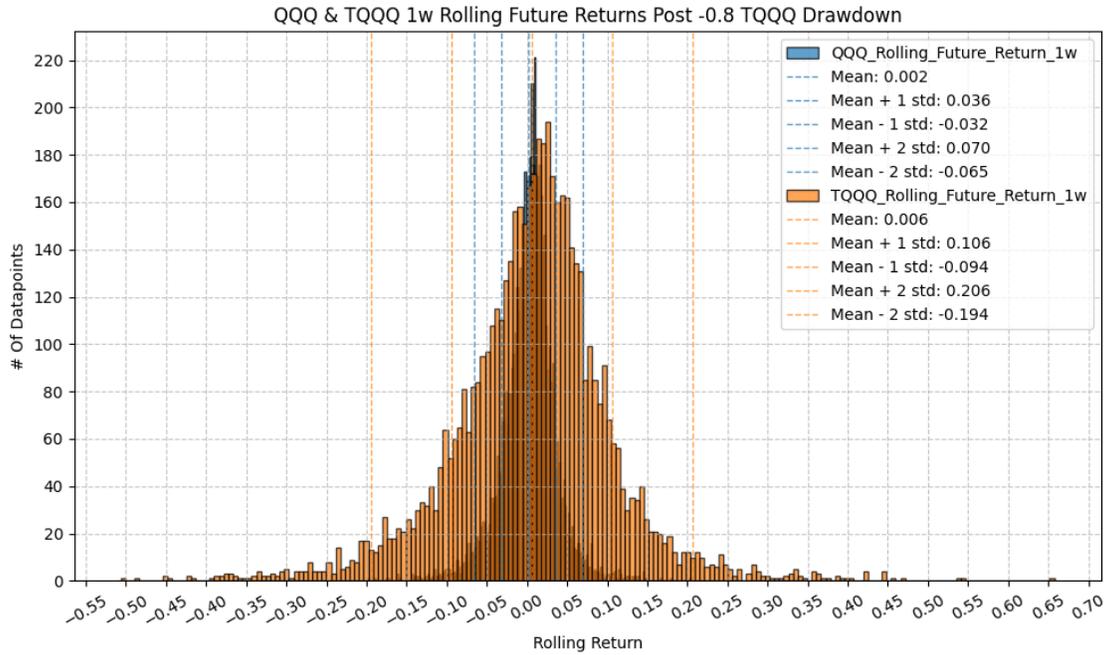
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-1.568e-05	2.24e-05	-0.699	0.485
-5.97e-05 2.83e-05				
QQQ_Rolling_Future_Return_1d	2.9531	0.001	2182.718	0.000
2.950 2.956				
=====				
Omnibus:	8179.872	Durbin-Watson:		2.578
Prob(Omnibus):	0.000	Jarque-Bera (JB):		30309716.309
Skew:	-8.324	Prob(JB):		0.00
Kurtosis:	368.029	Cond. No.		60.3
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1w R-squared:

```

0.994
Model: OLS Adj. R-squared:
0.994
Method: Least Squares F-statistic:
9.352e+05
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:39 Log-Likelihood:
18848.
No. Observations: 5448 AIC:
-3.769e+04
Df Residuals: 5446 BIC:
-3.768e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

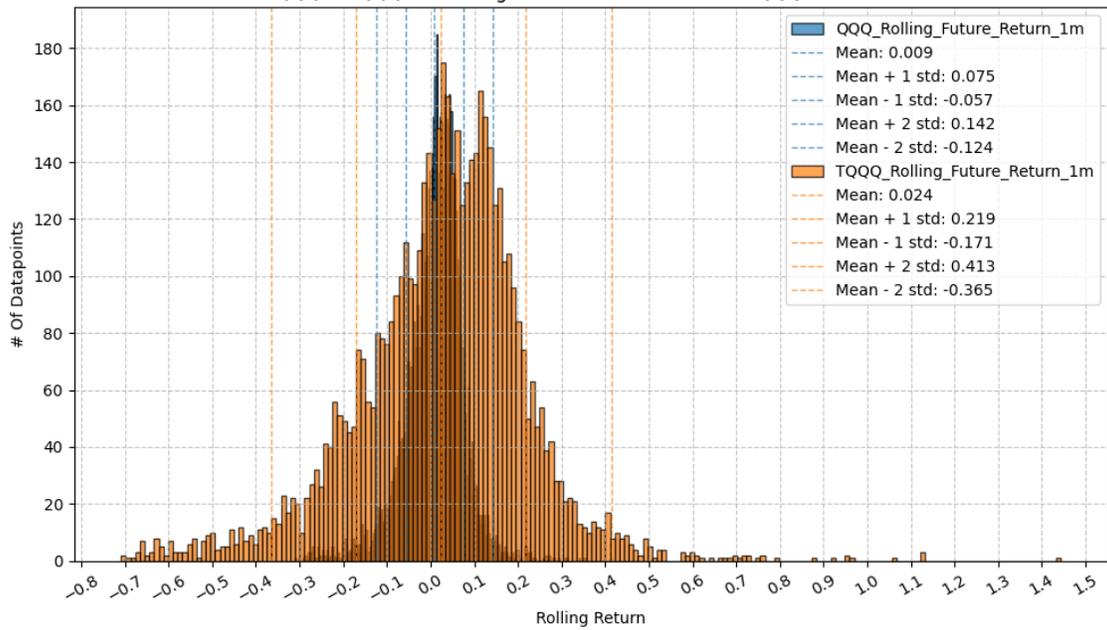
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0006	0.000	-5.487	0.000
-0.001 -0.000				
QQQ_Rolling_Future_Return_1w	2.9495	0.003	967.032	0.000
2.943 2.955				
=====				
Omnibus:	3225.193	Durbin-Watson:		0.872
Prob(Omnibus):	0.000	Jarque-Bera (JB):		383535.806
Skew:	-1.881	Prob(JB):		0.00
Kurtosis:	43.932	Cond. No.		29.6
=====				

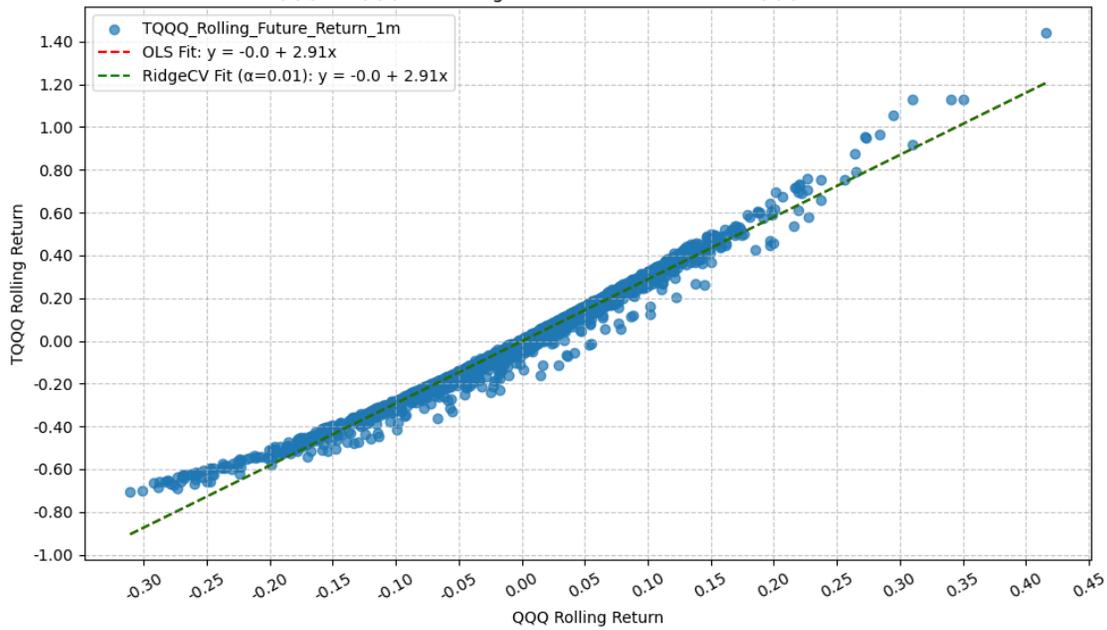
Notes:

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

QQQ & TQQQ 1m Rolling Future Returns Post -0.8 TQQQ Drawdown



QQQ & TQQQ 1m Rolling Future Returns Post -0.8 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1m R-squared:

```

0.982
Model: OLS Adj. R-squared:
0.982
Method: Least Squares F-statistic:
3.034e+05
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:40 Log-Likelihood:
12185.
No. Observations: 5448 AIC:
-2.437e+04
Df Residuals: 5446 BIC:
-2.435e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0021	0.000	-5.896	0.000
-0.003 -0.001				
QQQ_Rolling_Future_Return_1m	2.9063	0.005	550.837	0.000
2.896 2.917				

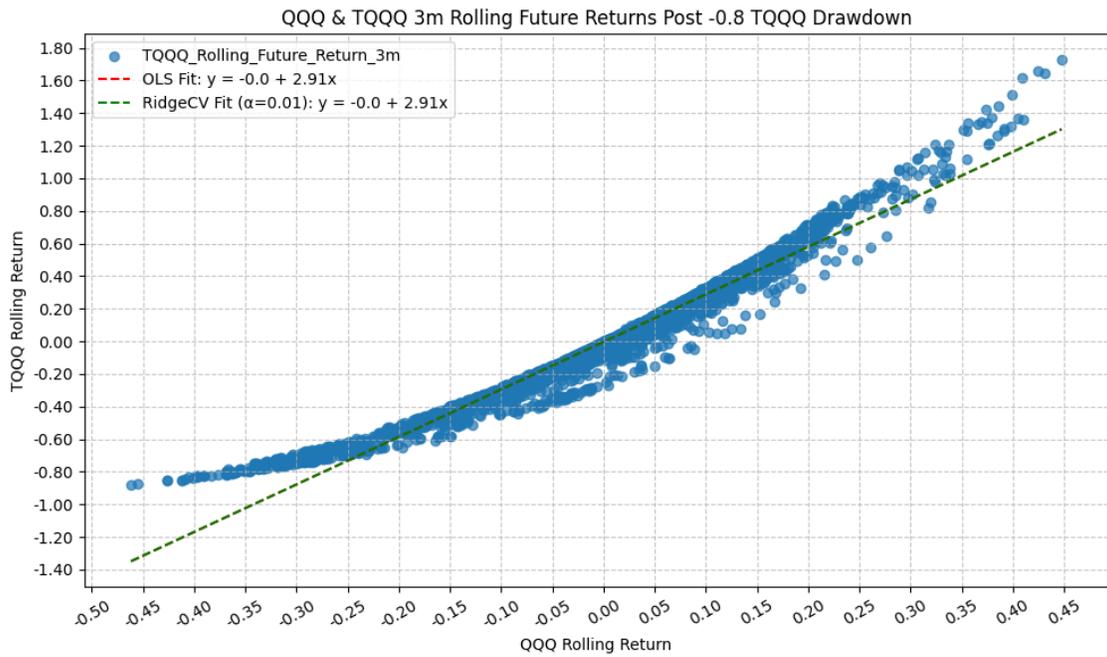
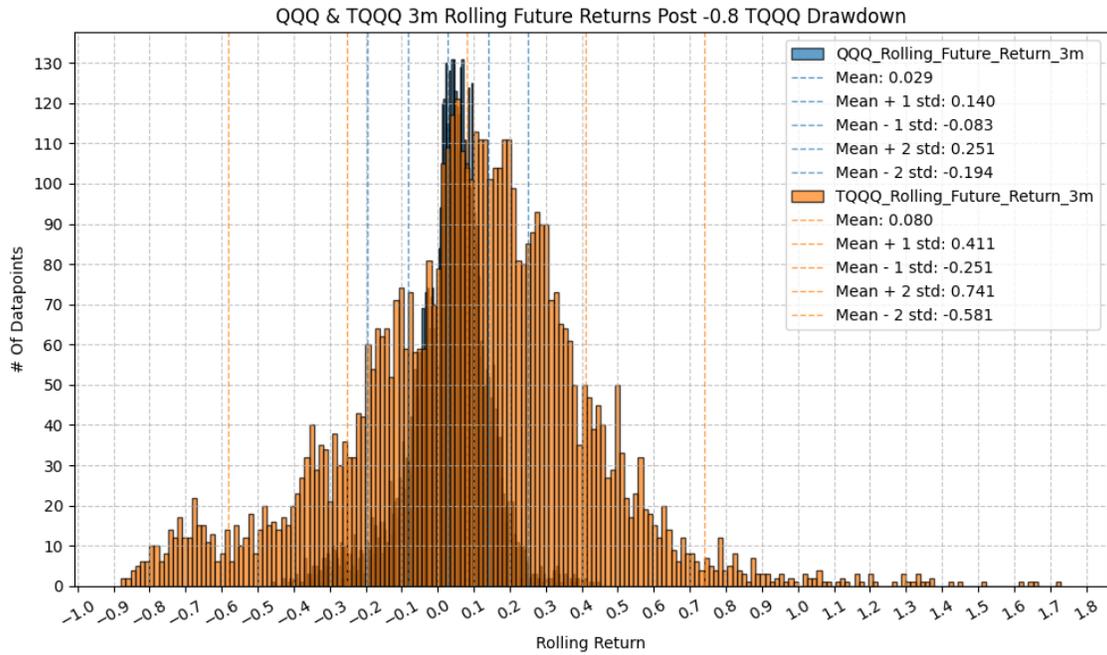
```

=====
Omnibus: 1330.394 Durbin-Watson: 0.299
Prob(Omnibus): 0.000 Jarque-Bera (JB): 76723.084
Skew: 0.205 Prob(JB): 0.00
Kurtosis: 21.380 Cond. No. 15.1
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3m R-squared:

```

0.961
Model: OLS Adj. R-squared:
0.961
Method: Least Squares F-statistic:
1.351e+05
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:41 Log-Likelihood:
7156.4
No. Observations: 5448 AIC:
-1.431e+04
Df Residuals: 5446 BIC:
-1.430e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

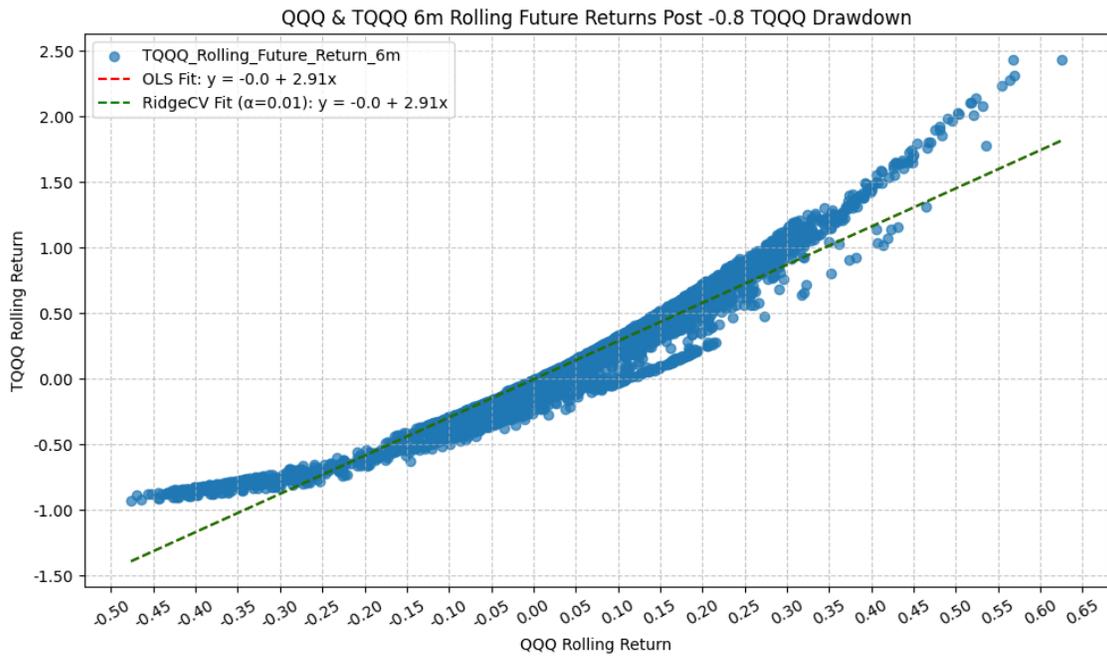
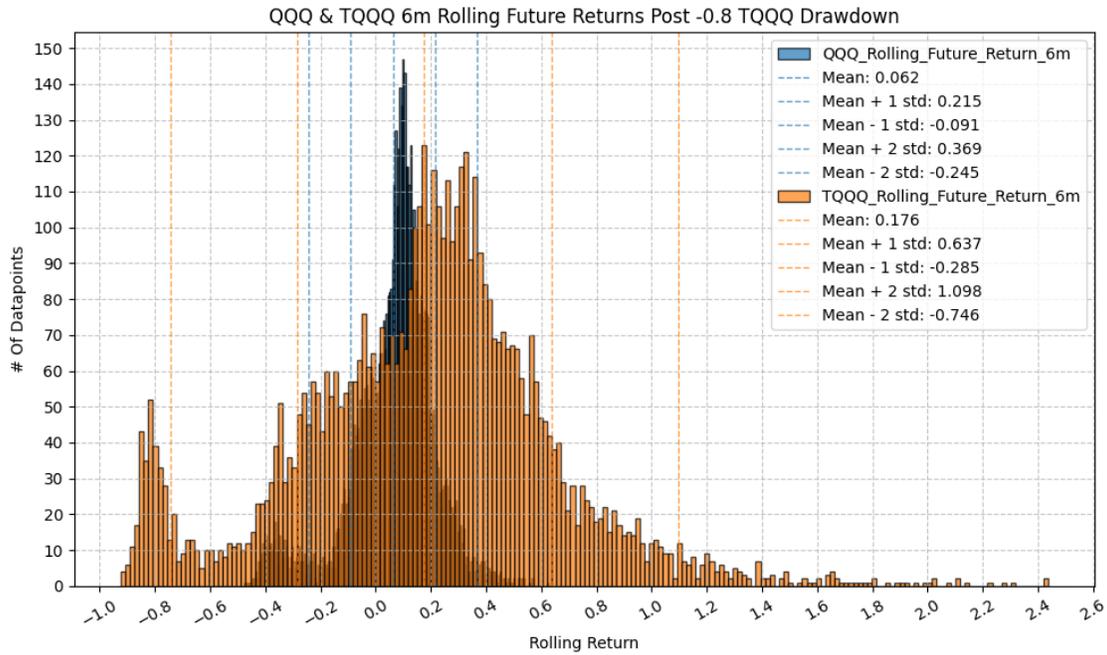
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0035	0.001	-3.894	0.000
-0.005 -0.002				
QQQ_Rolling_Future_Return_3m	2.9141	0.008	367.616	0.000
2.899 2.930				
=====				
Omnibus:	1264.052	Durbin-Watson:		0.097
Prob(Omnibus):	0.000	Jarque-Bera (JB):		15799.603
Skew:	0.751	Prob(JB):		0.00
Kurtosis:	11.206	Cond. No.		9.00
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_6m R-squared:

```

0.937
Model:                                OLS   Adj. R-squared:
0.937
Method:                                Least Squares   F-statistic:
8.113e+04
Date:                                   Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                   14:27:43   Log-Likelihood:
4025.3
No. Observations:                      5448   AIC:
-8047.
Df Residuals:                          5446   BIC:
-8033.
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0043	0.002	-2.530	0.011
-0.008 -0.001				
QQQ_Rolling_Future_Return_6m	2.9102	0.010	284.832	0.000
2.890 2.930				
=====				

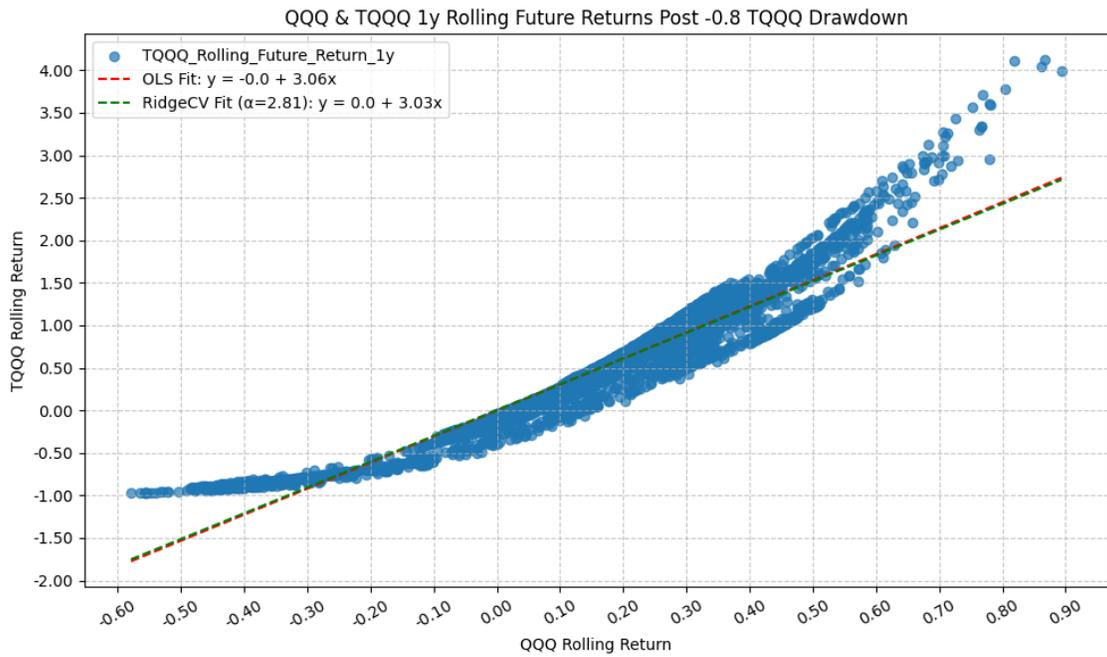
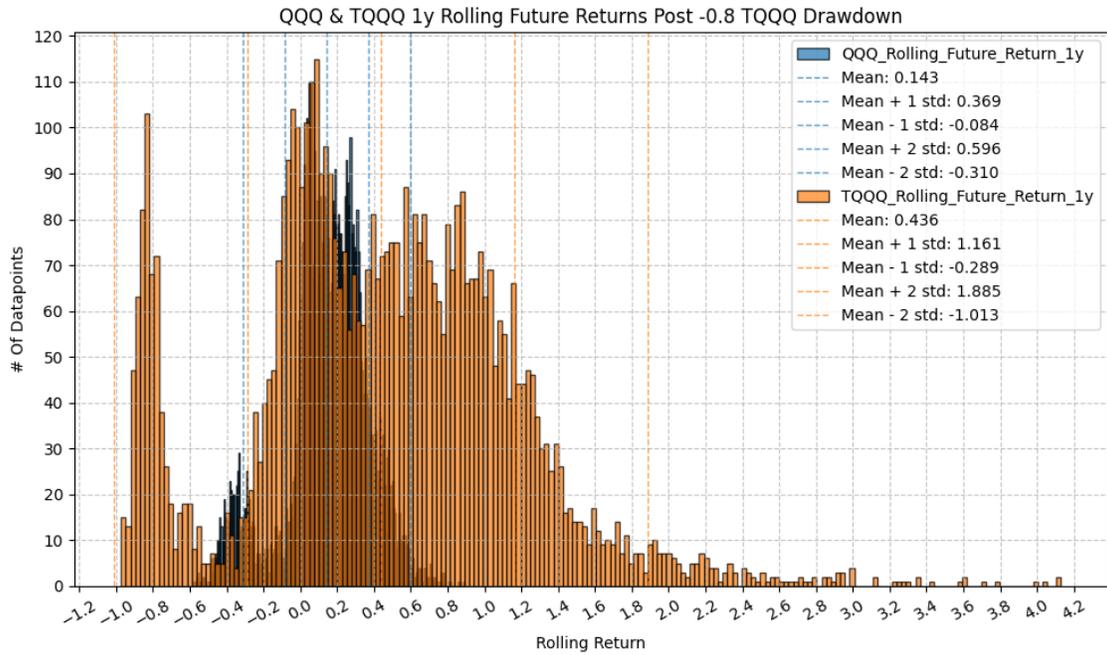
```

Omnibus:                               970.459   Durbin-Watson:                0.062
Prob(Omnibus):                          0.000   Jarque-Bera (JB):            4545.928
Skew:                                     0.789   Prob(JB):                    0.00
Kurtosis:                                7.188   Cond. No.:                   6.55
=====
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_1y R-squared:

```

0.917
Model: OLS Adj. R-squared:
0.917
Method: Least Squares F-statistic:
5.978e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:44 Log-Likelihood:
790.32
No. Observations: 5444 AIC:
-1577.
Df Residuals: 5442 BIC:
-1563.
Df Model: 1
Covariance Type: nonrobust
=====
=====

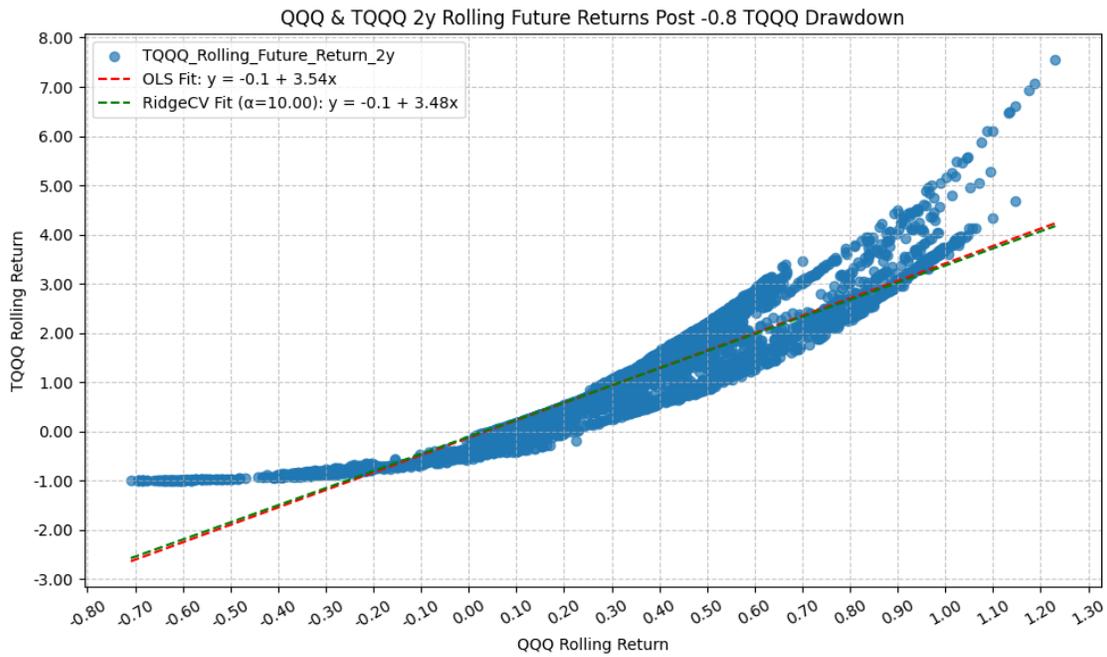
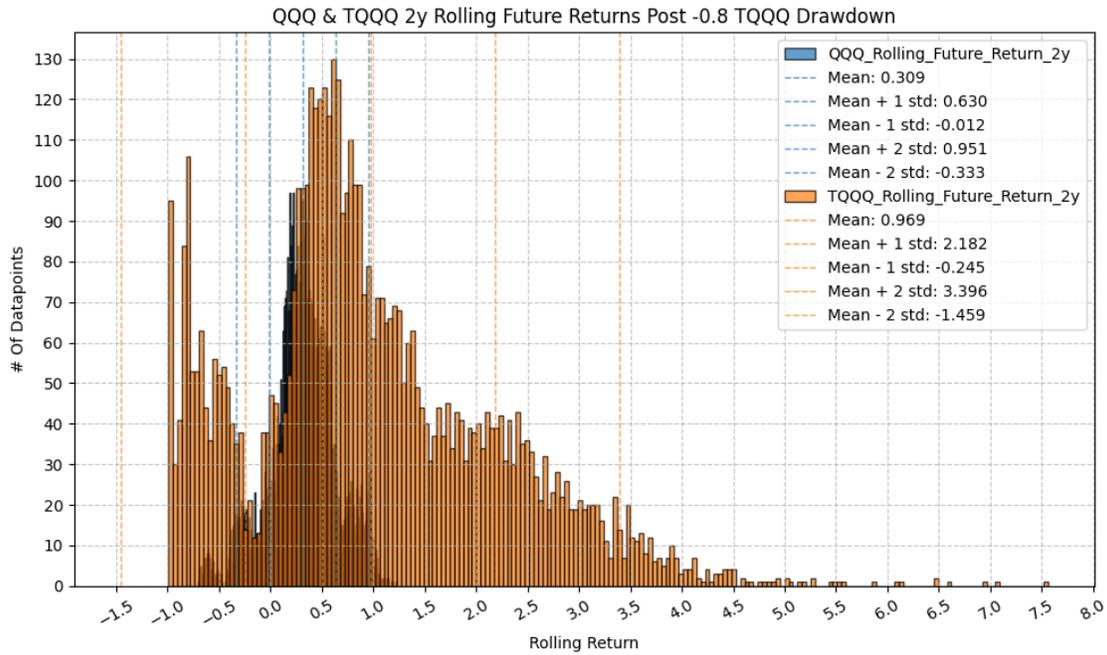
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0018	0.003	-0.540	0.589
-0.008 0.005				
QQQ_Rolling_Future_Return_1y	3.0627	0.013	244.506	0.000
3.038 3.087				
=====				
Omnibus:	1400.332	Durbin-Watson:		0.045
Prob(Omnibus):	0.000	Jarque-Bera (JB):		6204.356
Skew:	1.186	Prob(JB):		0.00
Kurtosis:	7.661	Cond. No.		4.51
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_2y R-squared:

```

0.876
Model: OLS Adj. R-squared:
0.876
Method: Least Squares F-statistic:
3.833e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:45 Log-Likelihood:
-3103.9
No. Observations: 5444 AIC:
6212.
Df Residuals: 5442 BIC:
6225.
Df Model: 1
Covariance Type: nonrobust
=====
=====

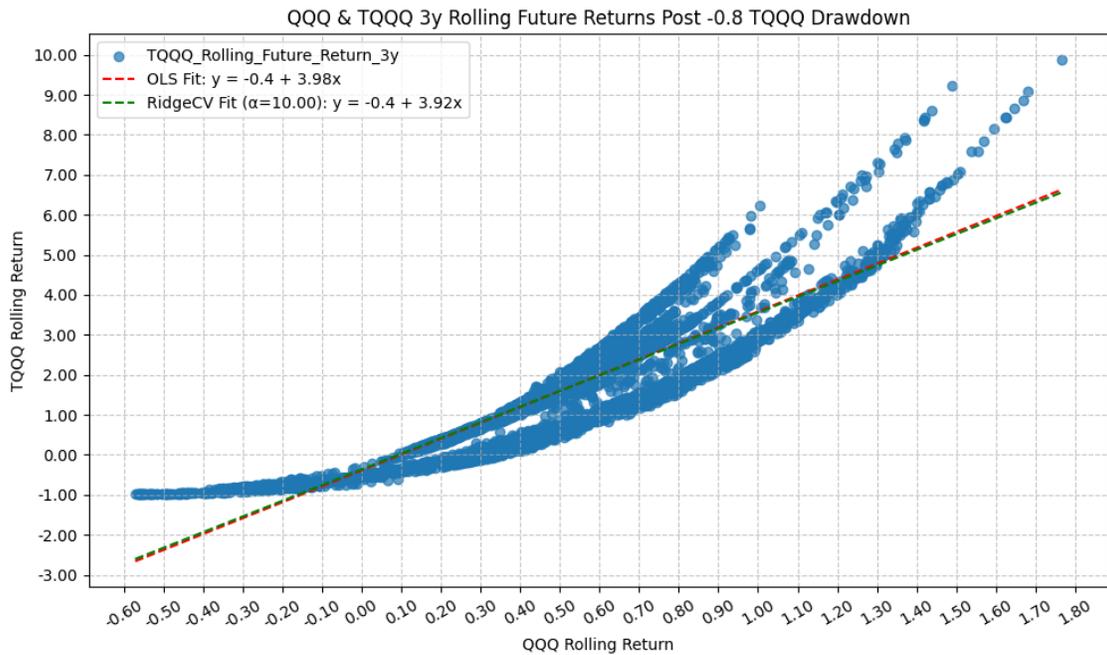
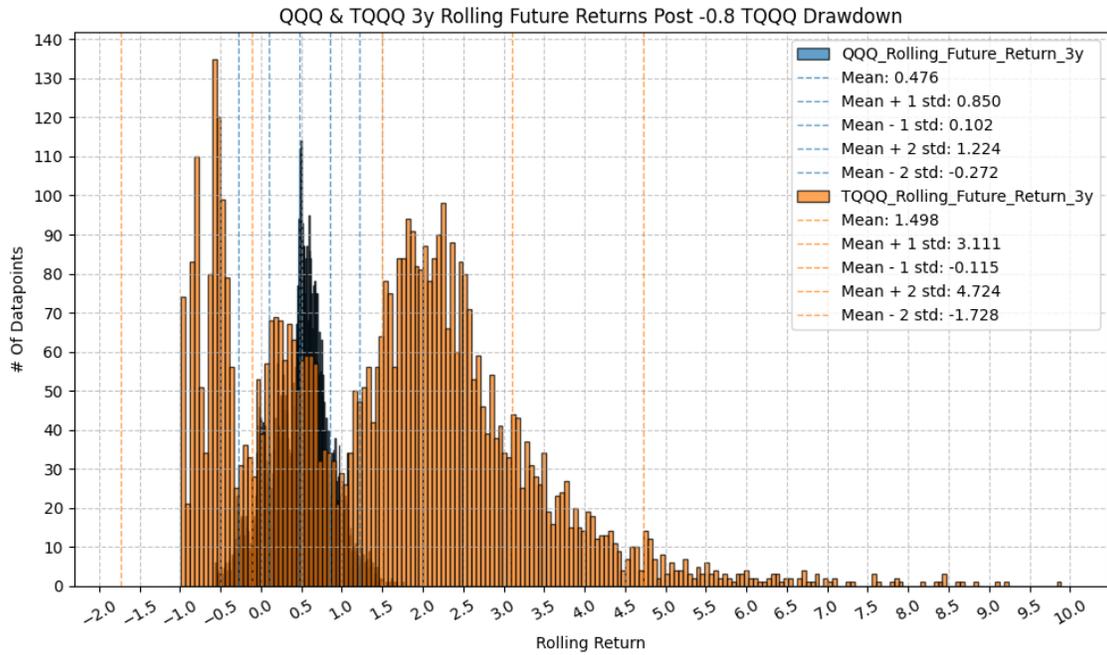
```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.1256	0.008	-15.596	0.000
-0.141 -0.110				
QQQ_Rolling_Future_Return_2y	3.5395	0.018	195.774	0.000
3.504 3.575				
=====				
Omnibus:	1478.767	Durbin-Watson:		0.022
Prob(Omnibus):	0.000	Jarque-Bera (JB):		5089.206
Skew:	1.346	Prob(JB):		0.00
Kurtosis:	6.898	Cond. No.		3.45
=====				

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_3y R-squared:

```

0.850
Model: OLS Adj. R-squared:
0.850
Method: Least Squares F-statistic:
2.988e+04
Date: Mon, 16 Mar 2026 Prob (F-statistic):
0.00
Time: 14:27:46 Log-Likelihood:
-5021.0
No. Observations: 5289 AIC:
1.005e+04
Df Residuals: 5287 BIC:
1.006e+04
Df Model: 1
Covariance Type: nonrobust
=====
=====

```

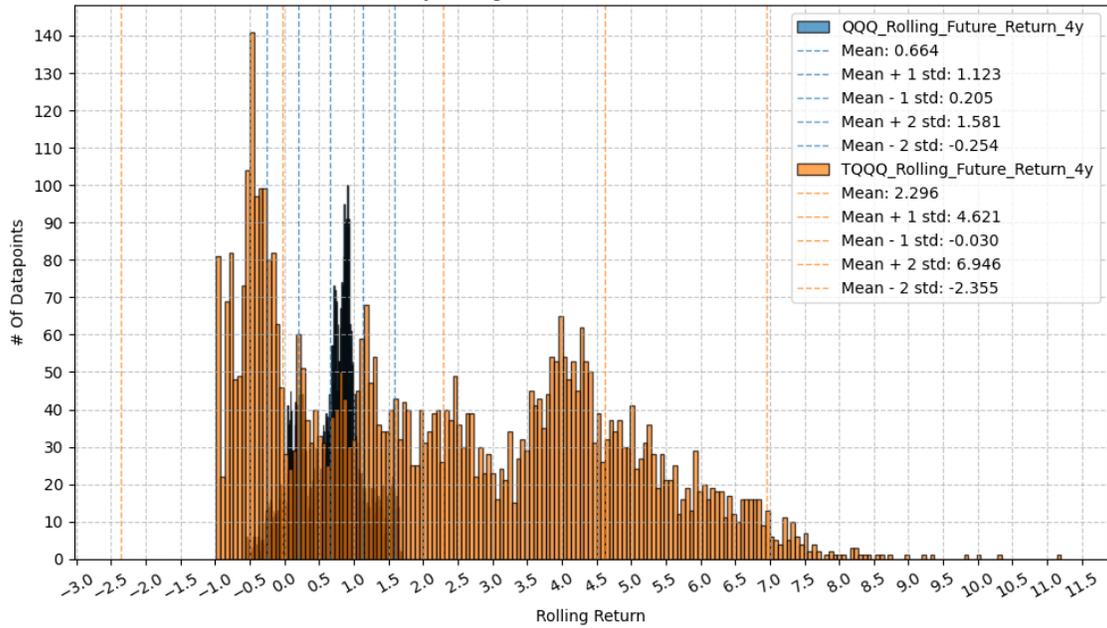
	coef	std err	t	P> t
[0.025 0.975]				

const	-0.3933	0.014	-28.260	0.000
-0.421 -0.366				
QQQ_Rolling_Future_Return_3y	3.9757	0.023	172.869	0.000
3.931 4.021				
=====				
Omnibus:	578.227	Durbin-Watson:		0.018
Prob(Omnibus):	0.000	Jarque-Bera (JB):		1146.794
Skew:	0.704	Prob(JB):		9.48e-250
Kurtosis:	4.795	Cond. No.		3.36
=====				

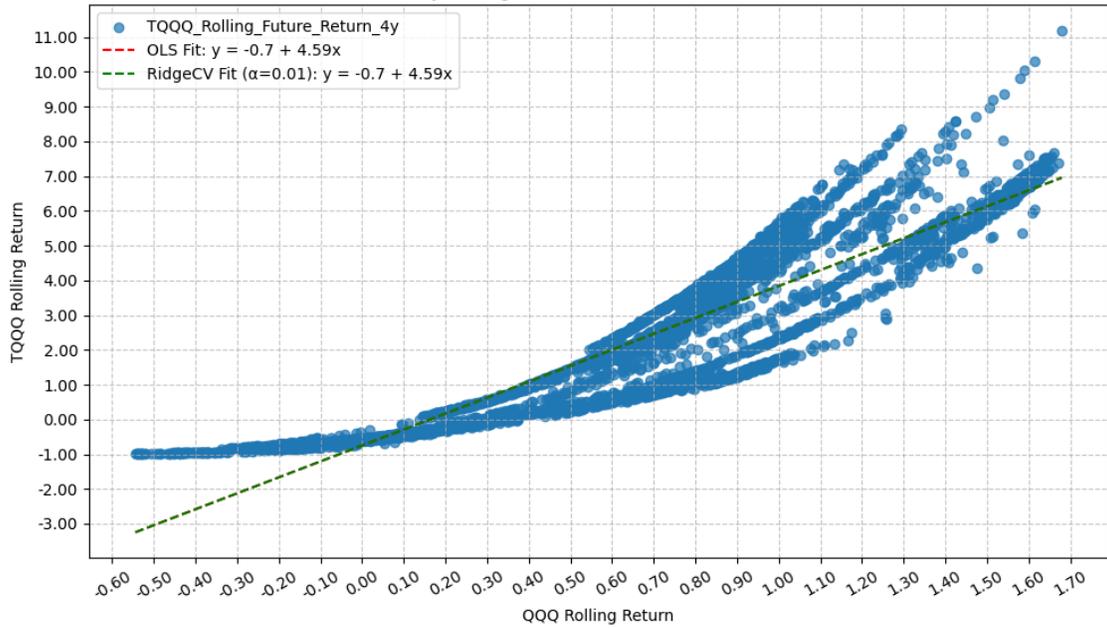
Notes:

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

QQQ & TQQQ 4y Rolling Future Returns Post -0.8 TQQQ Drawdown



QQQ & TQQQ 4y Rolling Future Returns Post -0.8 TQQQ Drawdown



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_4y R-squared:

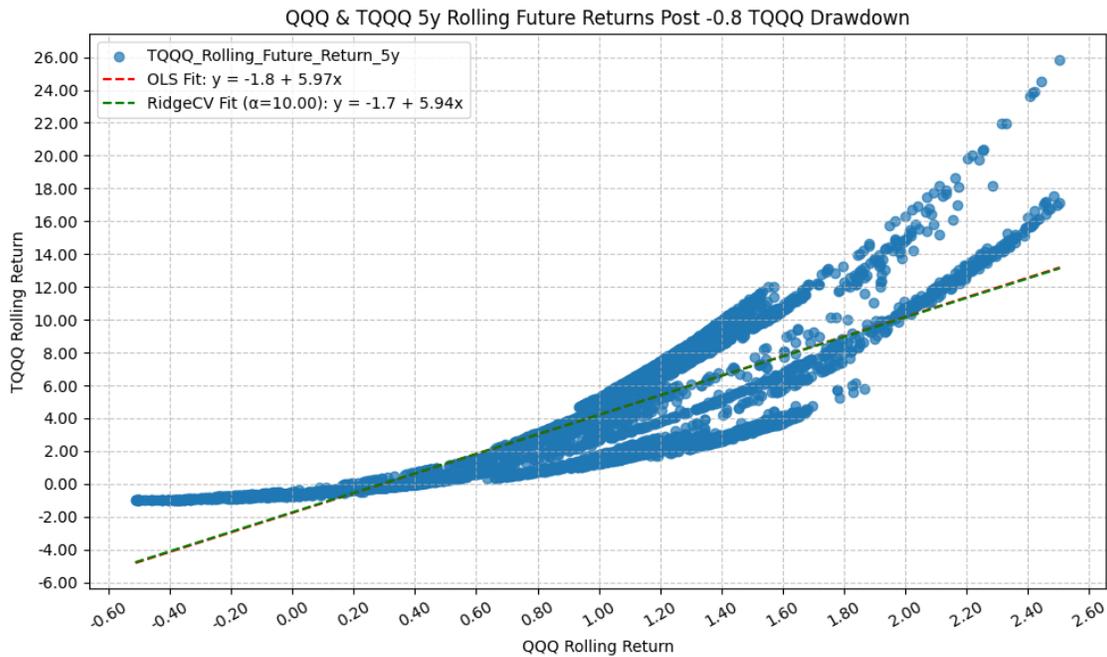
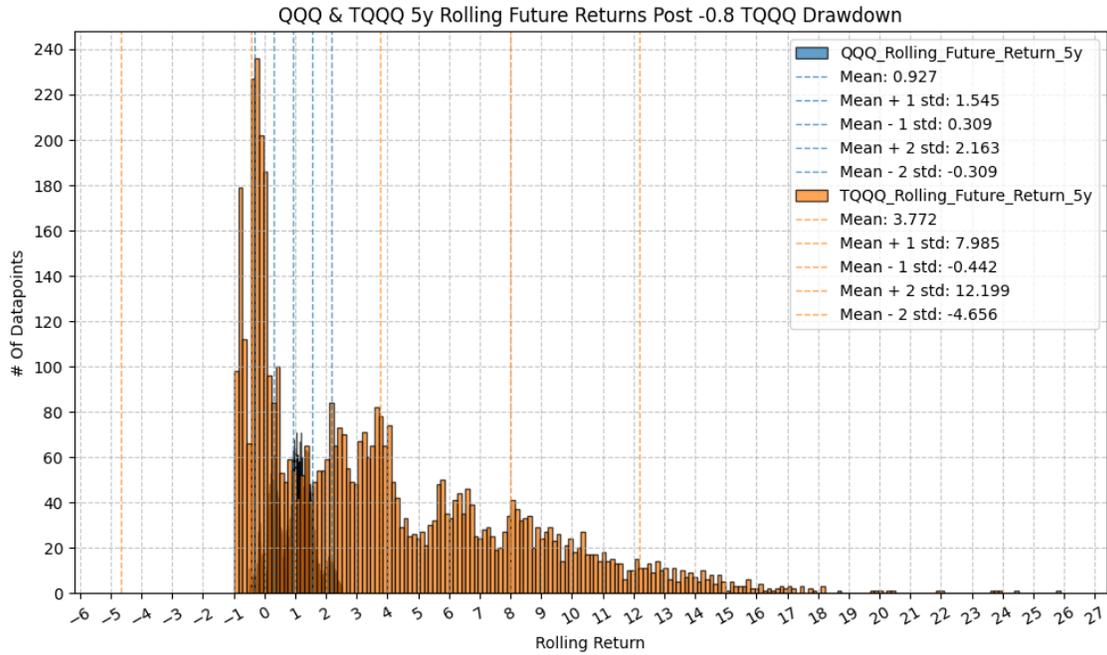
```

0.820
Model:                                OLS   Adj. R-squared:
0.820
Method:                               Least Squares   F-statistic:
2.303e+04
Date:                                 Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                 14:27:47   Log-Likelihood:
-7126.5
No. Observations:                    5068   AIC:
1.426e+04
Df Residuals:                        5066   BIC:
1.427e+04
Df Model:                             1
Covariance Type:                     nonrobust
=====
=====
                                coef   std err   t   P>|t|
[0.025   0.975]
-----
const                            -0.7486   0.024   -30.693   0.000
-0.796   -0.701
QQQ_Rolling_Future_Return_4y     4.5873   0.030   151.752   0.000
4.528   4.647
=====
Omnibus:                          13.154   Durbin-Watson:                0.011
Prob(Omnibus):                     0.001   Jarque-Bera (JB):             13.239
Skew:                               -0.121   Prob(JB):                     0.00133
Kurtosis:                           2.934   Cond. No.                      3.29
=====

```

Notes:

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



OLS Regression Results

=====

Dep. Variable: TQQQ_Rolling_Future_Return_5y R-squared:

```

0.766
Model:                                OLS   Adj. R-squared:
0.766
Method:                                Least Squares   F-statistic:
1.659e+04
Date:                                Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                14:27:48   Log-Likelihood:
-10800.
No. Observations:                    5068   AIC:
2.160e+04
Df Residuals:                        5066   BIC:
2.162e+04
Df Model:                            1
Covariance Type:                    nonrobust
=====
=====
                                coef   std err   t   P>|t|
-----
[0.025   0.975]
-----
const                                -1.7612   0.052   -34.112   0.000
-1.862   -1.660
QQQ_Rolling_Future_Return_5y        5.9669   0.046   128.790   0.000
5.876   6.058
=====
Omnibus:                            145.200   Durbin-Watson:                0.010
Prob(Omnibus):                      0.000   Jarque-Bera (JB):            276.778
Skew:                                0.210   Prob(JB):                    7.91e-61
Kurtosis:                            4.065   Cond. No.                     3.33
=====

```

Notes:

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

0.4.9 Rolling Returns Following Drawdowns Deviation (QQQ & TQQQ)

```

[37]: rolling_returns_positive_future_returns = pd.DataFrame(index=rolling_windows.
      ↪keys(), data=rolling_windows.values())
      rolling_returns_positive_future_returns.reset_index(inplace=True)
      rolling_returns_positive_future_returns.rename(columns={"index": "Period", 0:
      ↪ "Days"}, inplace=True)

      for drawdown in drawdown_levels:
          temp = rolling_returns_drawdown_stats.
          ↪loc[rolling_returns_drawdown_stats["Drawdown"] == drawdown]

```

```

temp = temp[["Period", "Positive_Future_Percentage"]]
temp.rename(columns={"Positive_Future_Percentage" :
↳"Positive_Future_Percentage_Post_{drawdown}_Drawdown"}, inplace=True)
rolling_returns_positive_future_returns = pd.
↳merge(rolling_returns_positive_future_returns, temp, left_on="Period",
↳right_on="Period", how="outer")
rolling_returns_positive_future_returns.sort_values(by="Days",
↳ascending=True, inplace=True)

rolling_returns_positive_future_returns.drop(columns={"Days"}, inplace=True)
rolling_returns_positive_future_returns.reset_index(drop=True, inplace=True)
display(rolling_returns_positive_future_returns)

```

Period	Positive_Future_Percentage_Post_-0.1_Drawdown	\
0	1d	0.544
1	1w	0.563
2	1m	0.597
3	3m	0.639
4	6m	0.665
5	1y	0.708
6	2y	0.734
7	3y	0.745
8	4y	0.731
9	5y	0.729

	Positive_Future_Percentage_Post_-0.2_Drawdown	\
0		0.543
1		0.562
2		0.596
3		0.638
4		0.665
5		0.708
6		0.743
7		0.755
8		0.741
9		0.740

	Positive_Future_Percentage_Post_-0.3_Drawdown	\
0		0.544
1		0.562
2		0.594
3		0.637
4		0.664
5		0.708
6		0.748
7		0.760
8		0.746

9 0.746

Positive_Future_Percentage_Post_-0.4_Drawdown \

0	0.543
1	0.562
2	0.594
3	0.637
4	0.664
5	0.708
6	0.749
7	0.761
8	0.748
9	0.747

Positive_Future_Percentage_Post_-0.5_Drawdown \

0	0.544
1	0.563
2	0.597
3	0.639
4	0.665
5	0.709
6	0.750
7	0.762
8	0.748
9	0.748

Positive_Future_Percentage_Post_-0.6_Drawdown \

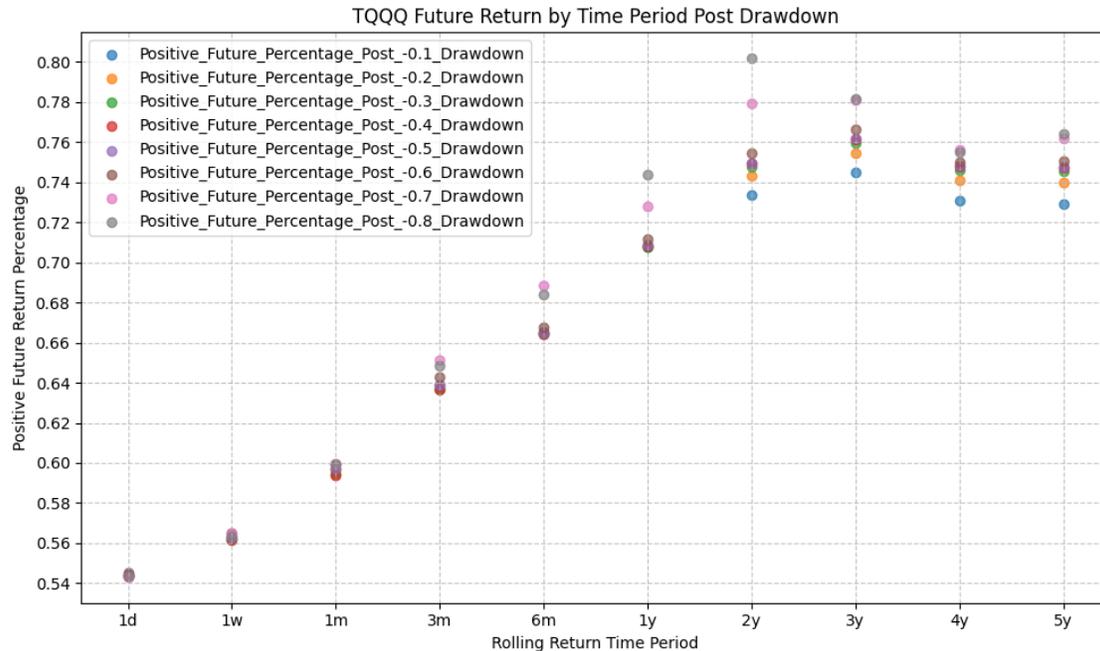
0	0.545
1	0.565
2	0.599
3	0.643
4	0.668
5	0.712
6	0.754
7	0.766
8	0.750
9	0.750

Positive_Future_Percentage_Post_-0.7_Drawdown \

0	0.543
1	0.565
2	0.600
3	0.651
4	0.689
5	0.728
6	0.780
7	0.781
8	0.756

9	0.762
	Positive_Future_Percentage_Post_-0.8_Drawdown
0	0.544
1	0.564
2	0.599
3	0.648
4	0.684
5	0.744
6	0.802
7	0.782
8	0.755
9	0.764

```
[38]: plot_scatter(
    df=rolling_returns_positive_future_returns,
    x_plot_column="Period",
    y_plot_columns=[col for col in rolling_returns_positive_future_returns.
↳columns if col != "Period"],
    title="TQQQ Future Return by Time Period Post Drawdown",
    x_label="Rolling Return Time Period",
    x_format="String",
    x_format_decimal_places=0,
    x_tick_spacing=1,
    x_tick_rotation=0,
    y_label="Positive Future Return Percentage",
    y_format="Decimal",
    y_format_decimal_places=2,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    plot_OLS_regression_line=False,
    OLS_column=None,
    plot_Ridge_regression_line=False,
    Ridge_column=None,
    plot_RidgeCV_regression_line=False,
    RidgeCV_column=None,
    regression_constant=False,
    grid=True,
    legend=True,
    export_plot=False,
    plot_file_name=None,
)
```



This plot summarizes the future rolling returns well. For rolling returns up to ~3 months *following* all drawdown levels, we see the rolling returns of TQQQ are positive ~65% of the time.

As we extend the time horizon, the percentage of positive rolling returns increases, which is consistent with the idea that the longer you hold through and post drawdown, the more likely you are to recover and achieve positive returns.

From a timing standpoint, this analysis suggests that the optimal time to buy TQQQ would be following a drawdown of 70% or more, and holding for at least 3 years. The data tells us that having a positive rolling return over time is ~75%.

One might consider the idea of allocating to TQQQ via a ladder, starting at a drawdown of 50%, and continuing to add to the position as the drawdown deepens, with the idea that the more severe the drawdown, the higher the expected future returns. However, this strategy could require enduring significant volatility, as one would be adding to the position during periods of paper losses.

0.5 SPY & UPRO

Next, we will repeat the same analysis for SPY and UPRO, and see how the results compare to those of QQQ and TQQQ.

0.5.1 Acquire & Plot Data (SPY)

First, let's get the data for SPY. If we already have the desired data, we can load it from a local file. Otherwise, we can download it from Yahoo Finance using the `yf_pull_data` function.

```
[39]: yf_pull_data(
      base_directory=DATA_DIR,
```

```

    ticker="SPY",
    adjusted=False,
    source="Yahoo_Finance",
    asset_class="Exchange_Traded_Funds",
    excel_export=True,
    pickle_export=True,
    output_confirmation=False,
)

spy = load_data(
    base_directory=DATA_DIR,
    ticker="SPY",
    source="Yahoo_Finance",
    asset_class="Exchange_Traded_Funds",
    timeframe="Daily",
    file_format="pickle",
)

# Rename columns to "SPY_Close", etc.
spy = spy.rename(columns={
    "Adj Close": "SPY_Adj_Close",
    "Close": "SPY_Close",
    "High": "SPY_High",
    "Low": "SPY_Low",
    "Open": "SPY_Open",
    "Volume": "SPY_Volume"
})

```

[*****100%*****] 1 of 1 completed

This gives us:

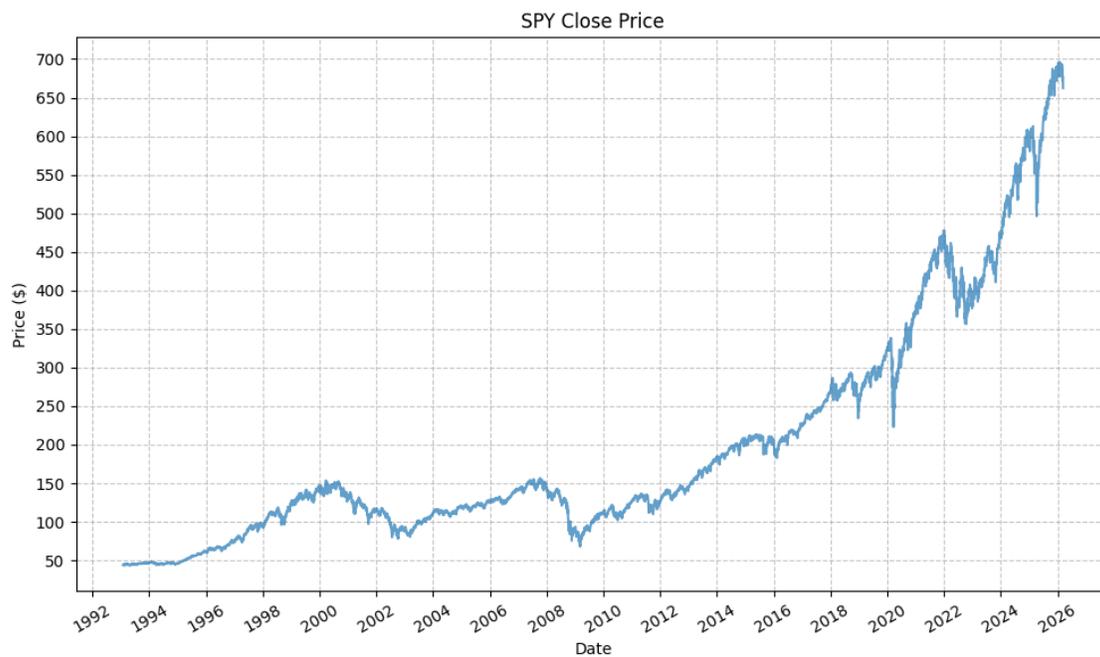
[40]: display(spy)

Date	SPY_Adj_Close	SPY_Close	SPY_High	SPY_Low	SPY_Open	SPY_Volume
1993-01-29	24.241	43.938	43.969	43.750	43.969	1003200
1993-02-01	24.414	44.250	44.250	43.969	43.969	480500
1993-02-02	24.466	44.344	44.375	44.125	44.219	201300
1993-02-03	24.724	44.812	44.844	44.375	44.406	529400
1993-02-04	24.828	45.000	45.094	44.469	44.969	531500
...
2026-03-09	678.270	678.270	679.920	662.390	666.390	102667700
2026-03-10	677.180	677.180	683.360	674.760	677.720	81505300
2026-03-11	676.330	676.330	680.080	673.340	677.580	68441700
2026-03-12	666.060	666.060	671.650	665.870	671.160	108882200
2026-03-13	662.290	662.290	672.340	661.360	669.270	96905100

[8337 rows x 6 columns]

And the plot of the timeseries of adjusted close prices:

```
[41]: plot_timeseries(  
    df=spy,  
    plot_start_date=None,  
    plot_end_date=None,  
    plot_columns=["SPY_Close"],  
    title="SPY Close Price",  
    x_label="Date",  
    x_format="Year",  
    x_tick_spacing=2,  
    x_tick_rotation=30,  
    y_label="Price ($)",  
    y_format="Decimal",  
    y_format_decimal_places=0,  
    y_tick_spacing="Auto",  
    y_tick_rotation=0,  
    grid=True,  
    legend=False,  
    export_plot=False,  
    plot_file_name=None,  
)
```



0.5.2 Acquire & Plot Data (UPRO)

Next, UPRO:

```
[42]: yf_pull_data(
      base_directory=DATA_DIR,
      ticker="UPRO",
      adjusted=False,
      source="Yahoo_Finance",
      asset_class="Exchange_Traded_Funds",
      excel_export=True,
      pickle_export=True,
      output_confirmation=False,
  )

  upro = load_data(
      base_directory=DATA_DIR,
      ticker="UPRO",
      source="Yahoo_Finance",
      asset_class="Exchange_Traded_Funds",
      timeframe="Daily",
      file_format="pickle",
  )

  # Rename columns to "UPRO_Close", etc.
  upro = upro.rename(columns={
      "Adj Close": "UPRO_Adj_Close",
      "Close": "UPRO_Close",
      "High": "UPRO_High",
      "Low": "UPRO_Low",
      "Open": "UPRO_Open",
      "Volume": "UPRO_Volume"
  })
```

```
[*****100%*****] 1 of 1 completed
```

This gives us:

```
[43]: display(upro)
```

Date	UPRO_Adj_Close	UPRO_Close	UPRO_High	UPRO_Low	UPRO_Open	\
2009-06-25	1.135	1.206	1.210	1.126	1.126	
2009-06-26	1.129	1.199	1.213	1.177	1.195	
2009-06-29	1.161	1.233	1.236	1.191	1.208	
2009-06-30	1.133	1.204	1.243	1.176	1.233	
2009-07-01	1.145	1.217	1.253	1.214	1.218	
...	

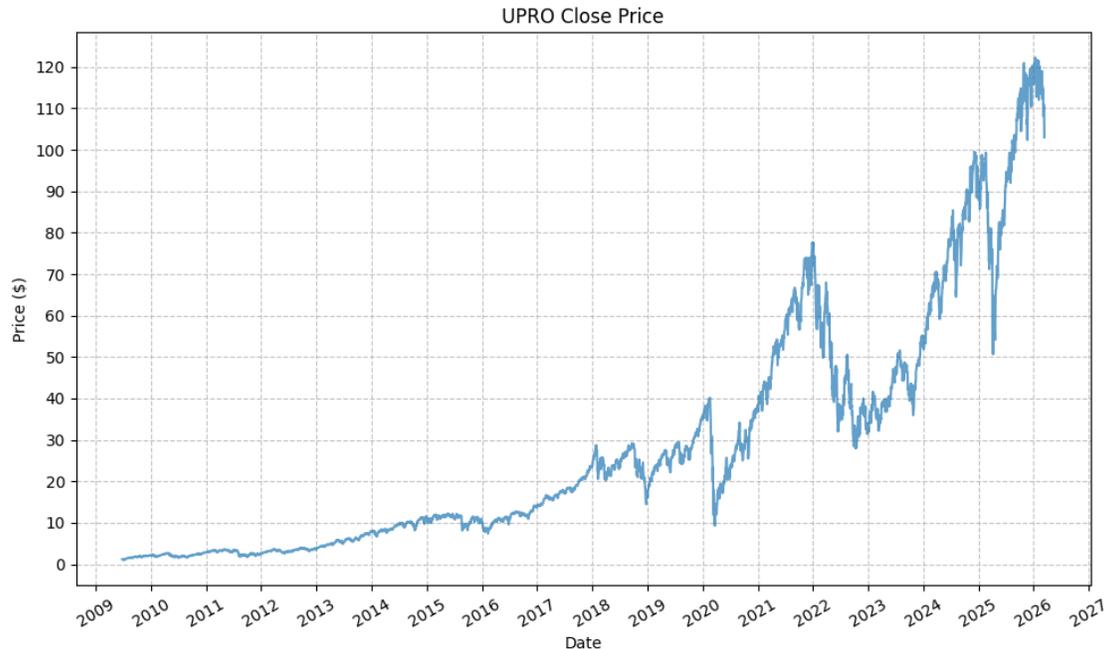
2026-03-09	110.970	110.970	111.740	103.270	105.200
2026-03-10	110.310	110.310	113.410	109.210	110.650
2026-03-11	109.940	109.940	111.760	108.490	110.540
2026-03-12	104.890	104.890	107.620	104.800	107.350
2026-03-13	103.010	103.010	107.760	102.600	106.300

Date	UPRO_Volume
2009-06-25	2577600
2009-06-26	13104000
2009-06-29	8690400
2009-06-30	17128800
2009-07-01	12038400
...	...
2026-03-09	9101400
2026-03-10	6155700
2026-03-11	4181000
2026-03-12	6085600
2026-03-13	6577000

[4205 rows x 6 columns]

And the plot of the timeseries of adjusted close prices:

```
[44]: plot_timeseries(
    df=upro,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["UPRO_Close"],
    title="UPRO Close Price",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=1,
    x_tick_rotation=30,
    y_label="Price ($)",
    y_format="Decimal",
    y_format_decimal_places=0,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    grid=True,
    legend=False,
    export_plot=False,
    plot_file_name=None,
)
```



Looking at the close prices doesn't give us a true picture of the magnitude of the difference in returns due to the leverage. In order to see that, we need to look at the cumulative returns and the drawdowns.

Calculate & Plot Cumulative Returns, Rolling Returns, and Drawdowns (SPY & UPRO)

Next, we will calculate the cumulative returns, rolling returns, and drawdowns. This involves aligning the data to start with the inception of UPRO. For this exercise, we will not extrapolate the data for SPY back to 1993, but rather just align the data from the inception of UPRO in 2009.

```
[45]: etfs = ["SPY", "UPRO"]

# Merge dataframes and drop rows with missing values
spy_upro_aligned = upro.merge(spy, left_index=True, right_index=True,
    ↪how='left')
spy_upro_aligned = spy_upro_aligned.dropna()

# Calculate cumulative returns
for etf in etfs:
    spy_upro_aligned[f"{etf}_Return"] = spy_upro_aligned[f"{etf}_Close"].
    ↪pct_change()
    spy_upro_aligned[f"{etf}_Cumulative_Return"] = (1 +
    ↪spy_upro_aligned[f"{etf}_Return"]).cumprod() - 1
    spy_upro_aligned[f"{etf}_Cumulative_Return_Plus_One"] = 1 +
    ↪spy_upro_aligned[f"{etf}_Cumulative_Return"]
```

```

spy_upro_aligned[f"{etf}_Rolling_Max"] =
↳spy_upro_aligned[f"{etf}_Cumulative_Return_Plus_One"].cummax()
spy_upro_aligned[f"{etf}_Drawdown"] =
↳spy_upro_aligned[f"{etf}_Cumulative_Return_Plus_One"] /
↳spy_upro_aligned[f"{etf}_Rolling_Max"] - 1
spy_upro_aligned.drop(columns=[f"{etf}_Cumulative_Return_Plus_One",
↳f"{etf}_Rolling_Max"], inplace=True)

# Define rolling windows in trading days
rolling_windows = {
    '1d': 1,      # 1 day
    '1w': 5,      # 1 week (5 trading days)
    '1m': 21,     # 1 month (~21 trading days)
    '3m': 63,     # 3 months (~63 trading days)
    '6m': 126,    # 6 months (~126 trading days)
    '1y': 252,    # 1 year (~252 trading days)
    '2y': 504,    # 2 years (~504 trading days)
    '3y': 756,    # 3 years (~756 trading days)
    '4y': 1008,   # 4 years (~1008 trading days)
    '5y': 1260,   # 5 years (~1260 trading days)
}

# Calculate rolling returns for each ETF and each window
for etf in etfs:
    for period_name, window in rolling_windows.items():
        spy_upro_aligned[f"{etf}_Rolling_Return_{period_name}"] = (
            spy_upro_aligned[f"{etf}_Close"].pct_change(periods=window)
        )

```

```
[46]: display(spy_upro_aligned)
```

Date	UPRO_Adj_Close	UPRO_Close	UPRO_High	UPRO_Low	UPRO_Open	\
2009-06-25	1.135	1.206	1.210	1.126	1.126	
2009-06-26	1.129	1.199	1.213	1.177	1.195	
2009-06-29	1.161	1.233	1.236	1.191	1.208	
2009-06-30	1.133	1.204	1.243	1.176	1.233	
2009-07-01	1.145	1.217	1.253	1.214	1.218	
...	
2026-03-09	110.970	110.970	111.740	103.270	105.200	
2026-03-10	110.310	110.310	113.410	109.210	110.650	
2026-03-11	109.940	109.940	111.760	108.490	110.540	
2026-03-12	104.890	104.890	107.620	104.800	107.350	
2026-03-13	103.010	103.010	107.760	102.600	106.300	

Date	UPRO_Volume	SPY_Adj_Close	SPY_Close	SPY_High	SPY_Low	...	\
...

2009-06-25	2577600	68.389	92.080	92.170	89.570	...
2009-06-26	13104000	68.211	91.840	92.240	91.270	...
2009-06-29	8690400	68.850	92.700	92.820	91.600	...
2009-06-30	17128800	68.293	91.950	93.060	91.270	...
2009-07-01	12038400	68.575	92.330	93.230	92.210	...
...
2026-03-09	9101400	678.270	678.270	679.920	662.390	...
2026-03-10	6155700	677.180	677.180	683.360	674.760	...
2026-03-11	4181000	676.330	676.330	680.080	673.340	...
2026-03-12	6085600	666.060	666.060	671.650	665.870	...
2026-03-13	6577000	662.290	662.290	672.340	661.360	...

Date	UPRO_Rolling_Return_1d	UPRO_Rolling_Return_1w	\
2009-06-25	NaN	NaN	
2009-06-26	-0.005	NaN	
2009-06-29	0.028	NaN	
2009-06-30	-0.024	NaN	
2009-07-01	0.011	NaN	
...	
2026-03-09	0.026	-0.038	
2026-03-10	-0.006	-0.017	
2026-03-11	-0.003	-0.041	
2026-03-12	-0.046	-0.069	
2026-03-13	-0.018	-0.048	

Date	UPRO_Rolling_Return_1m	UPRO_Rolling_Return_3m	\
2009-06-25	NaN	NaN	
2009-06-26	NaN	NaN	
2009-06-29	NaN	NaN	
2009-06-30	NaN	NaN	
2009-07-01	NaN	NaN	
...	
2026-03-09	-0.009	-0.056	
2026-03-10	-0.069	-0.065	
2026-03-11	-0.085	-0.060	
2026-03-12	-0.120	-0.101	
2026-03-13	-0.134	-0.133	

Date	UPRO_Rolling_Return_6m	UPRO_Rolling_Return_1y	\
2009-06-25	NaN	NaN	
2009-06-26	NaN	NaN	
2009-06-29	NaN	NaN	
2009-06-30	NaN	NaN	
2009-07-01	NaN	NaN	
...	

2026-03-09	0.084	0.383
2026-03-10	0.069	0.355
2026-03-11	0.059	0.467
2026-03-12	0.001	0.435
2026-03-13	-0.040	0.389

Date	UPRO_Rolling_Return_2y	UPRO_Rolling_Return_3y	\
2009-06-25	NaN	NaN	
2009-06-26	NaN	NaN	
2009-06-29	NaN	NaN	
2009-06-30	NaN	NaN	
2009-07-01	NaN	NaN	
...	
2026-03-09	0.668	2.110	
2026-03-10	0.710	1.952	
2026-03-11	0.679	1.933	
2026-03-12	0.556	1.934	
2026-03-13	0.557	1.869	

Date	UPRO_Rolling_Return_4y	UPRO_Rolling_Return_5y
2009-06-25	NaN	NaN
2009-06-26	NaN	NaN
2009-06-29	NaN	NaN
2009-06-30	NaN	NaN
2009-07-01	NaN	NaN
...
2026-03-09	1.007	1.656
2026-03-10	0.893	1.748
2026-03-11	0.914	1.847
2026-03-12	0.872	1.573
2026-03-13	1.017	1.565

[4205 rows x 38 columns]

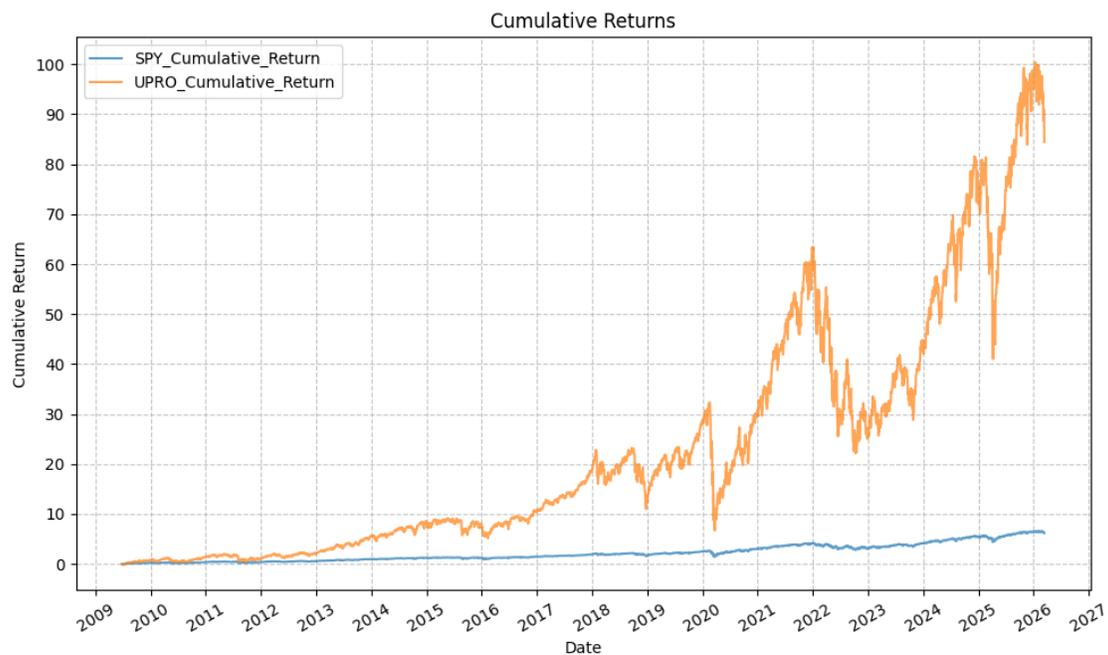
And now the plot for the cumulative returns:

```
[47]: plot_timeseries(
    df=spy_upro_aligned,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["SPY_Cumulative_Return", "UPRO_Cumulative_Return"],
    title="Cumulative Returns",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=1,
    x_tick_rotation=30,
```

```

y_label="Cumulative Return",
y_format="Decimal",
y_format_decimal_places=0,
y_tick_spacing="Auto",
y_tick_rotation=0,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



And the drawdown plot:

```

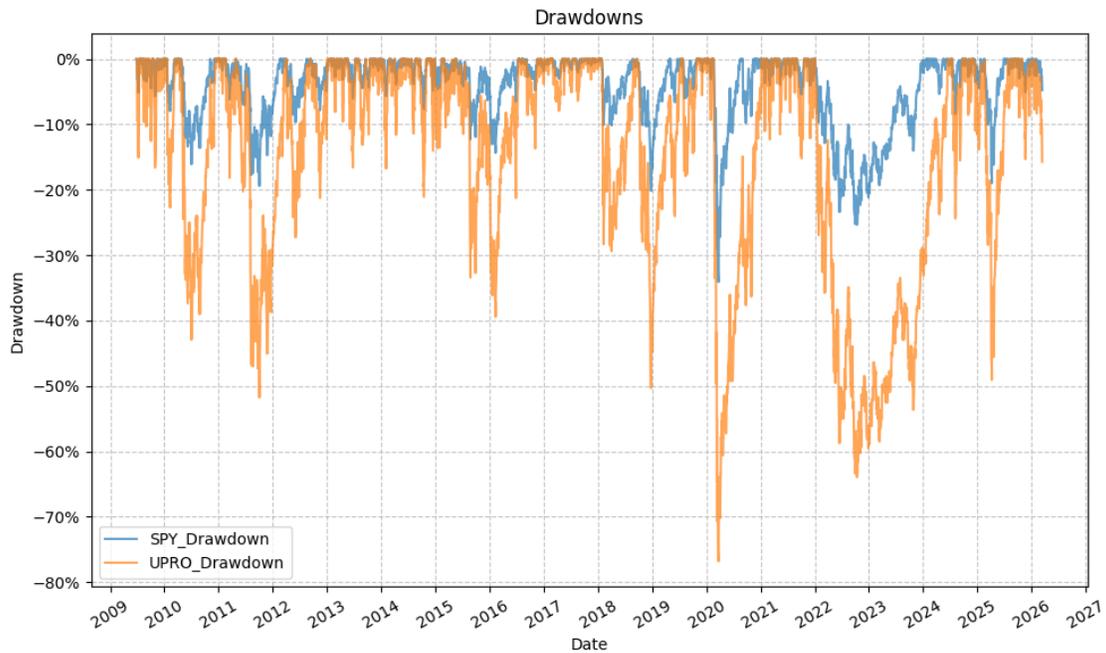
[48]: plot_timeseries(
    df=spy_upro_aligned,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["SPY_Drawdown", "UPRO_Drawdown"],
    title="Drawdowns",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=1,
    x_tick_rotation=30,
    y_label="Drawdown",
    y_format="Percentage",
    y_format_decimal_places=0,
)

```

```

y_tick_spacing="Auto",
y_tick_rotation=0,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



0.5.3 Summary Statistics (SPY & UPRO)

Looking at the summary statistics further confirms our intuitions about the volatility and drawdowns.

```

[49]: spy_sum_stats = summary_stats(
    fund_list=["SPY"],
    df=spy_upro_aligned[["SPY_Return"]],
    period="Daily",
    use_calendar_days=False,
    excel_export=False,
    pickle_export=False,
    output_confirmation=False,
)

upro_sum_stats = summary_stats(
    fund_list=["UPRO"],

```

```

df=spy_upro_aligned[["UPRO_Return"]],
period="Daily",
use_calendar_days=False,
excel_export=False,
pickle_export=False,
output_confirmation=False,
)

sum_stats = pd.concat([spy_sum_stats, upro_sum_stats])

display(sum_stats)

```

	Annual Mean Return (Arithmetic)	Annualized Volatility	\
SPY_Return	0.133	0.172	
UPRO_Return	0.400	0.513	

	Annualized Sharpe Ratio	CAGR (Geometric)	Daily Max Return	\
SPY_Return	0.774	0.126	0.105	
UPRO_Return	0.780	0.305	0.280	

	Daily Max Return (Date)	Daily Min Return	Daily Min Return (Date)	\
SPY_Return	2025-04-09	-0.109	2020-03-16	
UPRO_Return	2020-03-24	-0.349	2020-03-16	

	Max Drawdown	Peak	Trough	Recovery Date	\
SPY_Return	-0.341	2020-02-19	2020-03-23	2020-08-18	
UPRO_Return	-0.768	2020-02-19	2020-03-23	2021-01-08	

	Days to Recovery	MAR Ratio
SPY_Return	148	0.368
UPRO_Return	291	0.398

0.5.4 Plot Returns & Verify Beta (SPY & UPRO)

Before we look at the rolling returns, let us first verify that the daily returns for UPRO are in fact ~3x those of SPY.

```

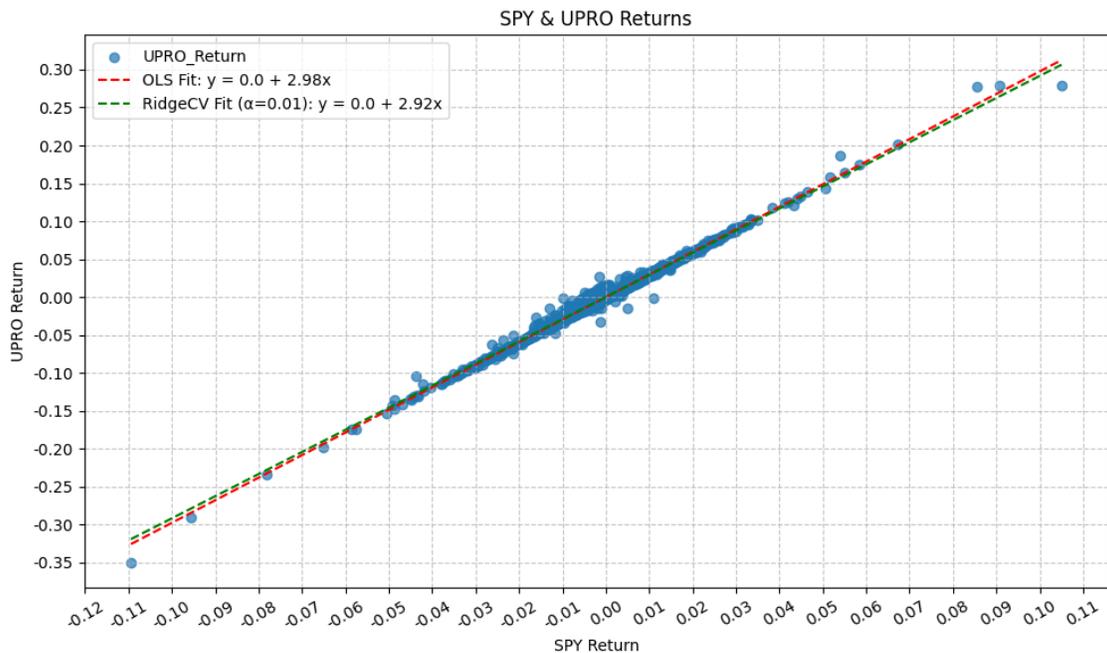
[50]: plot_scatter(
    df=spy_upro_aligned,
    x_plot_column="SPY_Return",
    y_plot_columns=["UPRO_Return"],
    title="SPY & UPRO Returns",
    x_label="SPY Return",
    x_format="Decimal",
    x_format_decimal_places=2,
    x_tick_spacing="Auto",
    x_tick_rotation=30,
    y_label="UPRO Return",

```

```

y_format="Decimal",
y_format_decimal_places=2,
y_tick_spacing="Auto",
y_tick_rotation=0,
plot_OLS_regression_line=True,
OLS_column="UPRO_Return",
plot_Ridge_regression_line=False,
Ridge_column=None,
plot_RidgeCV_regression_line=True,
RidgeCV_column="UPRO_Return",
regression_constant=True,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



```

[51]: model = run_linear_regression(
df=spy_upro_aligned,
x_plot_column="SPY_Return",
y_plot_column="UPRO_Return",
regression_model="OLS-statsmodels",
regression_constant=True,
)

```

```
print(model.summary())
```

```

                    OLS Regression Results
=====
Dep. Variable:      UPRO_Return      R-squared:      0.994
Model:              OLS              Adj. R-squared: 0.994
Method:             Least Squares    F-statistic:    6.745e+05
Date:               Mon, 16 Mar 2026  Prob (F-statistic): 0.00
Time:               14:27:52         Log-Likelihood: 19150.
No. Observations:  4204             AIC:            -3.830e+04
Df Residuals:      4202             BIC:            -3.828e+04
Df Model:           1
Covariance Type:   nonrobust
=====
                    coef      std err          t      P>|t|      [0.025      0.975]
-----
const          1.711e-05   3.93e-05     0.436     0.663   -5.99e-05   9.41e-05
SPY_Return      2.9760           0.004    821.252     0.000     2.969     2.983
=====
Omnibus:                2680.692   Durbin-Watson:      2.590
Prob(Omnibus):          0.000   Jarque-Bera (JB):   517107.129
Skew:                   1.986   Prob(JB):           0.00
Kurtosis:               57.188   Cond. No.           92.3
=====
```

Notes:

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

Visually, this plot makes sense and we can see that there is a strong clustering of points, but we double check with the regression, regressing the UPRO daily return (y) on the SPY daily return (X).

0.5.5 Extrapolate Data (SPY & UPRO)

We will now extrapolate the returns of SPY to backfill the data from the inception of SPY in 1993 to the inception of UPRO in 2009. For this, we'll use the coefficient of 2.98 that we found in the regression results above.

```
[52]: # Set leverage multiplier based on regression coefficient
LEVERAGE_MULTIPLIER = model.params[1]

# Merge dataframes and extrapolate return values for SPY back to 1993 using the
↳leverage multiplier
spy_upro_extrap = spy[["SPY_Close"]].merge(upro[["UPRO_Close"]],
↳left_index=True, right_index=True, how='left')

etfs = ["SPY", "UPRO"]
```

```

# Calculate cumulative returns
for etf in etfs:
    spy_upro_extrap[f"{etf}_Return"] = spy_upro_extrap[f"{etf}_Close"].
    ↪ pct_change()

# Extrapolate UPRO returns for missing values
spy_upro_extrap["UPRO_Return"] = spy_upro_extrap["UPRO_Return"].
    ↪ fillna(LEVERAGE_MULTIPLIER * spy_upro_extrap["SPY_Return"])

# Find the first valid UPRO_Close index and value
first_valid_idx = spy_upro_extrap['UPRO_Close'].first_valid_index()
print(first_valid_idx)
first_valid_price = spy_upro_extrap.loc[first_valid_idx, 'UPRO_Close']
print(first_valid_price)

```

2009-06-25 00:00:00

1.205556035041809

Before we extrapolate, let's first look at the data we have for SPY and UPRO around the inception of UPRO in 2009:

```

[53]: # Check values around the first valid index
print(spy_upro_extrap.loc["2009-06-20":"2009-06-30"])

```

Date	SPY_Close	UPRO_Close	SPY_Return	UPRO_Return
2009-06-22	89.280	NaN	-0.030	-0.089
2009-06-23	89.350	NaN	0.001	0.002
2009-06-24	90.120	NaN	0.009	0.026
2009-06-25	92.080	1.206	0.022	0.065
2009-06-26	91.840	1.199	-0.003	-0.005
2009-06-29	92.700	1.233	0.009	0.028
2009-06-30	91.950	1.204	-0.008	-0.024

Now, backfill the data for the UPRO close price:

```

[54]: # Iterate through the dataframe backwards
for i in range(spy_upro_extrap.index.get_loc(first_valid_idx) - 1, -1, -1):

    # The return that led to the price the next day
    current_return = spy_upro_extrap.iloc[i + 1]['UPRO_Return']

    # Get the next day's price
    next_price = spy_upro_extrap.iloc[i + 1]['UPRO_Close']

    # Price_{t} = Price_{t+1} / (1 + Return_{t})
    spy_upro_extrap.loc[spy_upro_extrap.index[i], 'UPRO_Close'] = next_price /
    ↪ (1 + current_return)

```

Finally, confirm the values are correct:

```
[55]: # Confirm values around the first valid index after extrapolation
print(spy_upro_extrap.loc["2009-06-20":"2009-06-30"])
```

Date	SPY_Close	UPRO_Close	SPY_Return	UPRO_Return
2009-06-22	89.280	1.101	-0.030	-0.089
2009-06-23	89.350	1.104	0.001	0.002
2009-06-24	90.120	1.132	0.009	0.026
2009-06-25	92.080	1.206	0.022	0.065
2009-06-26	91.840	1.199	-0.003	-0.005
2009-06-29	92.700	1.233	0.009	0.028
2009-06-30	91.950	1.204	-0.008	-0.024

And the complete DataFrame with the extrapolated values:

```
[56]: display(spy_upro_extrap)
```

Date	SPY_Close	UPRO_Close	SPY_Return	UPRO_Return
1993-01-29	43.938	0.926	NaN	NaN
1993-02-01	44.250	0.945	0.007	0.021
1993-02-02	44.344	0.951	0.002	0.006
1993-02-03	44.812	0.981	0.011	0.031
1993-02-04	45.000	0.993	0.004	0.012
...
2026-03-09	678.270	110.970	0.009	0.026
2026-03-10	677.180	110.310	-0.002	-0.006
2026-03-11	676.330	109.940	-0.001	-0.003
2026-03-12	666.060	104.890	-0.015	-0.046
2026-03-13	662.290	103.010	-0.006	-0.018

[8337 rows x 4 columns]

After the extrapolation, we now have the following plots for the prices, cumulative returns, and drawdowns:

```
[57]: etfs = ["SPY", "UPRO"]

# Calculate cumulative returns
for etf in etfs:
    spy_upro_extrap[f"{etf}_Return"] = spy_upro_extrap[f"{etf}_Close"].
    ↪ pct_change()
    spy_upro_extrap[f"{etf}_Cumulative_Return"] = (1 +
    ↪ spy_upro_extrap[f"{etf}_Return"]).cumprod() - 1
    spy_upro_extrap[f"{etf}_Cumulative_Return_Plus_One"] = 1 +
    ↪ spy_upro_extrap[f"{etf}_Cumulative_Return"]
```

```

spy_upro_extrap[f"{etf}_Rolling_Max"] =
↳ spy_upro_extrap[f"{etf}_Cumulative_Return_Plus_One"].cummax()
spy_upro_extrap[f"{etf}_Drawdown"] =
↳ spy_upro_extrap[f"{etf}_Cumulative_Return_Plus_One"] /
↳ spy_upro_extrap[f"{etf}_Rolling_Max"] - 1
spy_upro_extrap.drop(columns=[f"{etf}_Cumulative_Return_Plus_One",
↳ f"{etf}_Rolling_Max"], inplace=True)

```

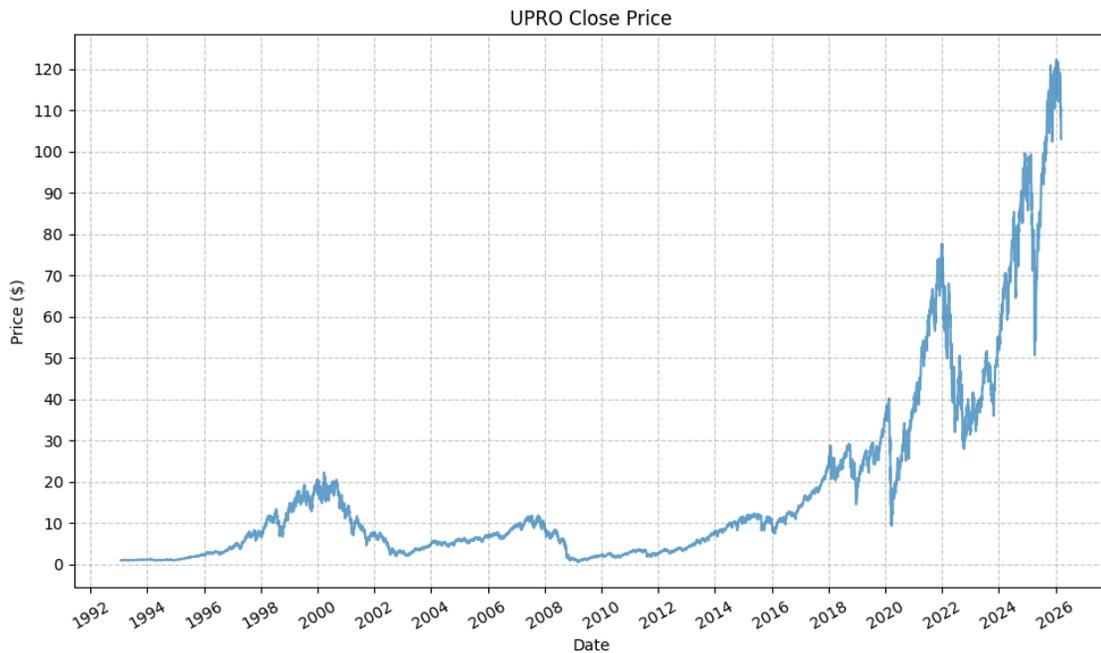
```

[58]: plot_timeseries(
df=spy_upro_extrap,
plot_start_date=None,
plot_end_date=None,
plot_columns=["SPY_Close"],
title="SPY Close Price",
x_label="Date",
x_format="Year",
x_tick_spacing=2,
x_tick_rotation=30,
y_label="Price ($)",
y_format="Decimal",
y_format_decimal_places=0,
y_tick_spacing="Auto",
y_tick_rotation=0,
grid=True,
legend=False,
export_plot=False,
plot_file_name=None,
)

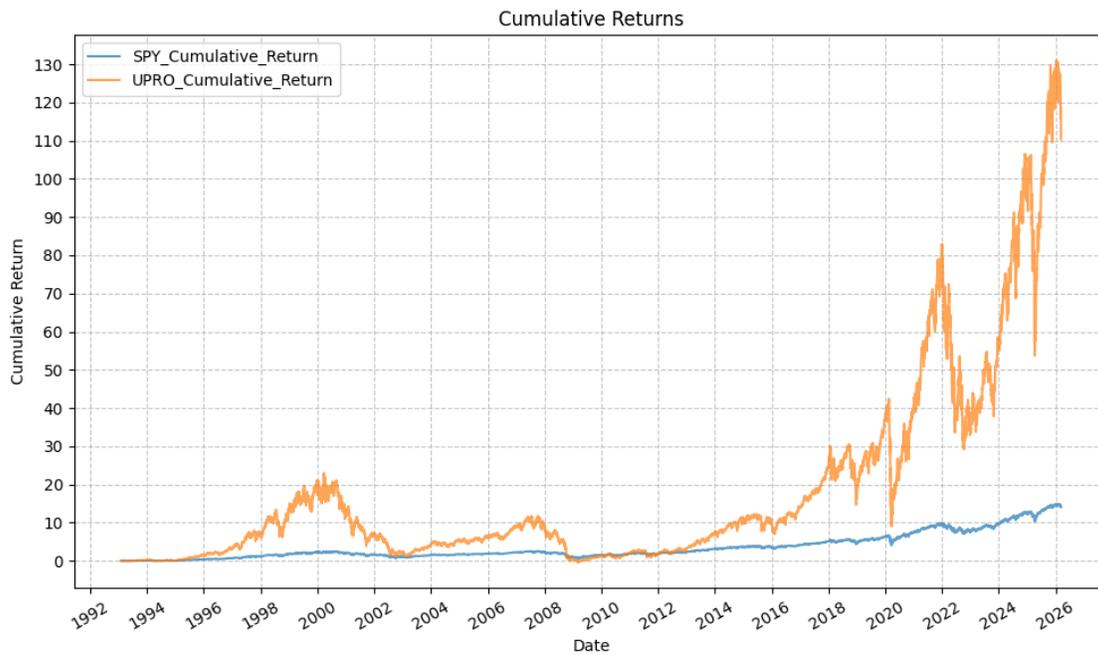
```



```
[59]: plot_timeseries(  
    df=spy_upro_extrap,  
    plot_start_date=None,  
    plot_end_date=None,  
    plot_columns=["UPRO_Close"],  
    title="UPRO Close Price",  
    x_label="Date",  
    x_format="Year",  
    x_tick_spacing=2,  
    x_tick_rotation=30,  
    y_label="Price ($)",  
    y_format="Decimal",  
    y_format_decimal_places=0,  
    y_tick_spacing="Auto",  
    y_tick_rotation=0,  
    grid=True,  
    legend=False,  
    export_plot=False,  
    plot_file_name=None,  
)
```



```
[60]: plot_timeseries(
    df=spy_upro_extrap,
    plot_start_date=None,
    plot_end_date=None,
    plot_columns=["SPY_Cumulative_Return", "UPRO_Cumulative_Return"],
    title="Cumulative Returns",
    x_label="Date",
    x_format="Year",
    x_tick_spacing=2,
    x_tick_rotation=30,
    y_label="Cumulative Return",
    y_format="Decimal",
    y_format_decimal_places=0,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    grid=True,
    legend=True,
    export_plot=False,
    plot_file_name=None,
)
```

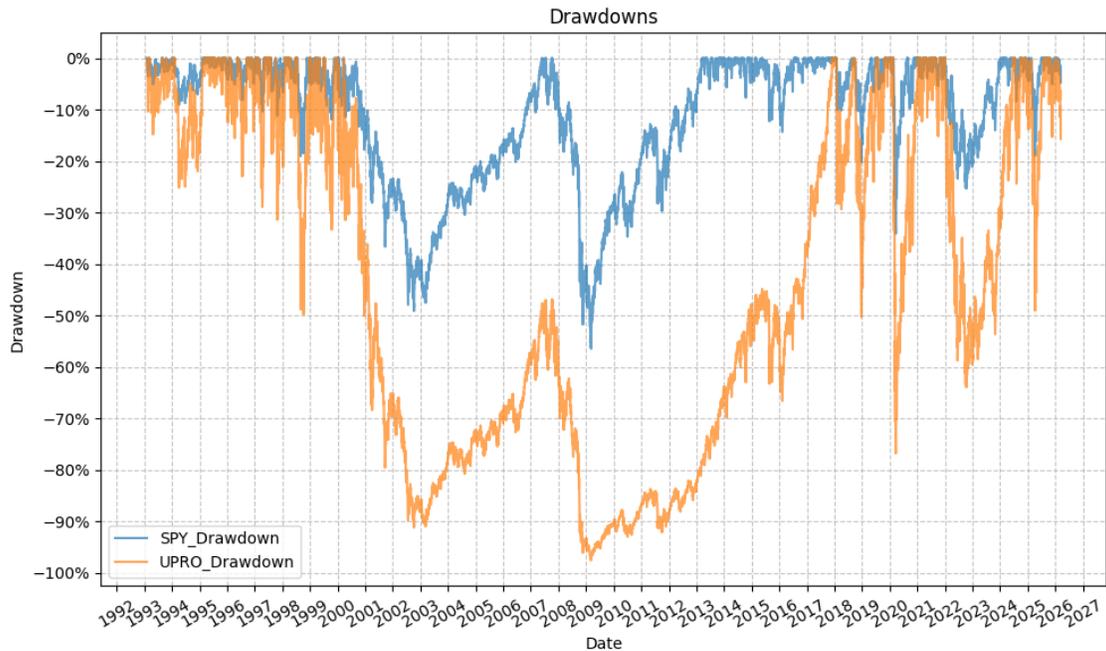


```
[61]: plot_timeseries(
    df=spy_upro_extrap,
    plot_start_date=None,
    plot_end_date=None,
```

```

plot_columns=["SPY_Drawdown", "UPRO_Drawdown"],
title="Drawdowns",
x_label="Date",
x_format="Year",
x_tick_spacing=1,
x_tick_rotation=30,
y_label="Drawdown",
y_format="Percentage",
y_format_decimal_places=0,
y_tick_spacing="Auto",
y_tick_rotation=0,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



Interestingly, the drawdown for UPRO is not nearly as severe as that of TQQQ, which may be due to the fact that SPY has not had the same extreme return profile as QQQ over the past 15 years. This highlights the importance of the underlying asset’s return profile on the performance of leveraged ETFs.

0.5.6 Plot Rolling Returns (SPY & UPRO)

Next, we will consider the following:

- Histogram and scatter plots of the rolling returns of SPY and UPRO

- Regressions to establish a “leverage factor” for the rolling returns
- The deviation from a 3x return for each time period

For this set of regressions, we will also allow the constant. First, we need the rolling returns for various time periods:

```
[62]: # Define rolling windows in trading days
rolling_windows = {
    '1d': 1,      # 1 day
    '1w': 5,      # 1 week (5 trading days)
    '1m': 21,     # 1 month (~21 trading days)
    '3m': 63,     # 3 months (~63 trading days)
    '6m': 126,   # 6 months (~126 trading days)
    '1y': 252,   # 1 year (~252 trading days)
    '2y': 504,   # 2 years (~504 trading days)
    '3y': 756,   # 3 years (~756 trading days)
    '4y': 1008,  # 4 years (~1008 trading days)
    '5y': 1260,  # 5 years (~1260 trading days)
}

# Calculate rolling returns for each ETF and each window
for etf in etfs:
    for period_name, window in rolling_windows.items():
        spy_upro_extrap[f"{etf}_Rolling_Return_{period_name}"] = (
            spy_upro_extrap[f"{etf}_Close"].pct_change( periods=window)
        )
```

This gives us the following series of histograms, scatter plots, and regression model results:

```
[63]: # Create a dataframe to hold rolling returns stats
rolling_returns_stats = pd.DataFrame()

for period_name, window in rolling_windows.items():
    plot_histogram(
        df=spy_upro_extrap,
        plot_columns=[f"SPY_Rolling_Return_{period_name}",
                     f"UPRO_Rolling_Return_{period_name}"],
        title=f"SPY & UPRO {period_name} Rolling Returns",
        x_label="Rolling Return",
        x_tick_spacing="Auto",
        x_tick_rotation=30,
        y_label="# Of Datapoints",
        y_tick_spacing="Auto",
        y_tick_rotation=0,
        grid=True,
        legend=True,
        export_plot=False,
        plot_file_name=None,
```

```

)

plot_scatter(
  df=spy_upro_extrap,
  x_plot_column=f"SPY_Rolling_Return_{period_name}",
  y_plot_columns=[f"UPRO_Rolling_Return_{period_name}"],
  title=f"SPY & UPRO {period_name} Rolling Returns",
  x_label="SPY Rolling Return",
  x_format="Decimal",
  x_format_decimal_places=2,
  x_tick_spacing="Auto",
  x_tick_rotation=30,
  y_label="UPRO Rolling Return",
  y_format="Decimal",
  y_format_decimal_places=2,
  y_tick_spacing="Auto",
  y_tick_rotation=0,
  plot_OLS_regression_line=True,
  OLS_column=f"UPRO_Rolling_Return_{period_name}",
  plot_Ridge_regression_line=False,
  Ridge_column=None,
  plot_RidgeCV_regression_line=True,
  RidgeCV_column=f"UPRO_Rolling_Return_{period_name}",
  regression_constant=True,
  grid=True,
  legend=True,
  export_plot=False,
  plot_file_name=None,
)

# Run OLS regression with statsmodels
model = run_linear_regression(
  df=spy_upro_extrap,
  x_plot_column=f"SPY_Rolling_Return_{period_name}",
  y_plot_column=f"UPRO_Rolling_Return_{period_name}",
  regression_model="OLS-statsmodels",
  regression_constant=True,
)
print(model.summary())

# Add the regression results to the rolling returns stats dataframe
intercept = model.params[0]
intercept_pvalue = model.pvalues[0] # p-value for Intercept
slope = model.params[1]
slope_pvalue = model.pvalues[1] # p-value for SPY_Return
r_squared = model.rsquared

```

```

# Calc skew
return_ratio = spy_upro_extrap[f'UPRO_Rolling_Return_{period_name}'] /
↳spy_upro_extrap[f'SPY_Rolling_Return_{period_name}']
skew = return_ratio.skew()

# Calc conditional symmetry
up_markets =
↳spy_upro_extrap[spy_upro_extrap[f'SPY_Rolling_Return_{period_name}'] > 0]
down_markets =
↳spy_upro_extrap[spy_upro_extrap[f'SPY_Rolling_Return_{period_name}'] <= 0]

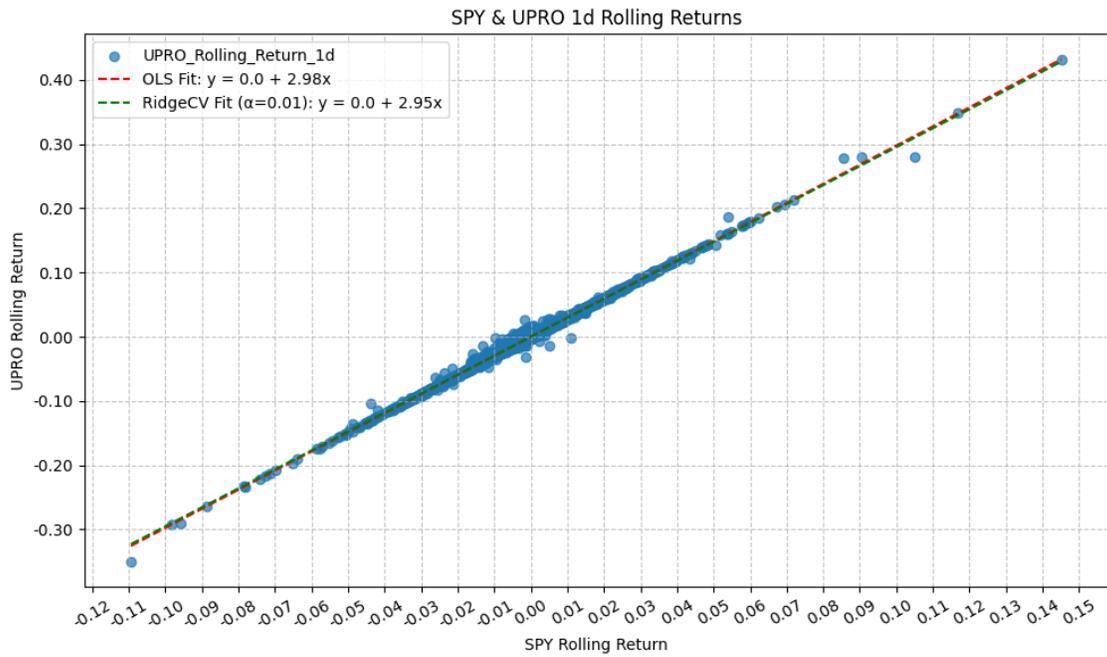
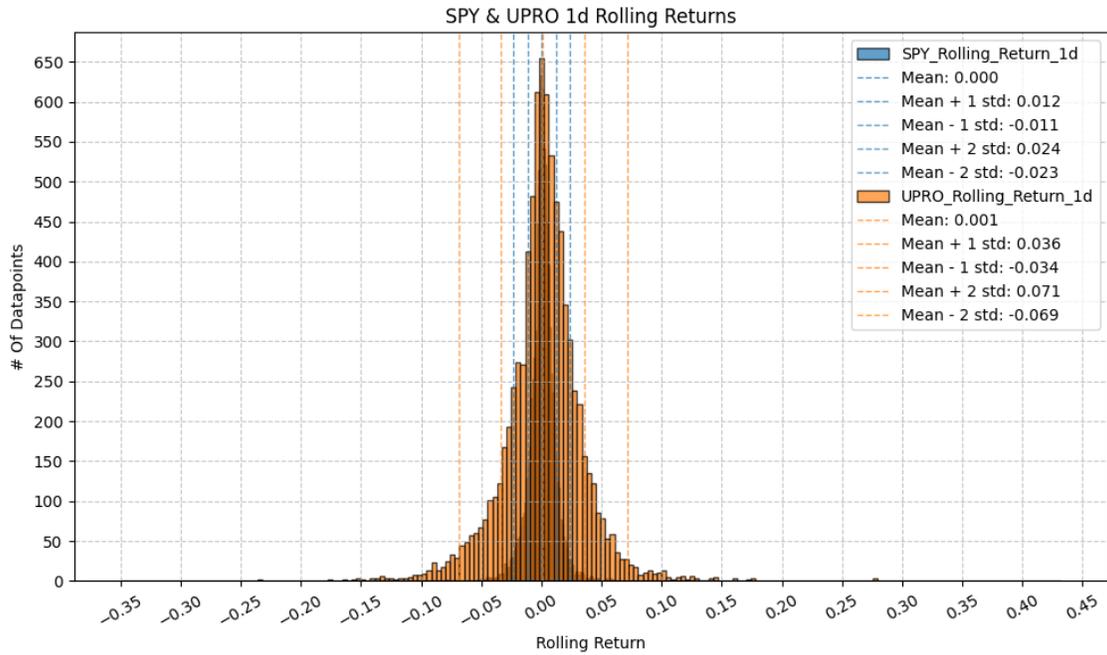
avg_beta_up = (up_markets[f'UPRO_Rolling_Return_{period_name}'] /
↳up_markets[f'SPY_Rolling_Return_{period_name}']).mean()
avg_beta_down = (down_markets[f'UPRO_Rolling_Return_{period_name}'] /
↳down_markets[f'SPY_Rolling_Return_{period_name}']).mean()

asymmetry = avg_beta_up - avg_beta_down

rolling_returns_slope_int = pd.DataFrame({
    "Period": period_name,
    "Intercept": [intercept],
    # "Intercept_PValue": [intercept_pvalue],
    "Slope": [slope],
    # "Slope_PValue": [slope_pvalue],
    "R_Squared": [r_squared],
    "Skew": [skew],
    "Average Upside Beta": [avg_beta_up],
    "Average Downside Beta": [avg_beta_down],
    "Asymmetry": [asymmetry]
})

rolling_returns_stats = pd.concat([rolling_returns_stats,
↳rolling_returns_slope_int])

```



OLS Regression Results

=====

==

Dep. Variable: UPRO_Rolling_Return_1d R-squared:

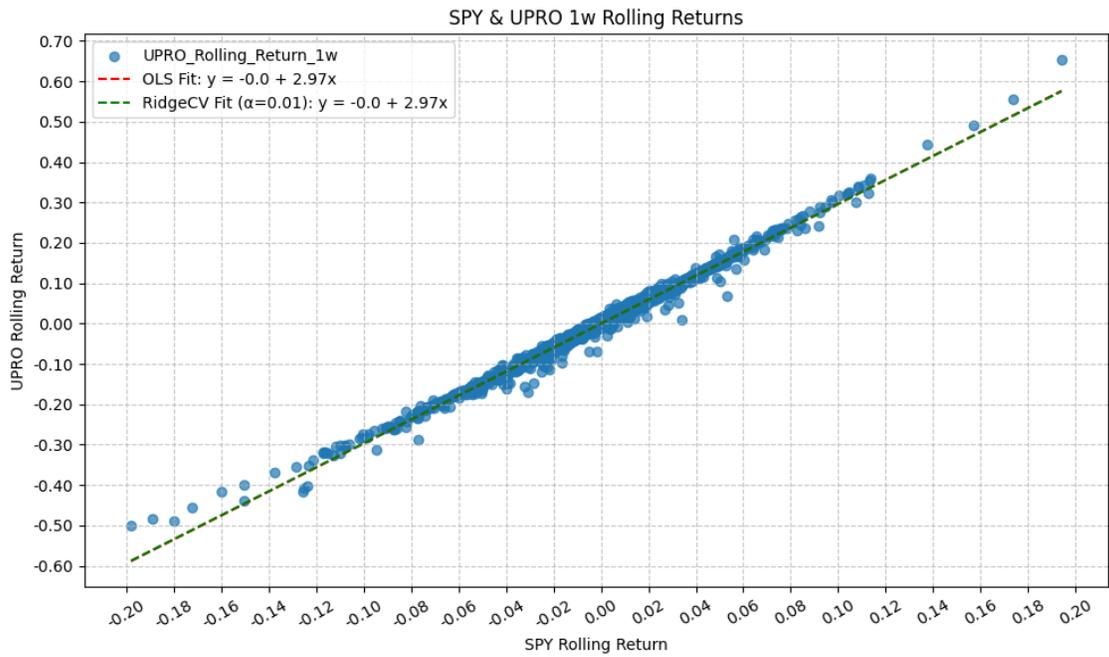
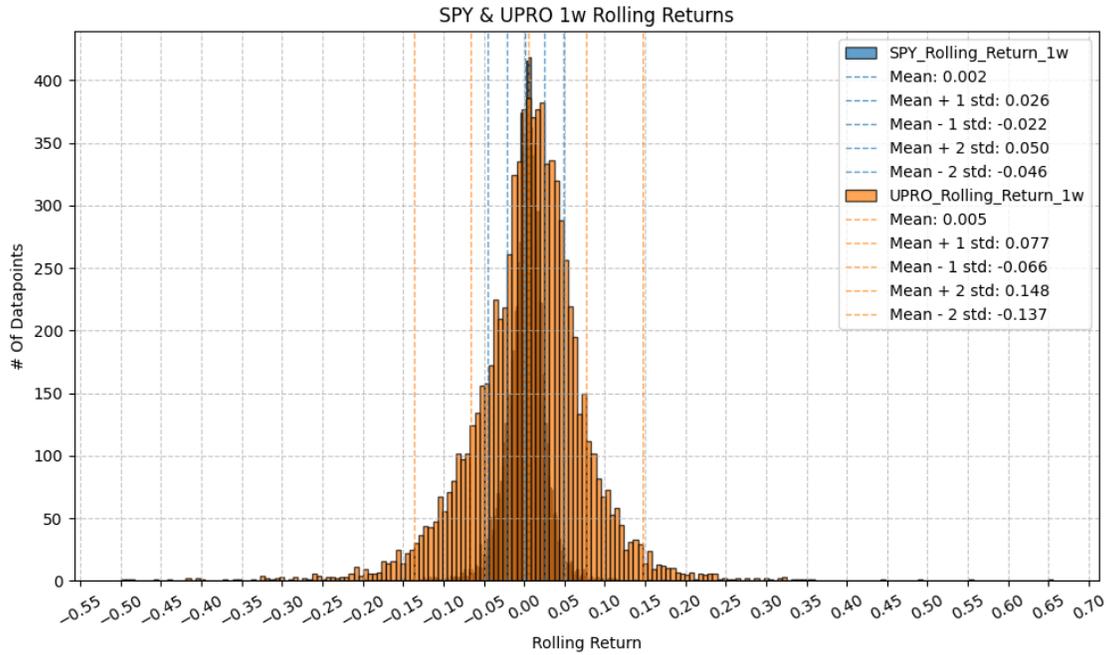
```

0.997
Model:                      OLS   Adj. R-squared:
0.997
Method:                     Least Squares   F-statistic:
3.117e+06
Date:                       Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                       14:27:55   Log-Likelihood:
40824.
No. Observations:          8336   AIC:
-8.164e+04
Df Residuals:              8334   BIC:
-8.163e+04
Df Model:                   1
Covariance Type:           nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                8.628e-06   1.98e-05     0.436     0.663   -3.02e-05
4.74e-05
SPY_Rolling_Return_1d  2.9760     0.002   1765.423     0.000     2.973
2.979
=====
Omnibus:              6871.164   Durbin-Watson:              2.591
Prob(Omnibus):        0.000   Jarque-Bera (JB):          4247760.442
Skew:                 2.811   Prob(JB):                  0.00
Kurtosis:             113.445   Cond. No.                  85.2
=====

```

Notes:

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



OLS Regression Results

=====

==

Dep. Variable: UPRO_Rolling_Return_1w R-squared:

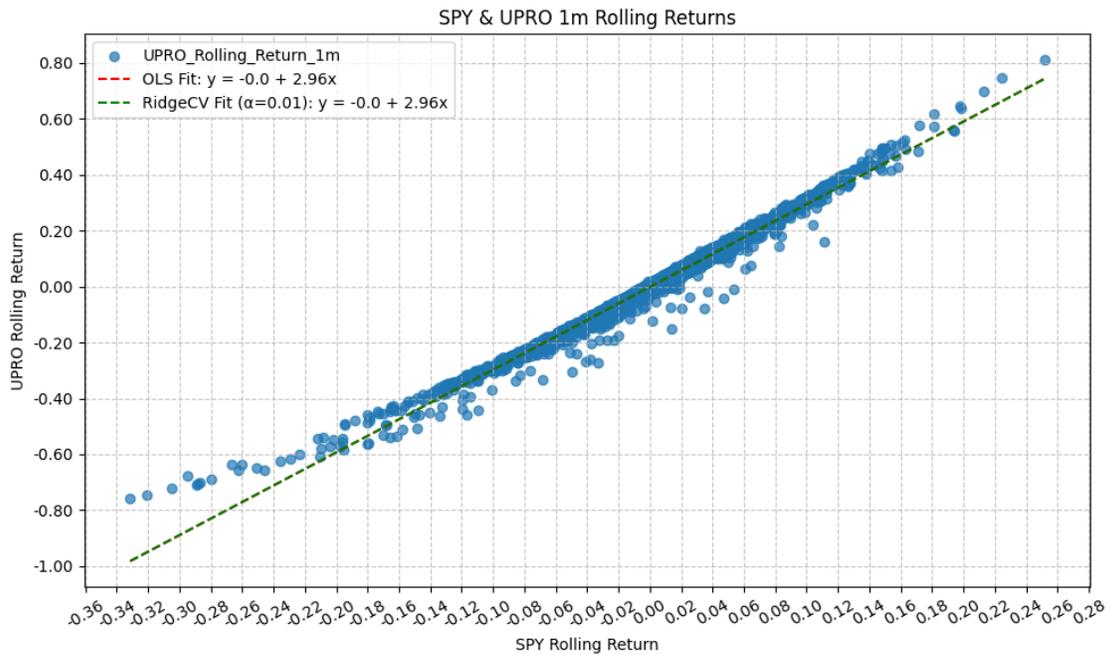
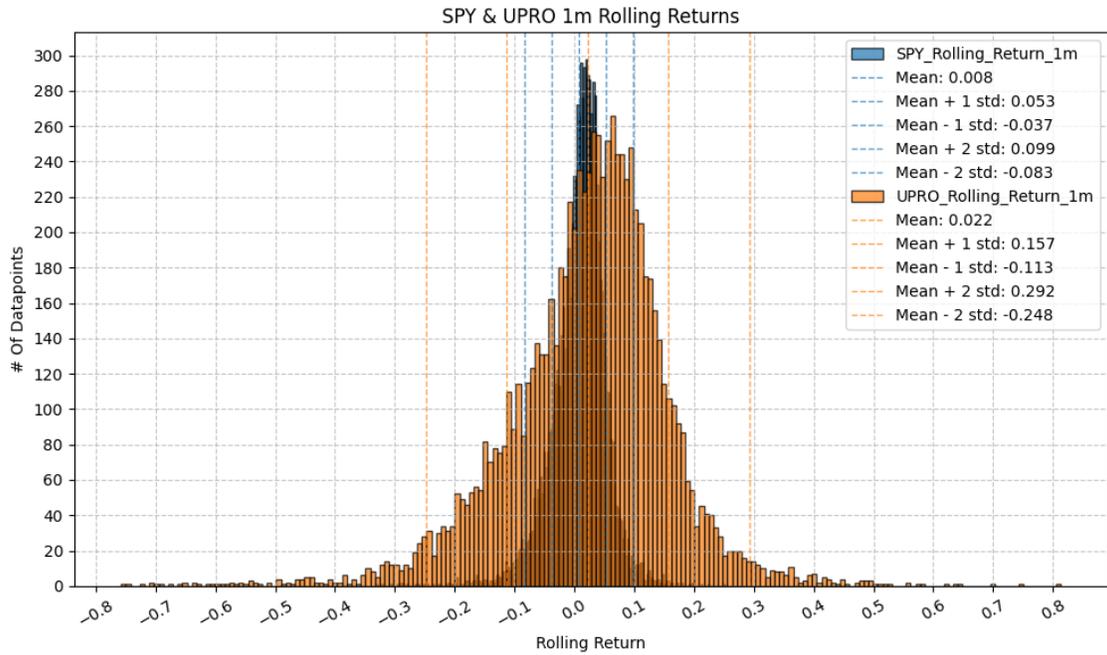
```

0.994
Model:                      OLS   Adj. R-squared:
0.994
Method:                      Least Squares   F-statistic:
1.404e+06
Date:                        Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                        14:27:56   Log-Likelihood:
31594.
No. Observations:           8332   AIC:
-6.318e+04
Df Residuals:               8330   BIC:
-6.317e+04
Df Model:                    1
Covariance Type:            nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -0.0003      6e-05      -4.277      0.000      -0.000
-0.000
SPY_Rolling_Return_1w  2.9725      0.003     1184.942      0.000      2.968
2.977
=====
Omnibus:              3741.895   Durbin-Watson:              0.955
Prob(Omnibus):        0.000   Jarque-Bera (JB):          1489497.909
Skew:                 -0.847   Prob(JB):                  0.00
Kurtosis:             68.480   Cond. No.                  42.0
=====

```

Notes:

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



OLS Regression Results

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==

Dep. Variable: UPRO_Rolling_Return_1m R-squared:

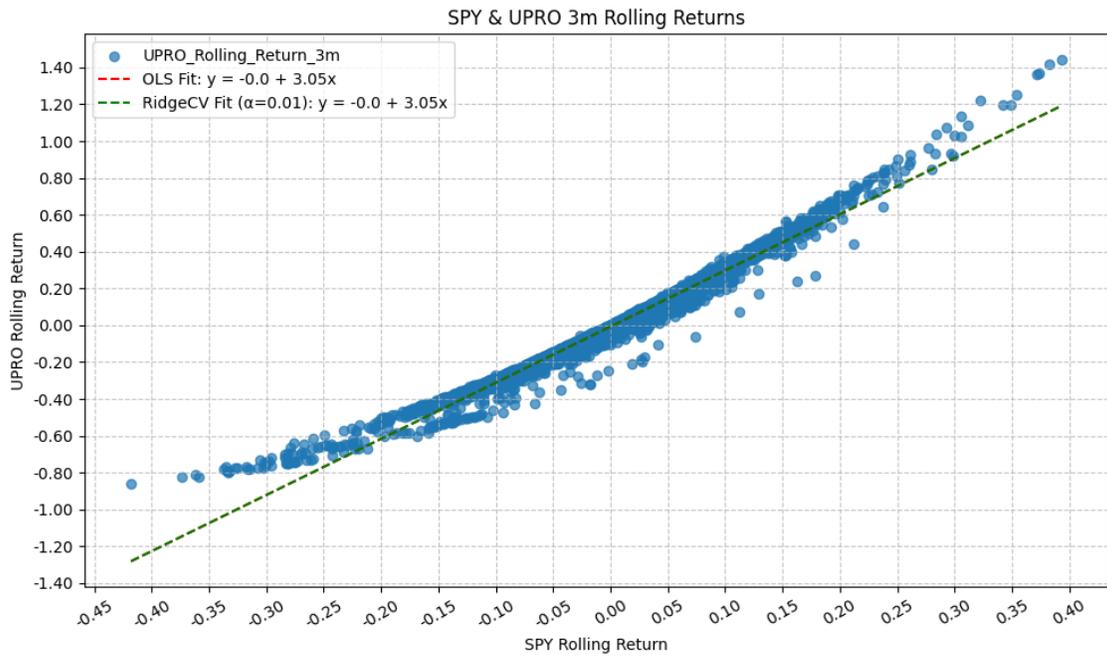
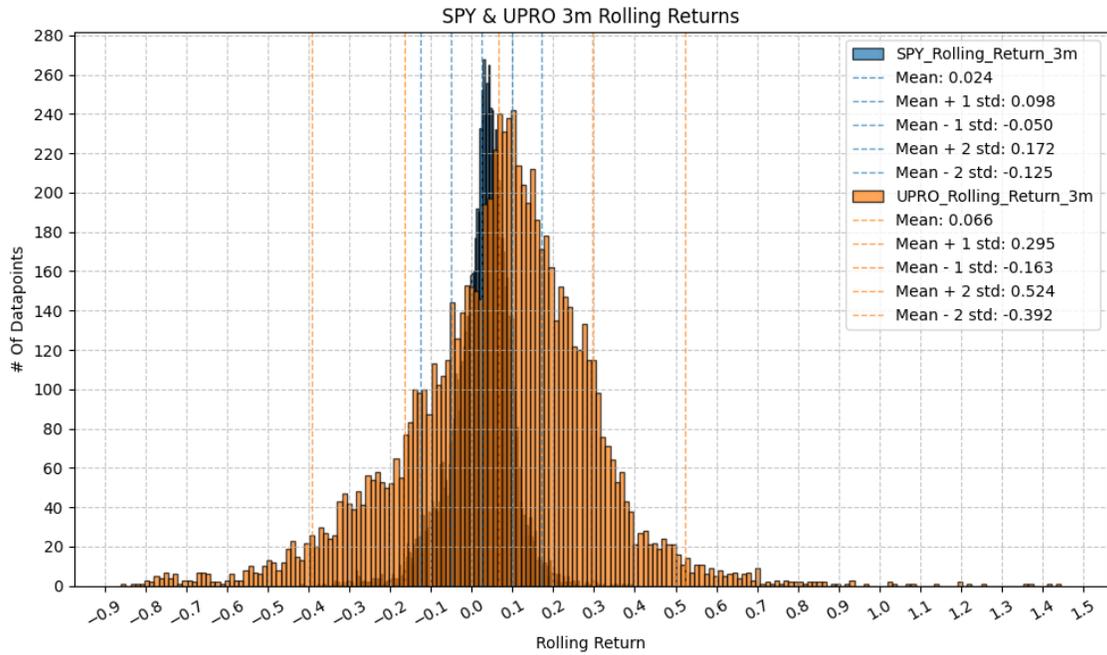
```

0.988
Model:                      OLS   Adj. R-squared:
0.988
Method:                     Least Squares   F-statistic:
6.653e+05
Date:                       Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                       14:27:58   Log-Likelihood:
23130.
No. Observations:          8316   AIC:
-4.626e+04
Df Residuals:              8314   BIC:
-4.624e+04
Df Model:                  1
Covariance Type:          nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -0.0015      0.000      -9.029      0.000      -0.002
-0.001
SPY_Rolling_Return_1m  2.9603      0.004     815.680      0.000      2.953
2.967
=====
Omnibus:              2879.641   Durbin-Watson:              0.314
Prob(Omnibus):        0.000   Jarque-Bera (JB):          855364.296
Skew:                 -0.291   Prob(JB):                  0.00
Kurtosis:             52.681   Cond. No.                  22.1
=====

```

Notes:

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



OLS Regression Results

=====

==

Dep. Variable: UPRO_Rolling_Return_3m R-squared:

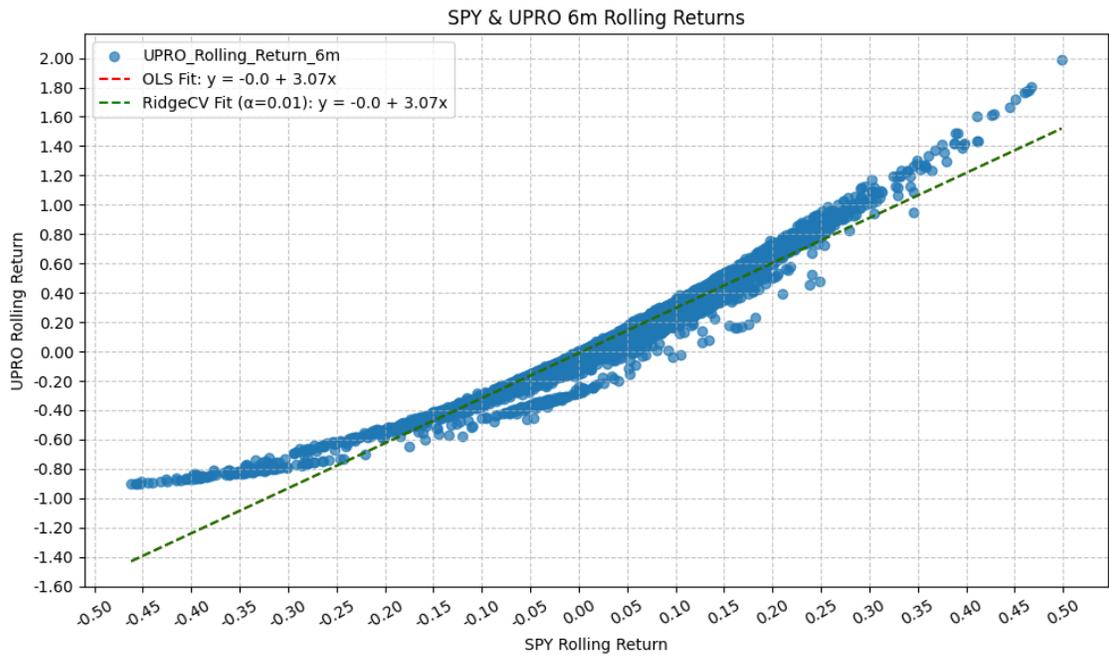
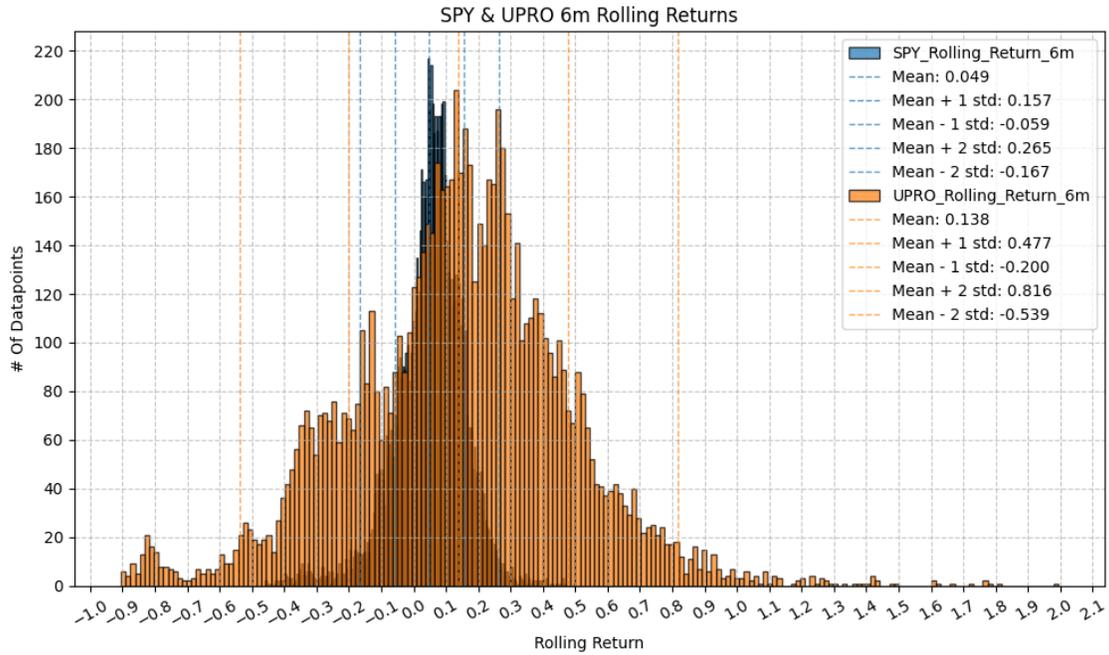
```

0.979
Model:                      OLS   Adj. R-squared:
0.979
Method:                      Least Squares   F-statistic:
3.832e+05
Date:                        Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                        14:27:59   Log-Likelihood:
16419.
No. Observations:           8274   AIC:
-3.283e+04
Df Residuals:               8272   BIC:
-3.282e+04
Df Model:                   1
Covariance Type:           nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -0.0068      0.000    -17.721     0.000     -0.008
-0.006
SPY_Rolling_Return_3m  3.0481      0.005    619.009     0.000     3.038
3.058
=====
Omnibus:              2412.574   Durbin-Watson:           0.136
Prob(Omnibus):        0.000   Jarque-Bera (JB):       132831.172
Skew:                 0.582   Prob(JB):                0.00
Kurtosis:             22.594   Cond. No.                13.5
=====

```

Notes:

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



OLS Regression Results

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==

Dep. Variable: UPRO_Rolling_Return_6m R-squared:

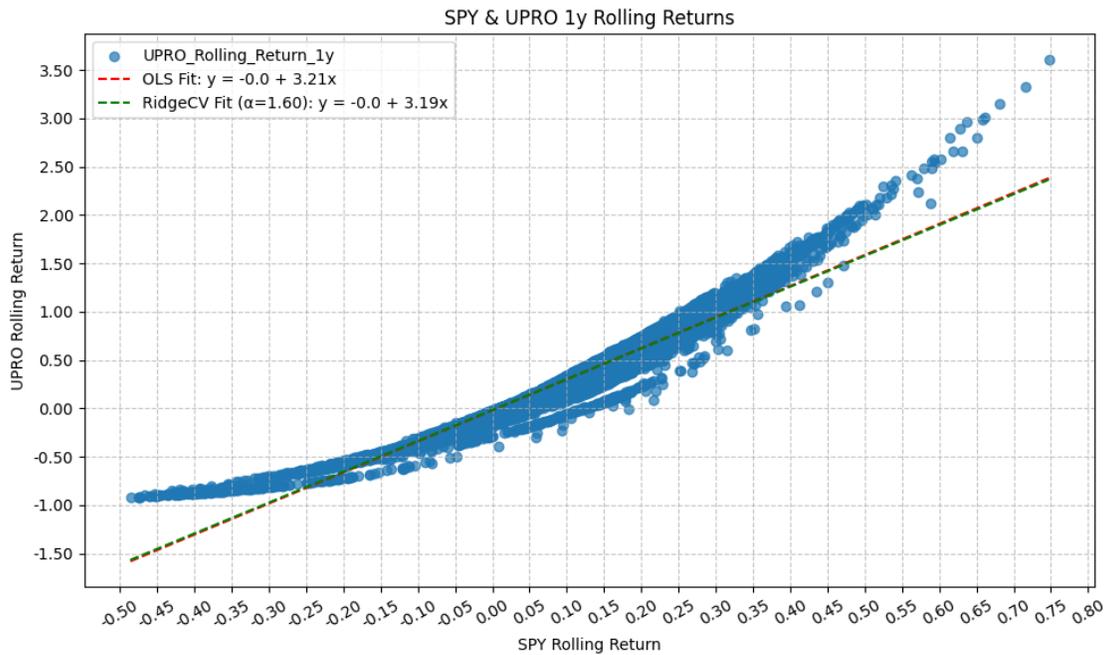
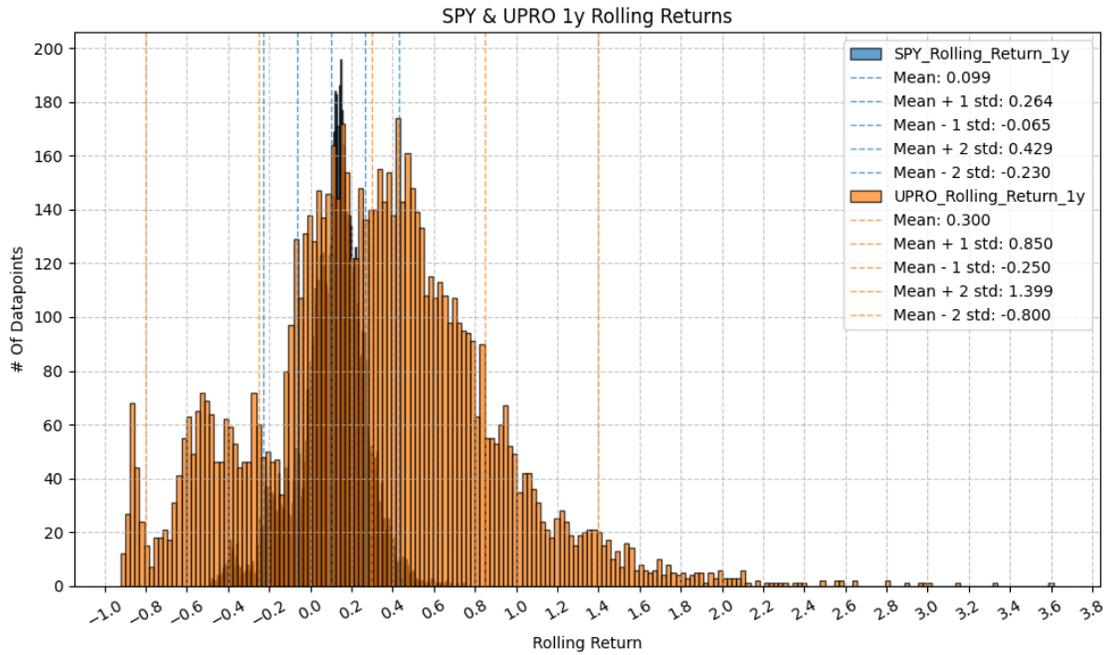
```

0.957
Model:                                OLS   Adj. R-squared:
0.957
Method:                                Least Squares   F-statistic:
1.830e+05
Date:                                   Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                                   14:28:00   Log-Likelihood:
10161.
No. Observations:                      8211   AIC:
-2.032e+04
Df Residuals:                          8209   BIC:
-2.030e+04
Df Model:                               1
Covariance Type:                       nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -0.0109      0.001    -12.883     0.000     -0.013
-0.009
SPY_Rolling_Return_6m  3.0707      0.007    427.780     0.000     3.057
3.085
=====
Omnibus:                2066.367   Durbin-Watson:                0.055
Prob(Omnibus):          0.000   Jarque-Bera (JB):            26461.991
Skew:                   0.843   Prob(JB):                    0.00
Kurtosis:               11.631   Cond. No.                    9.29
=====

```

Notes:

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



OLS Regression Results

=====

==

Dep. Variable: UPRO_Rolling_Return_1y R-squared:

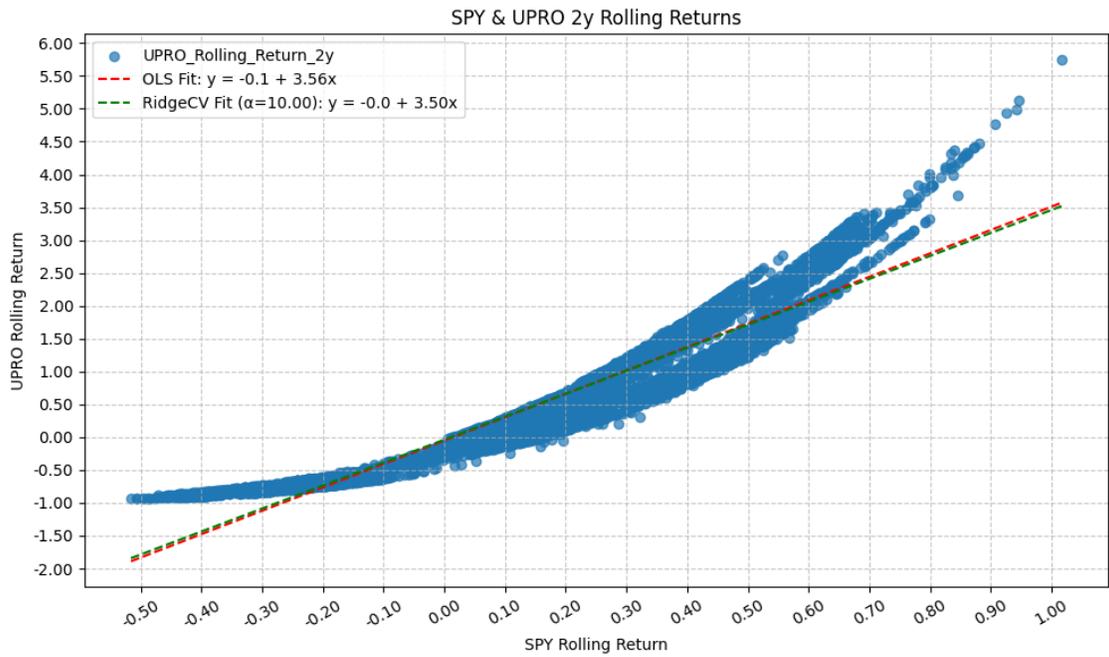
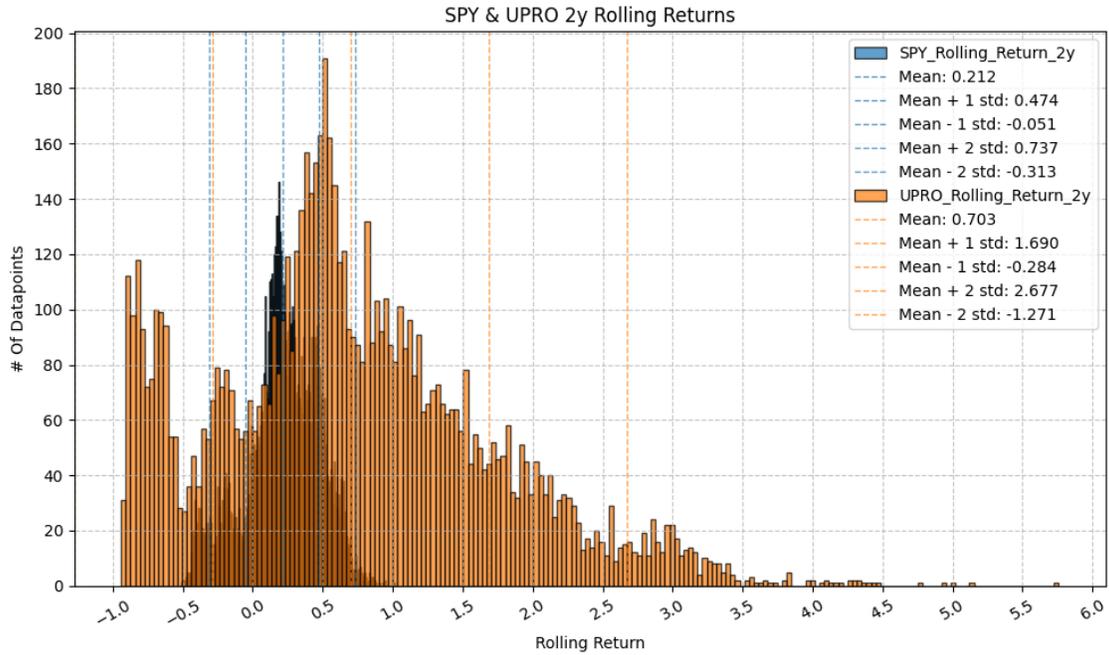
```

0.927
Model:                      OLS   Adj. R-squared:
0.927
Method:                      Least Squares   F-statistic:
1.024e+05
Date:                        Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                        14:28:01   Log-Likelihood:
3932.3
No. Observations:           8085   AIC:
-7861.
Df Residuals:               8083   BIC:
-7847.
Df Model:                    1
Covariance Type:            nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -0.0196      0.002    -10.120      0.000     -0.023
-0.016
SPY_Rolling_Return_1y  3.2120      0.010    319.930      0.000      3.192
3.232
=====
Omnibus:              1394.260   Durbin-Watson:           0.031
Prob(Omnibus):        0.000   Jarque-Bera (JB):       6548.397
Skew:                 0.764   Prob(JB):                0.00
Kurtosis:             7.136   Cond. No.                6.13
=====

```

Notes:

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



OLS Regression Results

=====

==

Dep. Variable: UPRO_Rolling_Return_2y R-squared:

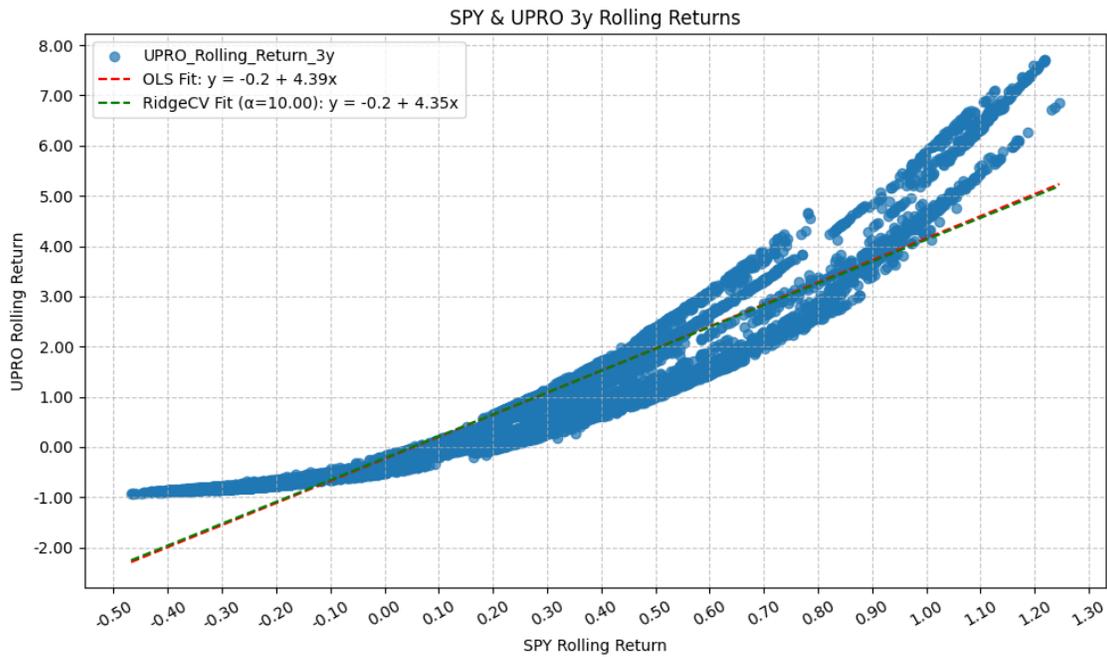
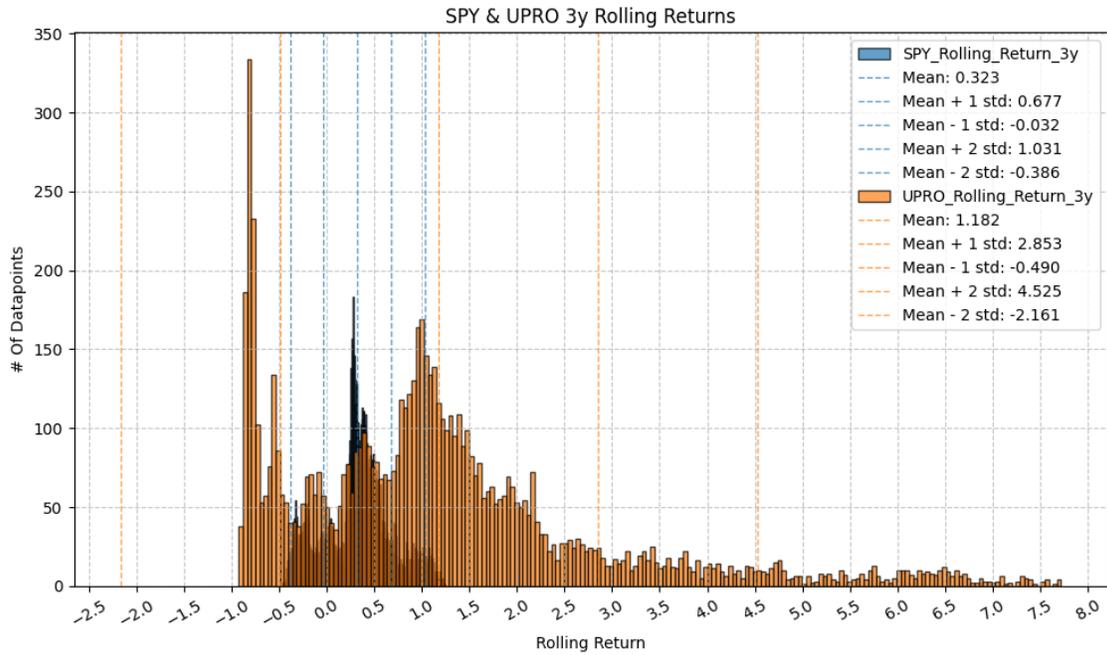
```

0.897
Model:                      OLS   Adj. R-squared:
0.897
Method:                      Least Squares   F-statistic:
6.796e+04
Date:                        Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                        14:28:02   Log-Likelihood:
-2121.4
No. Observations:           7833   AIC:
4247.
Df Residuals:                7831   BIC:
4261.
Df Model:                    1
Covariance Type:            nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -0.0512      0.005    -11.120      0.000     -0.060
-0.042
SPY_Rolling_Return_2y  3.5614      0.014    260.683      0.000      3.535
3.588
=====
Omnibus:              950.225   Durbin-Watson:           0.018
Prob(Omnibus):        0.000   Jarque-Bera (JB):       1486.222
Skew:                 0.866   Prob(JB):                0.00
Kurtosis:             4.246   Cond. No.                3.99
=====

```

Notes:

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



OLS Regression Results

=====

==

Dep. Variable: UPRO_Rolling_Return_3y R-squared:

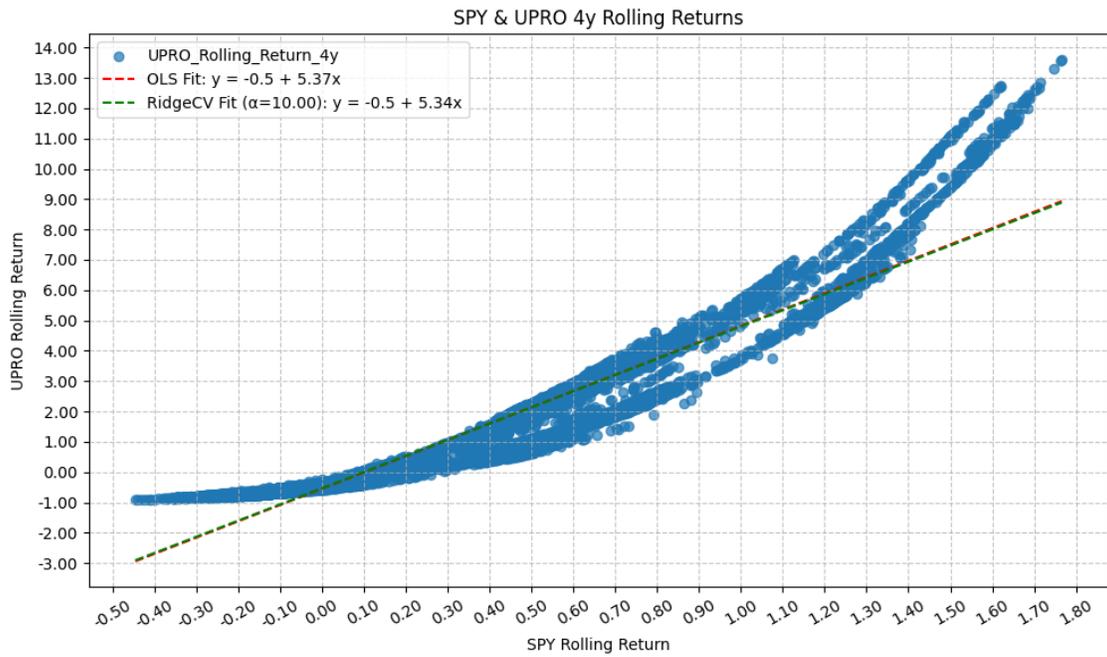
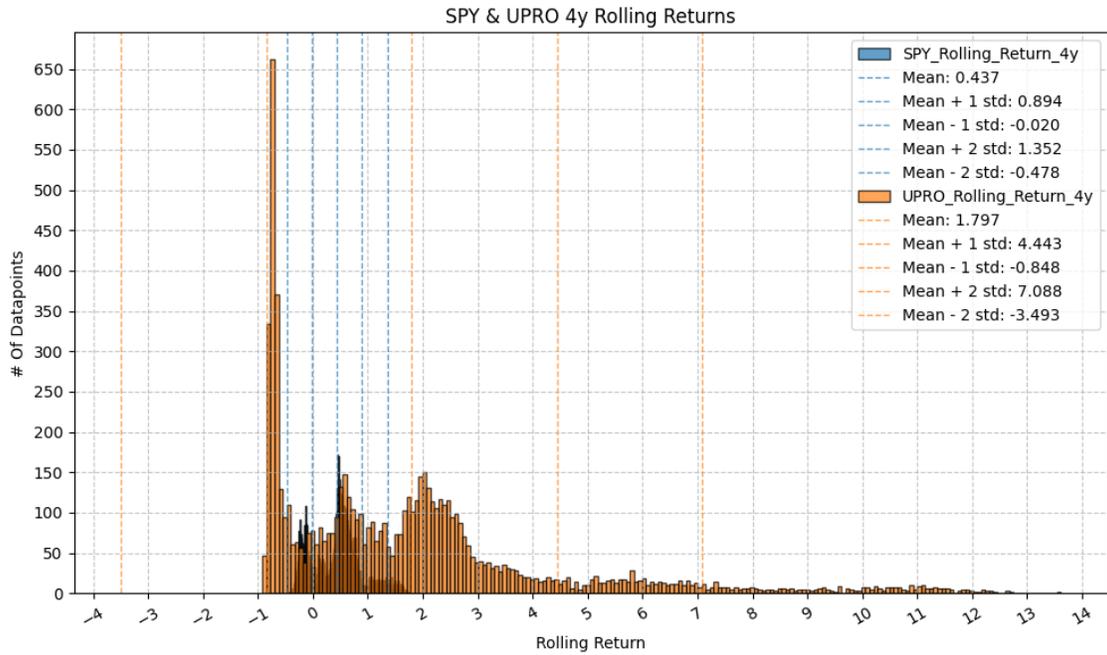
```

0.867
Model:                      OLS   Adj. R-squared:
0.867
Method:                     Least Squares   F-statistic:
4.922e+04
Date:                       Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                       14:28:04   Log-Likelihood:
-7016.3
No. Observations:          7581   AIC:
1.404e+04
Df Residuals:              7579   BIC:
1.405e+04
Df Model:                   1
Covariance Type:           nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -0.2356      0.009    -24.832     0.000     -0.254
-0.217
SPY_Rolling_Return_3y  4.3927      0.020    221.847     0.000      4.354
4.432
=====
Omnibus:              1286.625   Durbin-Watson:           0.008
Prob(Omnibus):        0.000   Jarque-Bera (JB):       2437.416
Skew:                 1.053   Prob(JB):                0.00
Kurtosis:             4.812   Cond. No.                3.15
=====

```

Notes:

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



OLS Regression Results

=====

==

Dep. Variable: UPRO_Rolling_Return_4y R-squared:

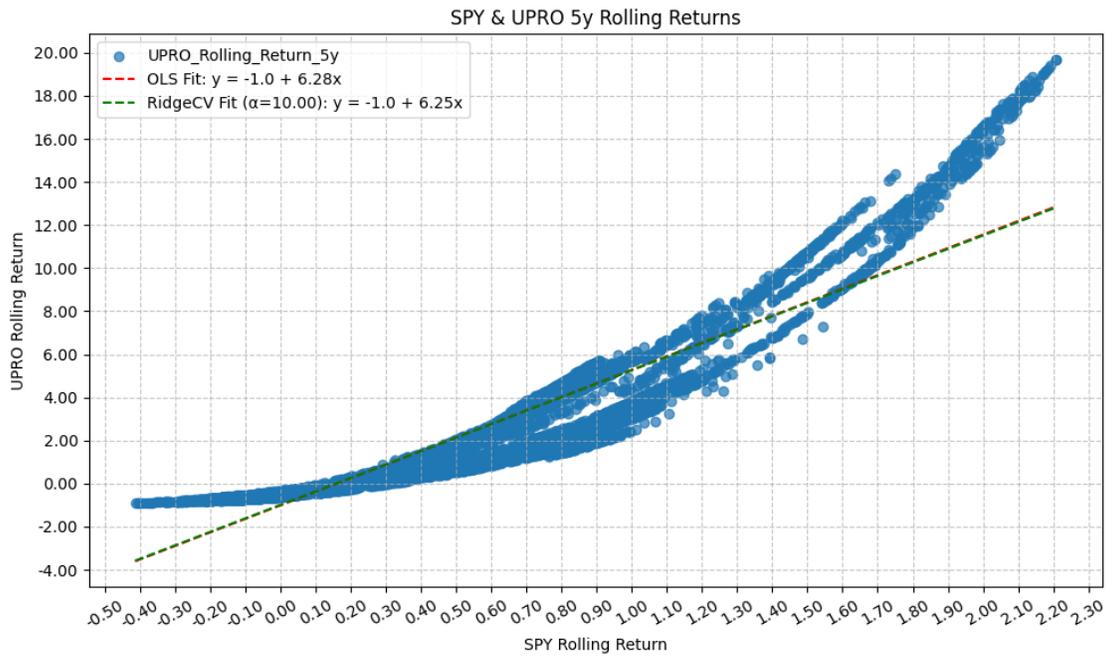
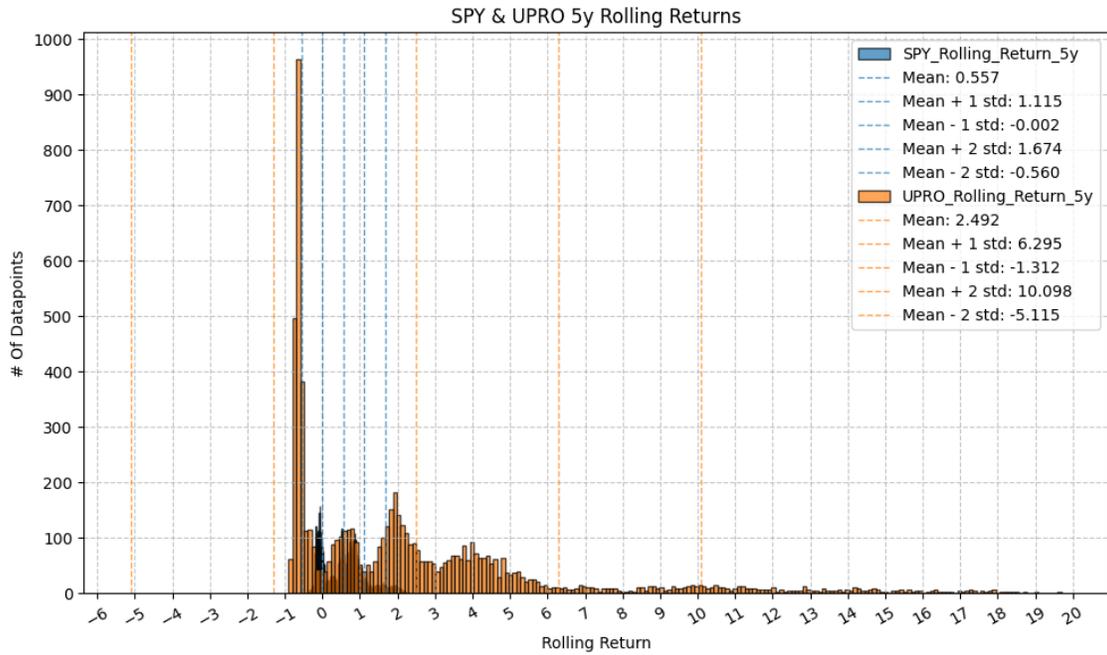
```

0.863
Model:                      OLS   Adj. R-squared:
0.863
Method:                      Least Squares   F-statistic:
4.605e+04
Date:                        Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                        14:28:05   Log-Likelihood:
-10251.
No. Observations:           7329   AIC:
2.051e+04
Df Residuals:                7327   BIC:
2.052e+04
Df Model:                    1
Covariance Type:            nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -0.5499      0.016    -34.731     0.000     -0.581
-0.519
SPY_Rolling_Return_4y  5.3711      0.025    214.593     0.000      5.322
5.420
=====
Omnibus:              1107.340   Durbin-Watson:           0.008
Prob(Omnibus):        0.000   Jarque-Bera (JB):       2298.081
Skew:                 0.913   Prob(JB):                0.00
Kurtosis:             5.048   Cond. No.                2.69
=====

```

Notes:

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



OLS Regression Results

=====

==

Dep. Variable: UPRO_Rolling_Return_5y R-squared:

```

0.850
Model:                               OLS   Adj. R-squared:
0.850
Method:                               Least Squares   F-statistic:
4.018e+04
Date:                               Mon, 16 Mar 2026   Prob (F-statistic):
0.00
Time:                               14:28:06   Log-Likelihood:
-12776.
No. Observations:                   7077   AIC:
2.556e+04
Df Residuals:                       7075   BIC:
2.557e+04
Df Model:                             1
Covariance Type:                    nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const                -1.0034      0.025    -40.626    0.000    -1.052
-0.955
SPY_Rolling_Return_5y  6.2796      0.031    200.453    0.000     6.218
6.341
=====
Omnibus:              685.964   Durbin-Watson:          0.007
Prob(Omnibus):        0.000   Jarque-Bera (JB):      1311.055
Skew:                 0.650   Prob(JB):              2.03e-285
Kurtosis:             4.660   Cond. No.              2.50
=====

```

Notes:

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

0.5.7 Rolling Returns Deviation (SPY & UPRO)

Next, we will the rolling returns deviation from the expected 3x return for each time period. This will give us a better picture of the volatility decay effect and how it changes over different time horizons.

```
[64]: rolling_returns_stats["Return_Deviation_From_3x"] =
      ↪rolling_returns_stats["Slope"] - 3.0
```

```
[65]: display(rolling_returns_stats)
```

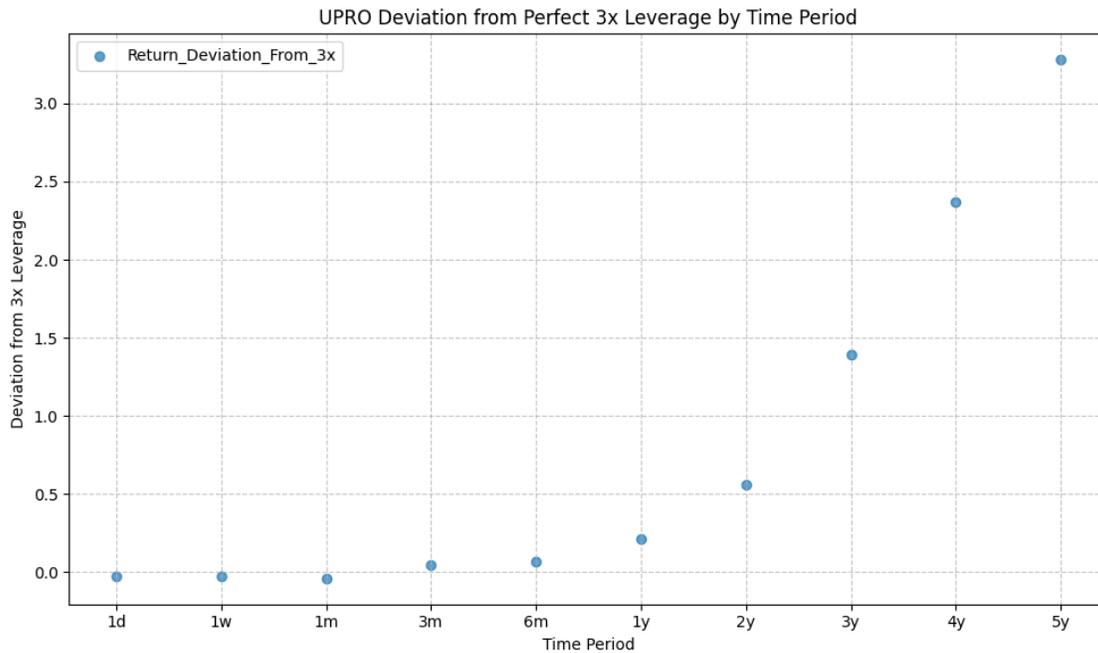
Period	Intercept	Slope	R_Squared	Skew	Average Upside Beta	\
0	1d	0.000	2.976	0.997	NaN	2.939

0	1w	-0.000	2.972	0.994	NaN	2.757
0	1m	-0.002	2.960	0.988	NaN	2.494
0	3m	-0.007	3.048	0.979	NaN	2.006
0	6m	-0.011	3.071	0.957	NaN	1.038
0	1y	-0.020	3.212	0.927	NaN	1.640
0	2y	-0.051	3.561	0.897	0.349	1.862
0	3y	-0.236	4.393	0.867	-6.067	1.578
0	4y	-0.550	5.371	0.863	-65.924	0.021
0	5y	-1.003	6.280	0.850	-35.218	-2.261

	Average	Downside	Beta	Asymmetry	Return_Deviation_From_3x
0			NaN	NaN	-0.024
0			NaN	NaN	-0.028
0			-inf	inf	-0.040
0			-inf	inf	0.048
0			-inf	inf	0.071
0			-inf	inf	0.212
0			9.298	-7.436	0.561
0			8.621	-7.042	1.393
0			7.235	-7.214	2.371
0			21.003	-23.265	3.280

```
[66]: plot_scatter(
    df=rolling_returns_stats,
    x_plot_column="Period",
    y_plot_columns=["Return_Deviation_From_3x"],
    title="UPRO Deviation from Perfect 3x Leverage by Time Period",
    x_label="Time Period",
    x_format="String",
    x_format_decimal_places=0,
    x_tick_spacing=1,
    x_tick_rotation=0,
    y_label="Deviation from 3x Leverage",
    y_format="Decimal",
    y_format_decimal_places=1,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    plot_OLS_regression_line=False,
    OLS_column=None,
    plot_Ridge_regression_line=False,
    Ridge_column=None,
    plot_RidgeCV_regression_line=False,
    RidgeCV_column=None,
    regression_constant=False,
    grid=True,
    legend=True,
    export_plot=False,
```

```
plot_file_name=None,  
)
```

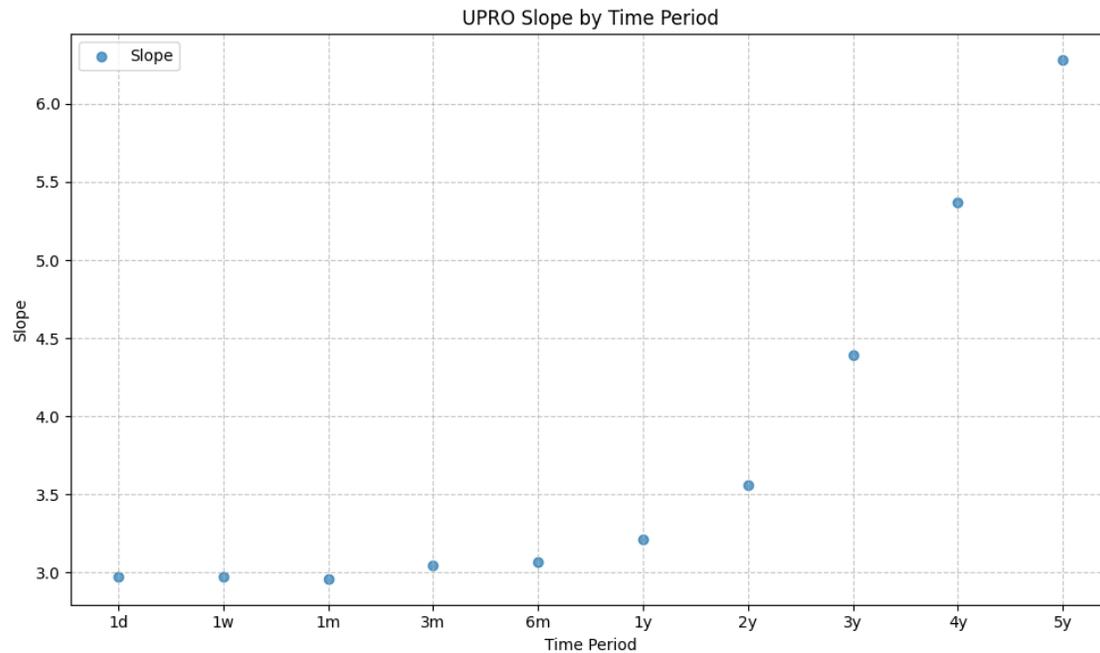


```
[67]: plot_scatter(  
    df=rolling_returns_stats,  
    x_plot_column="Period",  
    y_plot_columns=["Slope"],  
    title="UPRO Slope by Time Period",  
    x_label="Time Period",  
    x_format="String",  
    x_format_decimal_places=0,  
    x_tick_spacing=1,  
    x_tick_rotation=0,  
    y_label="Slope",  
    y_format="Decimal",  
    y_format_decimal_places=1,  
    y_tick_spacing="Auto",  
    y_tick_rotation=0,  
    plot_OLS_regression_line=False,  
    OLS_column=None,  
    plot_Ridge_regression_line=False,  
    Ridge_column=None,  
    plot_RidgeCV_regression_line=False,  
    RidgeCV_column=None,  
    regression_constant=False,  
)
```

```

grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



```

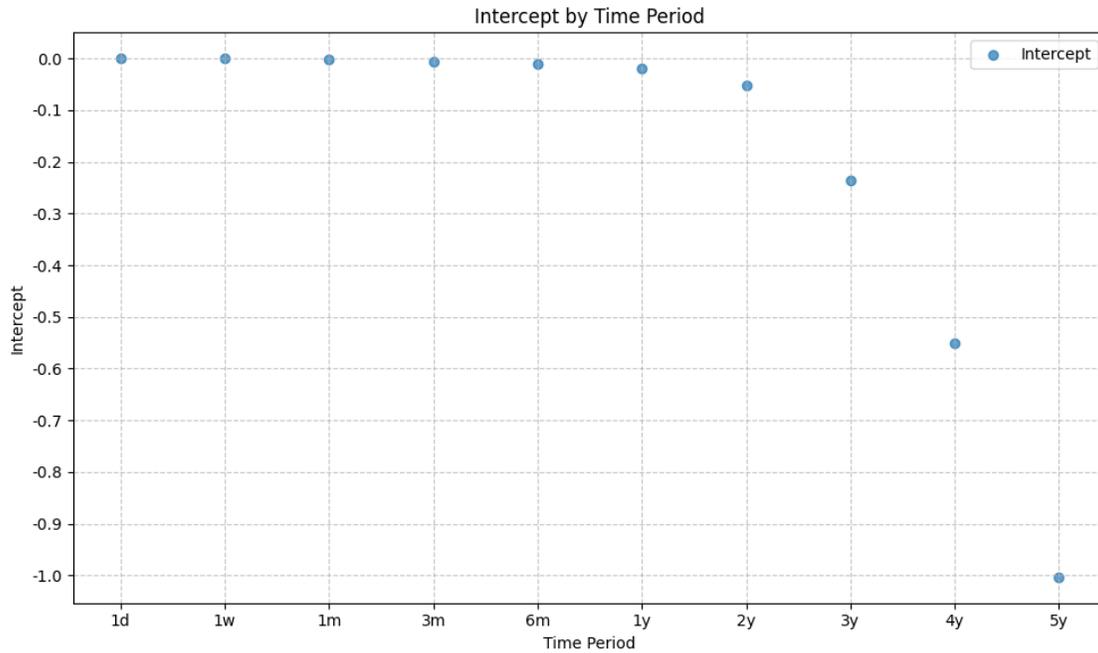
[68]: plot_scatter(
    df=rolling_returns_stats,
    x_plot_column="Period",
    y_plot_columns=["Intercept"],
    title="Intercept by Time Period",
    x_label="Time Period",
    x_format="String",
    x_format_decimal_places=0,
    x_tick_spacing=1,
    x_tick_rotation=0,
    y_label="Intercept",
    y_format="Decimal",
    y_format_decimal_places=1,
    y_tick_spacing="Auto",
    y_tick_rotation=0,
    plot_OLS_regression_line=False,
    OLS_column=None,
    plot_Ridge_regression_line=False,
    Ridge_column=None,
)

```

```

plot_RidgeCV_regression_line=False,
RidgeCV_column=None,
regression_constant=False,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



```

[69]: pandas_set_decimal_places(3)
display(rolling_returns_stats.set_index("Period"))

```

Period	Intercept	Slope	R_Squared	Skew	Average Upside Beta	\
1d	0.000	2.976	0.997	NaN		2.939
1w	-0.000	2.972	0.994	NaN		2.757
1m	-0.002	2.960	0.988	NaN		2.494
3m	-0.007	3.048	0.979	NaN		2.006
6m	-0.011	3.071	0.957	NaN		1.038
1y	-0.020	3.212	0.927	NaN		1.640
2y	-0.051	3.561	0.897	0.349		1.862
3y	-0.236	4.393	0.867	-6.067		1.578
4y	-0.550	5.371	0.863	-65.924		0.021
5y	-1.003	6.280	0.850	-35.218		-2.261

Period	Average Downside Beta	Asymmetry	Return_Deviation_From_3x
1d			
1w			
1m			
3m			
6m			
1y			
2y			
3y			
4y			
5y			

Period			
1d	NaN	NaN	-0.024
1w	NaN	NaN	-0.028
1m	-inf	inf	-0.040
3m	-inf	inf	0.048
6m	-inf	inf	0.071
1y	-inf	inf	0.212
2y	9.298	-7.436	0.561
3y	8.621	-7.042	1.393
4y	7.235	-7.214	2.371
5y	21.003	-23.265	3.280

Similar as to QQQ/TQQQ, up to 1 year, there is minimal difference between the mean UPRO 1 year rolling return and the hypothetical 3x leverage, with an R^2 of greater than 0.9.

However, as we extend the time period, we see that

- The “leverage factor” increases significantly, resulting in a deviation from the perfect 3x leverage.
- The intercept also begins to deviate significantly from 0.

0.5.8 Rolling Returns Following Drawdowns (SPY & UPRO)

We will identify the drawdown levels of UPRO and then look at the subsequent rolling returns over various time horizons.

```
[70]: # Copy DataFrame
spy_upro_extrap_future = spy_upro_extrap.copy()

# Create a list of drawdown levels to analyze
drawdown_levels = [-0.10, -0.20, -0.30, -0.40, -0.50, -0.60, -0.70, -0.80]

# Shift the rolling return columns by the number of days in the rolling window
↳ to get the returns following the drawdown
for etf in etfs:
    for period_name, window in rolling_windows.items():
        spy_upro_extrap_future[f"{etf}_Rolling_Future_Return_{period_name}"] =
↳ spy_upro_extrap_future[f"{etf}_Rolling_Return_{period_name}"].shift(-window)
```

Now, we can analyze the future rolling returns following specific drawdown levels:

```
[71]: # Create a dataframe to hold rolling returns stats
rolling_returns_drawdown_stats = pd.DataFrame()

for drawdown in drawdown_levels:

    for period_name, window in rolling_windows.items():

        try:
            plot_histogram(
```

```

        )
    plot_scatter(
        df=spy_upro_extrap_future[spy_upro_extrap_future["UPRO_Drawdown"] <=
drawdown],
        plot_columns=[f"SPY_Rolling_Future_Return_{period_name}",
f"UPRO_Rolling_Future_Return_{period_name}"],
        title=f"SPY & UPRO {period_name} Rolling Future Returns Post
drawdown UPRO Drawdown",
        x_label="Rolling Return",
        x_tick_spacing="Auto",
        x_tick_rotation=30,
        y_label="# Of Datapoints",
        y_tick_spacing="Auto",
        y_tick_rotation=0,
        grid=True,
        legend=True,
        export_plot=False,
        plot_file_name=None,
    )

    plot_scatter(
        df=spy_upro_extrap_future[spy_upro_extrap_future["UPRO_Drawdown"] <=
drawdown],
        x_plot_column=f"SPY_Rolling_Future_Return_{period_name}",
        y_plot_columns=[f"UPRO_Rolling_Future_Return_{period_name}"],
        title=f"SPY & UPRO {period_name} Rolling Future Returns Post
drawdown UPRO Drawdown",
        x_label="SPY Rolling Return",
        x_format="Decimal",
        x_format_decimal_places=2,
        x_tick_spacing="Auto",
        x_tick_rotation=30,
        y_label="UPRO Rolling Return",
        y_format="Decimal",
        y_format_decimal_places=2,
        y_tick_spacing="Auto",
        y_tick_rotation=0,
        plot_OLS_regression_line=True,
        OLS_column=f"UPRO_Rolling_Future_Return_{period_name}",
        plot_Ridge_regression_line=False,
        Ridge_column=None,
        plot_RidgeCV_regression_line=True,
        RidgeCV_column=f"UPRO_Rolling_Future_Return_{period_name}",
        regression_constant=True,
        grid=True,
        legend=True,
        export_plot=False,
    )

```

```

        plot_file_name=None,
    )

    # Run OLS regression with statsmodels
    model = run_linear_regression(
        ↵
        ↪df=spy_upro_extrap_future[spy_upro_extrap_future["UPRO_Drawdown"] <=↵
        ↪drawdown],
        x_plot_column=f"SPY_Rolling_Future_Return_{period_name}",
        y_plot_column=f"UPRO_Rolling_Future_Return_{period_name}",
        regression_model="OLS-statsmodels",
        regression_constant=True,
    )
    print(model.summary())

    # Filter by drawdown
    drawdown_filter =↵
    ↪spy_upro_extrap_future[spy_upro_extrap_future["UPRO_Drawdown"] <= drawdown]

    # Filter by period, drop rows with missing values
    future_filter =↵
    ↪drawdown_filter[[f"UPRO_Rolling_Future_Return_{period_name}"]].dropna()

    # Find length of future dataframe
    future_length = len(future_filter)

    # Find length of future dataframe where return is positive
    positive_future_length =↵
    ↪len(future_filter[future_filter[f"UPRO_Rolling_Future_Return_{period_name}"]↵
    ↪ > 0])

    # Calculate percentage of future returns that are positive
    positive_future_percentage = (positive_future_length /↵
    ↪future_length) if future_length > 0 else 0

    # Add the regression results to the rolling returns stats dataframe
    intercept = model.params[0]
    # intercept_pvalue = model.pvalues[0] # p-value for Intercept
    slope = model.params[1]
    # slope_pvalue = model.pvalues[1] # p-value for Slope
    r_squared = model.rsquared

    rolling_returns_slope_int = pd.DataFrame({
        "Drawdown": drawdown,
        "Period": period_name,
        "Intercept": [intercept],
        # "Intercept_PValue": [intercept_pvalue],
    })

```

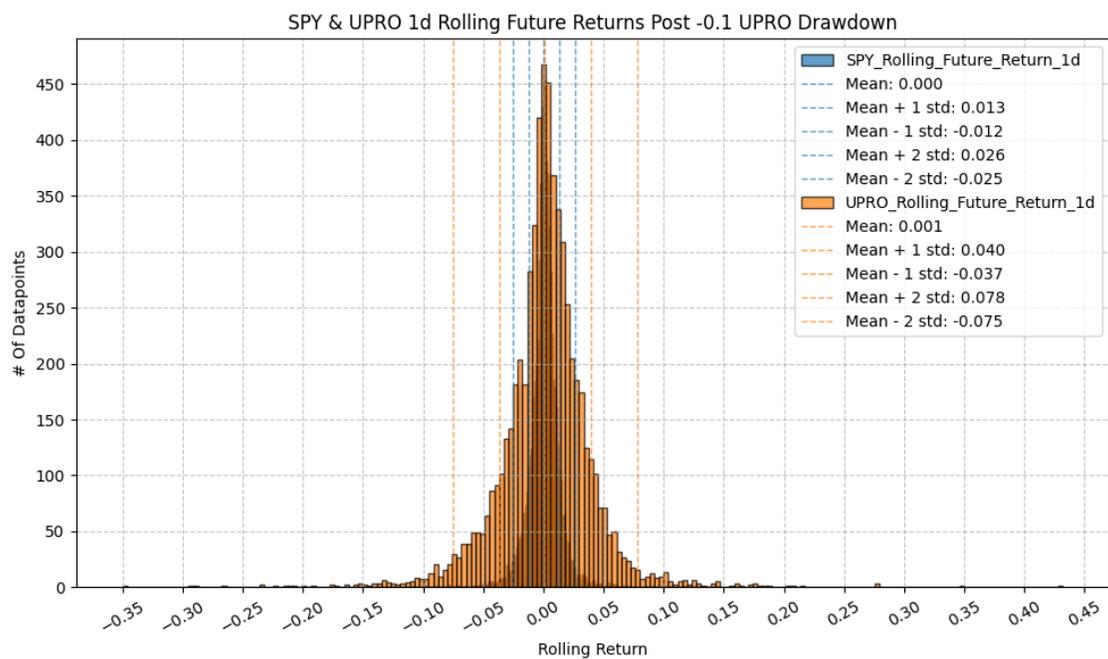
```

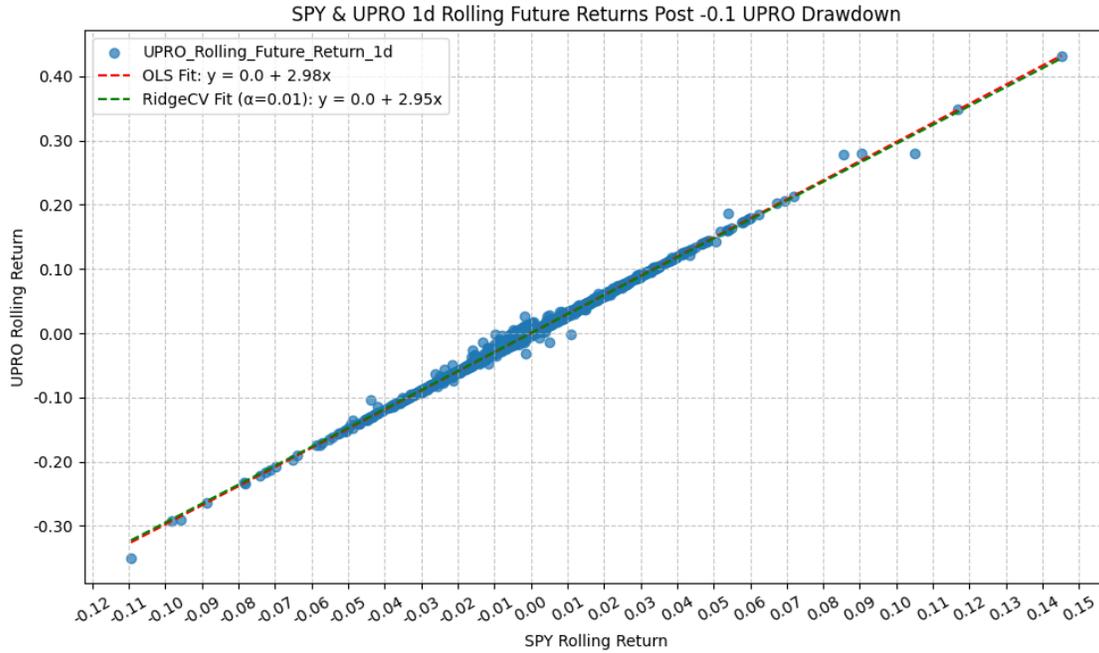
        "Slope": [slope],
        # "Slope_PValue": [slope_pvalue],
        "R_Squared": [r_squared],
        "Positive_Future_Percentage": [positive_future_percentage],
    })

    rolling_returns_drawdown_stats = pd.
↳concat([rolling_returns_drawdown_stats, rolling_returns_slope_int])

    except:
        print(f"Not enough data points for drawdown level {drawdown} and_
↳period {period_name} to run regression.")

```





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_1d    R-squared:
0.997
Model:              OLS                            Adj. R-squared:
0.997
Method:             Least Squares                 F-statistic:
2.285e+06
Date:               Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:               14:28:07                      Log-Likelihood:
29859.
No. Observations:  6221                          AIC:
-5.971e+04
Df Residuals:      6219                          BIC:
-5.970e+04
Df Model:          1
Covariance Type:   nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                2.196e-05  2.53e-05    0.869    0.385

```

-2.76e-05 7.15e-05
 SPY_Rolling_Future_Return_1d 2.9765 0.002 1511.654 0.000
 2.973 2.980

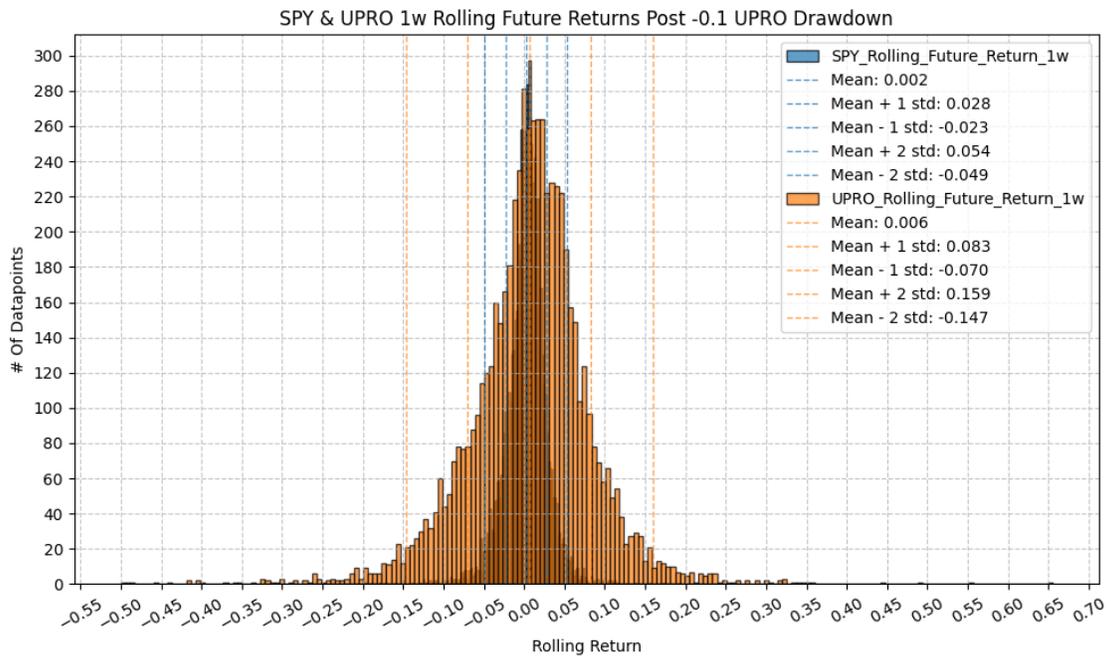
```
=====
```

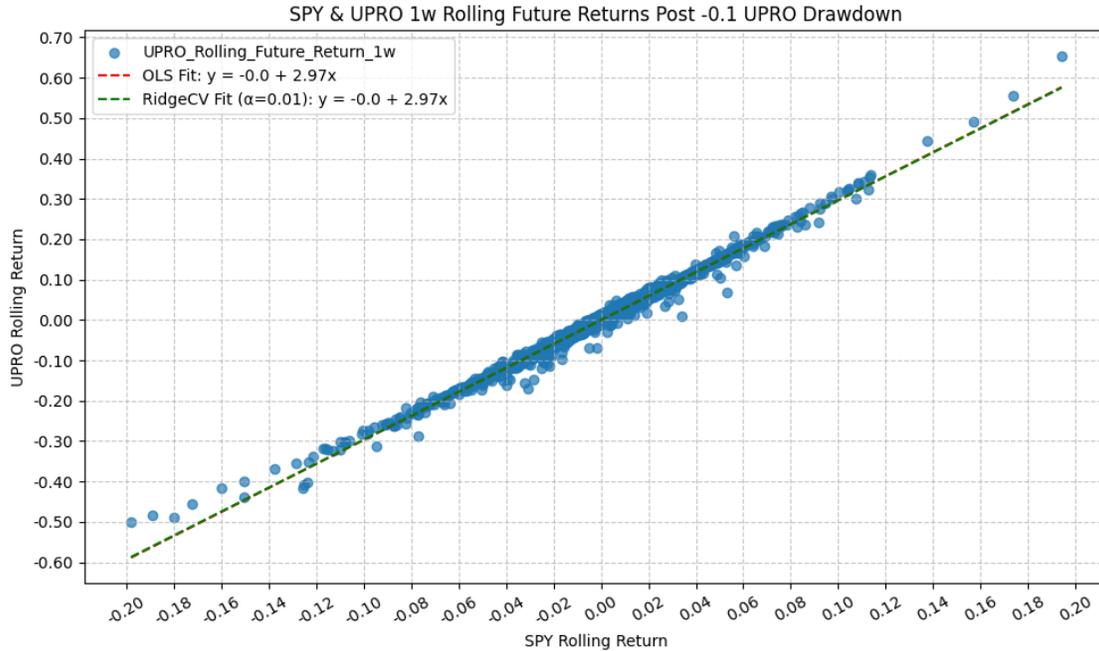
Omnibus:	4600.809	Durbin-Watson:	2.630
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2414888.124
Skew:	2.321	Prob(JB):	0.00
Kurtosis:	99.410	Cond. No.	78.0

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1w    R-squared:
0.994
Model:                  OLS                            Adj. R-squared:
0.994
Method:                 Least Squares                  F-statistic:
9.665e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:09                      Log-Likelihood:
22872.
No. Observations:      6219                          AIC:
-4.574e+04
Df Residuals:          6217                          BIC:
-4.573e+04
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

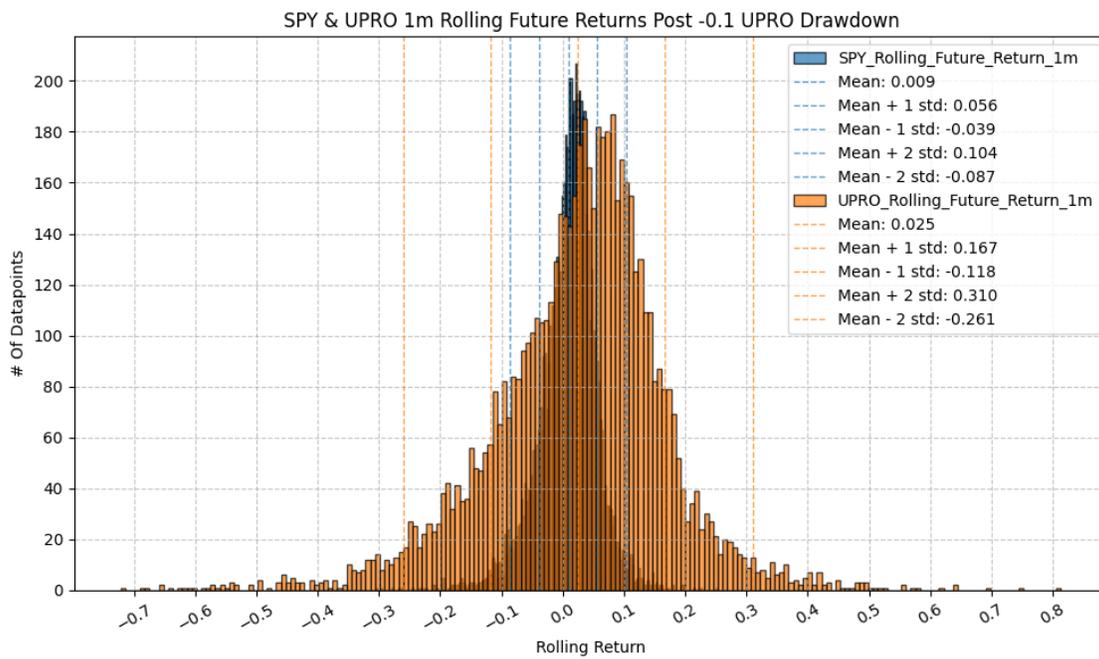
	coef	std err	t	P> t
[0.025 0.975]				
const	-0.0002	7.79e-05	-3.047	0.002

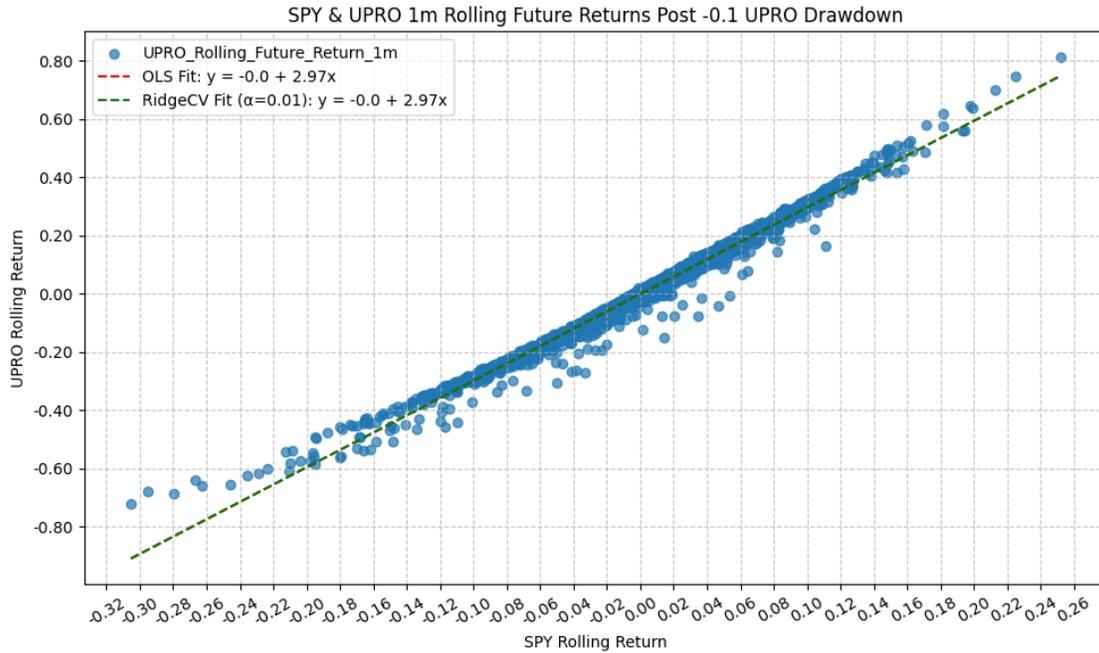
-0.000 -8.46e-05
 SPY_Rolling_Future_Return_1w 2.9732 0.003 983.115 0.000
 2.967 2.979

```
=====
Omnibus:                    2734.500    Durbin-Watson:                    0.978
Prob(Omnibus):              0.000    Jarque-Bera (JB):                782234.894
Skew:                        -0.876    Prob(JB):                         0.00
Kurtosis:                    57.915    Cond. No.                         39.0
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1m    R-squared:
0.988
Model:                  OLS                            Adj. R-squared:
0.988
Method:                 Least Squares                 F-statistic:
4.994e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:10                      Log-Likelihood:
16962.
No. Observations:      6218                          AIC:
-3.392e+04
Df Residuals:          6216                          BIC:
-3.391e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0015    0.000       -7.184    0.000

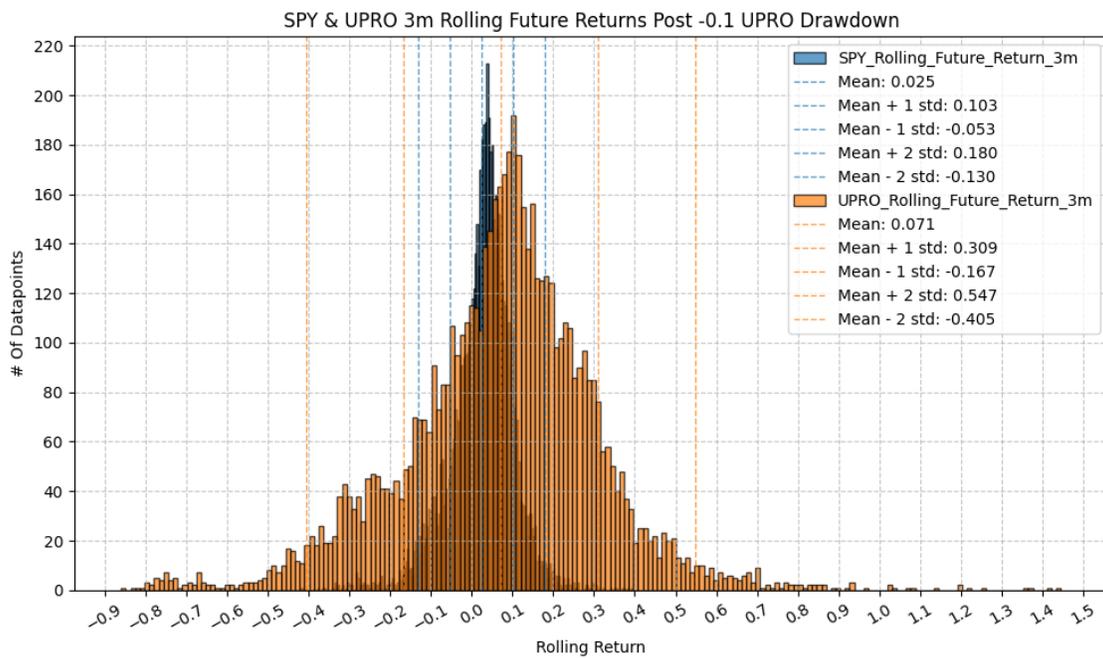
```

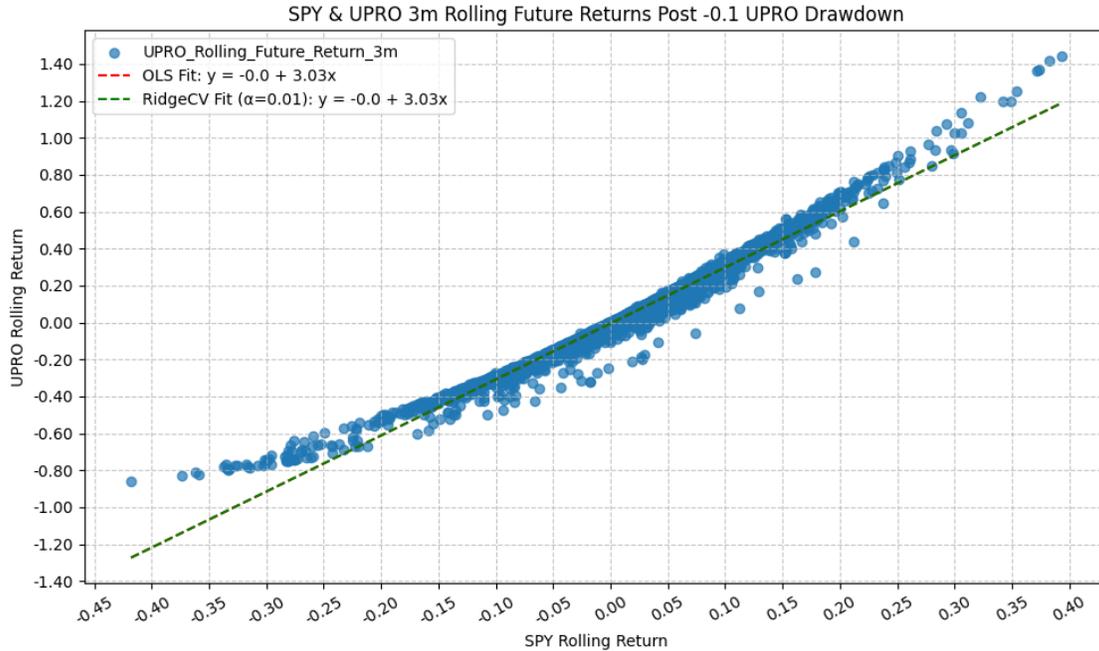
-0.002 -0.001
 SPY_Rolling_Future_Return_1m 2.9746 0.004 706.661 0.000
 2.966 2.983

```
=====
Omnibus:                            3371.444      Durbin-Watson:                            0.336
Prob(Omnibus):                      0.000      Jarque-Bera (JB):                        387348.606
Skew:                                -1.631      Prob(JB):                                 0.00
Kurtosis:                            41.528      Cond. No.                                 21.0
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3m    R-squared:
0.978
Model:                  OLS                            Adj. R-squared:
0.978
Method:                 Least Squares                 F-statistic:
2.716e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:11                      Log-Likelihood:
11917.
No. Observations:      6218                          AIC:
-2.383e+04
Df Residuals:          6216                          BIC:
-2.382e+04
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0048    0.000   -10.061    0.000

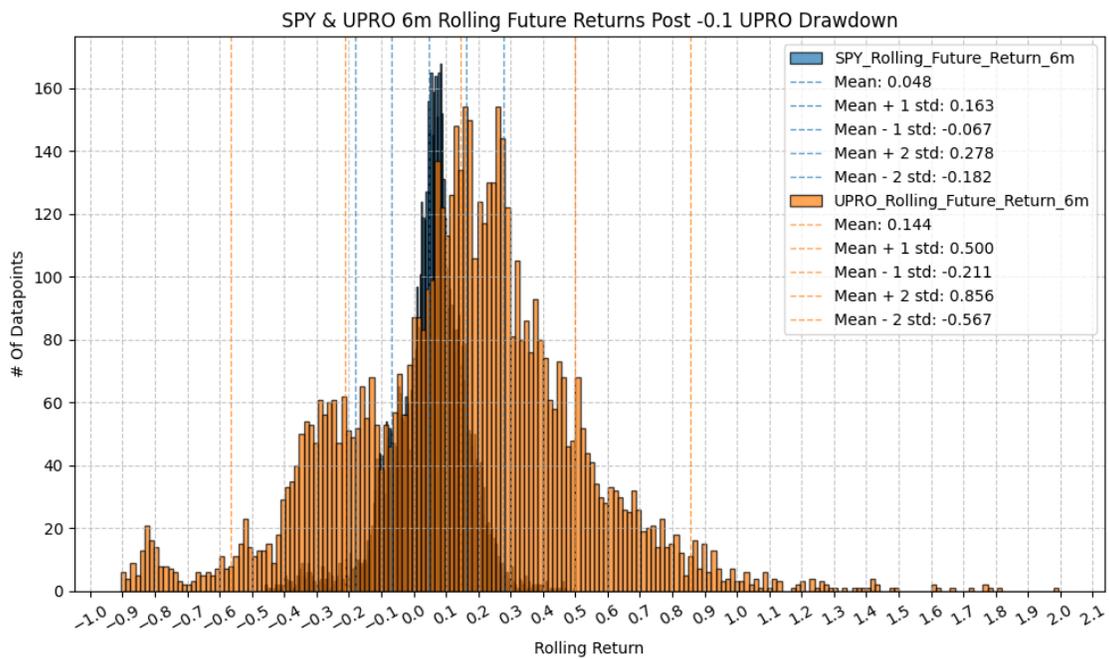
```

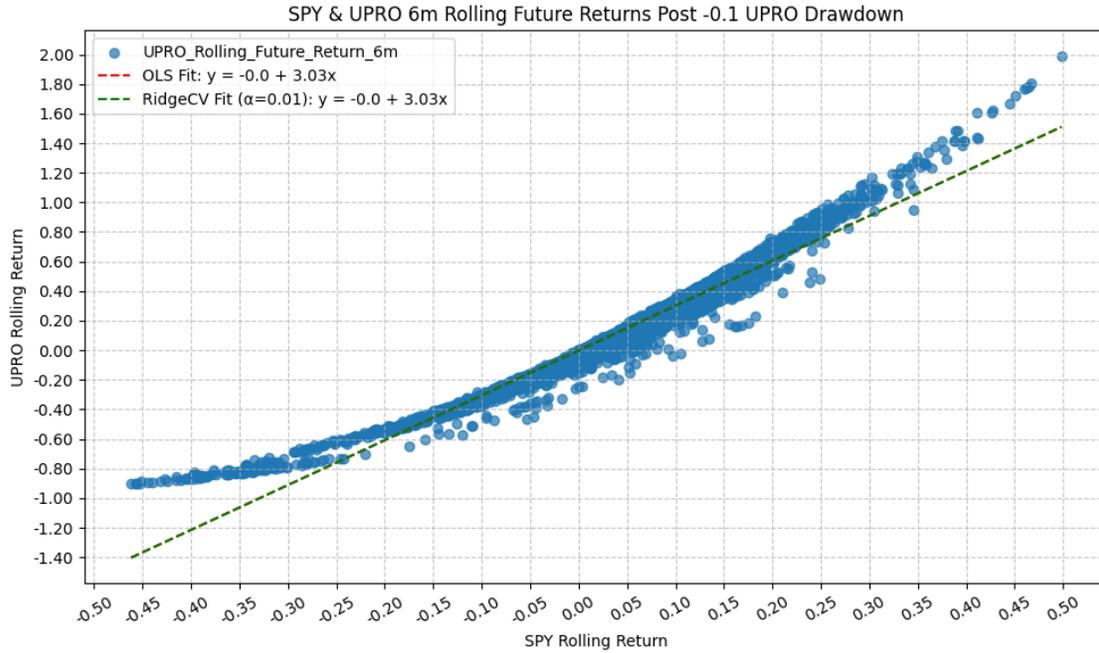
-0.006	-0.004				
SPY_Rolling_Future_Return_3m	3.0334	0.006	521.161	0.000	
3.022	3.045				

```
=====
Omnibus:                1724.576   Durbin-Watson:           0.148
Prob(Omnibus):          0.000     Jarque-Bera (JB):       87846.616
Skew:                   0.522     Prob(JB):                0.00
Kurtosis:               21.384    Cond. No.                12.9
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_6m    R-squared:
0.961
Model:                  OLS                            Adj. R-squared:
0.961
Method:                 Least Squares                 F-statistic:
1.537e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:12                      Log-Likelihood:
7698.5
No. Observations:      6214                          AIC:
-1.539e+04
Df Residuals:          6212                          BIC:
-1.538e+04
Df Model:              1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -0.0015    0.001    -1.526    0.127

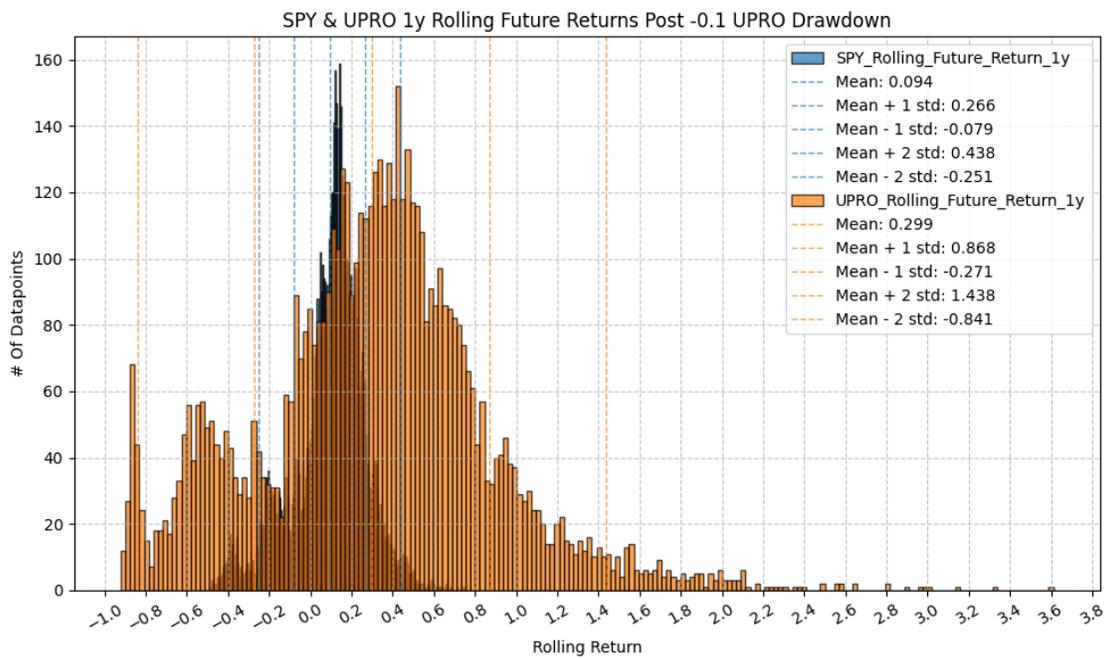
```

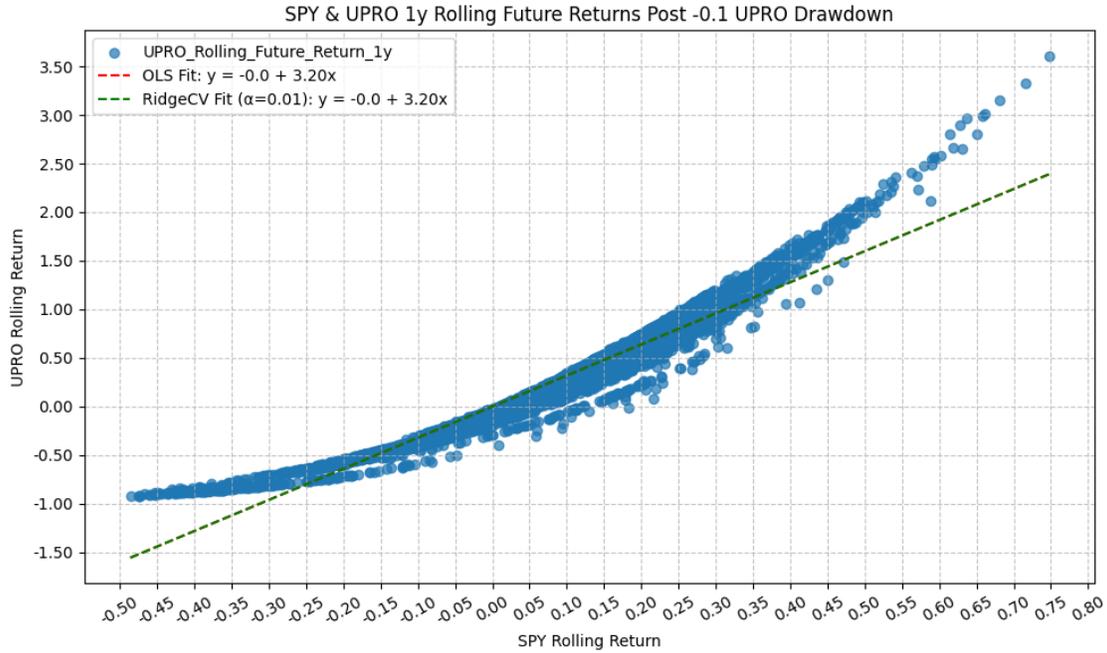
-0.003	0.000				
SPY_Rolling_Future_Return_6m	3.0330	0.008	391.990	0.000	
3.018	3.048				

```
=====
Omnibus:                2086.730    Durbin-Watson:           0.070
Prob(Omnibus):          0.000    Jarque-Bera (JB):       20739.746
Skew:                   1.316    Prob(JB):                0.00
Kurtosis:               11.554    Cond. No.                8.72
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1y    R-squared:
0.934
Model:                  OLS                            Adj. R-squared:
0.934
Method:                 Least Squares                 F-statistic:
8.620e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:13                      Log-Likelihood:
3064.8
No. Observations:      6141                          AIC:
-6126.
Df Residuals:          6139                          BIC:
-6112.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.0007	0.002	-0.314	0.754

-0.005	0.004				
SPY_Rolling_Future_Return_1y	3.1993	0.011	293.600	0.000	
3.178	3.221				

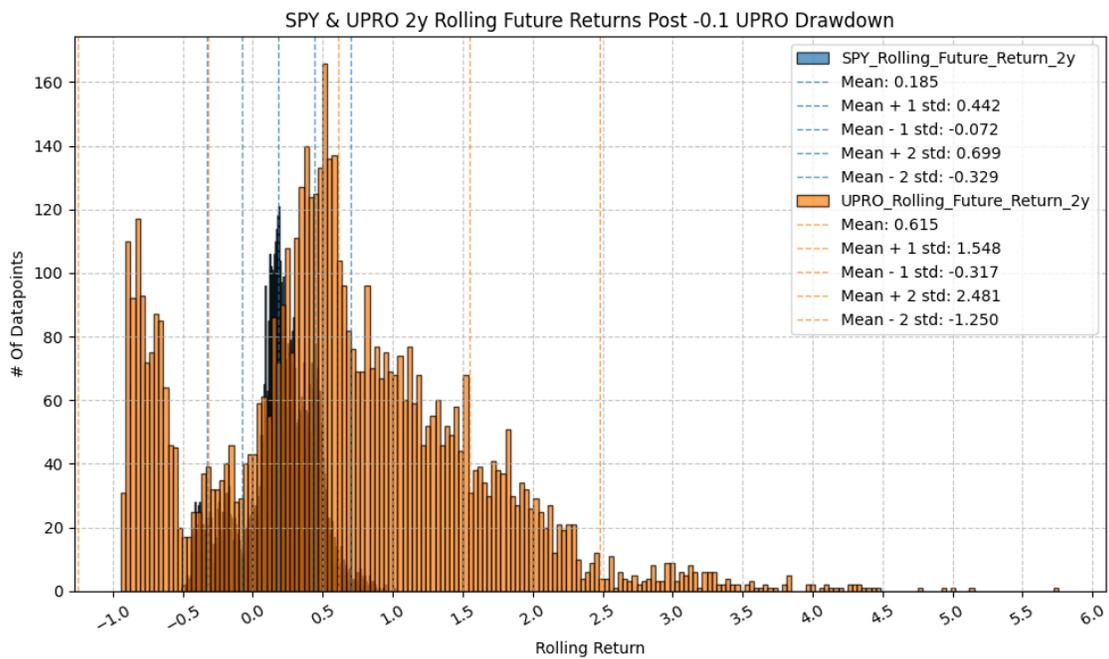
```

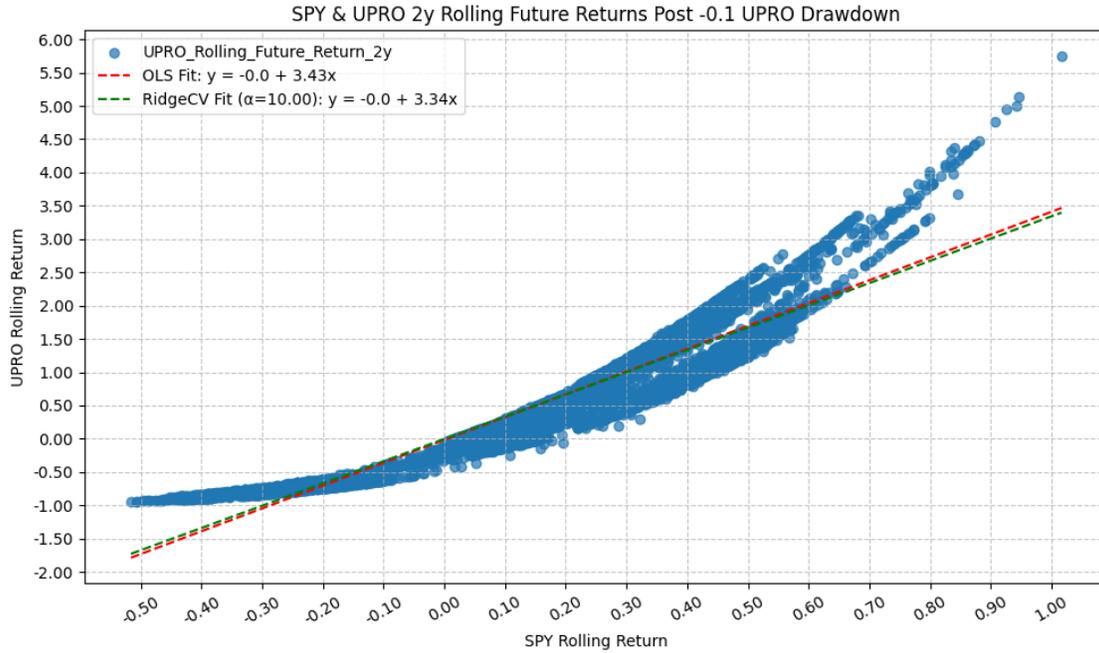
=====
Omnibus:                1575.656   Durbin-Watson:           0.041
Prob(Omnibus):          0.000   Jarque-Bera (JB):       7484.757
Skew:                   1.162   Prob(JB):                0.00
Kurtosis:               7.883   Cond. No.                5.86
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_2y    R-squared:
0.892
Model:                  OLS                            Adj. R-squared:
0.892
Method:                 Least Squares                 F-statistic:
4.980e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:14                     Log-Likelihood:
-1446.2
No. Observations:      6061                          AIC:
2896.
Df Residuals:          6059                          BIC:
2910.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0175    0.005     -3.607    0.000
=====

```

-0.027 -0.008
 SPY_Rolling_Future_Return_2y 3.4272 0.015 223.154 0.000
 3.397 3.457

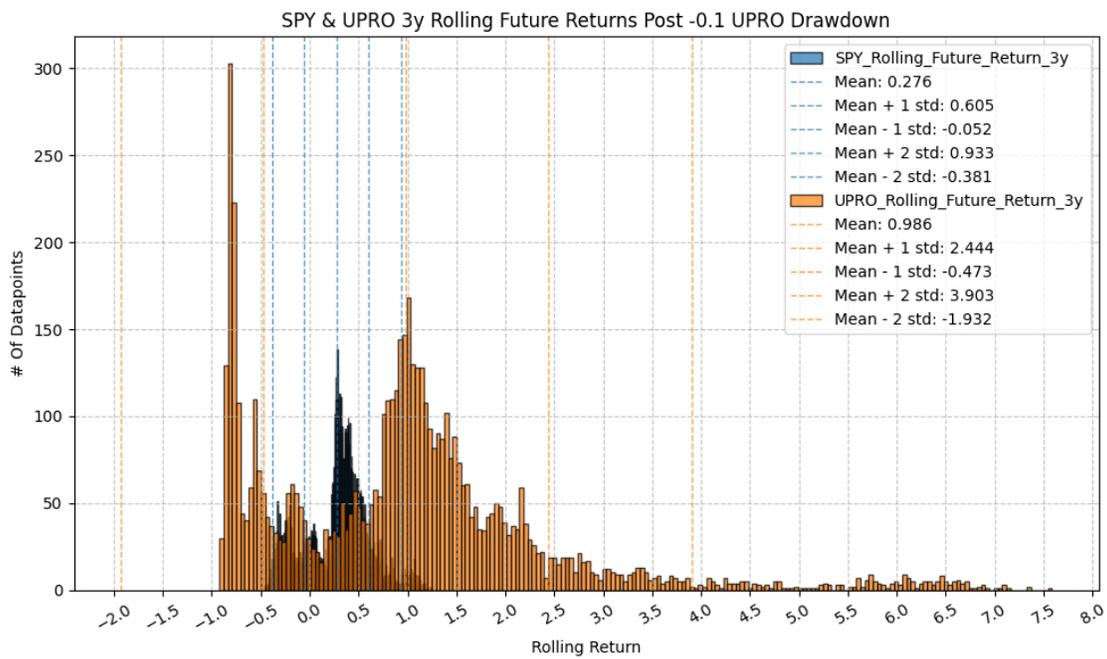
```
=====
```

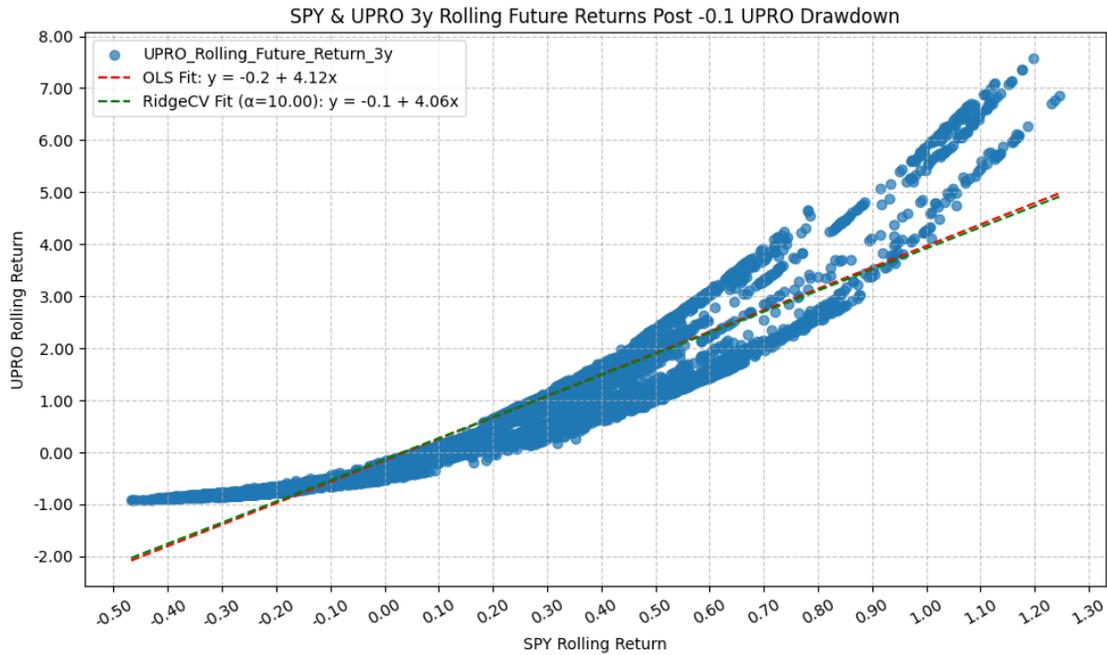
Omnibus:	1154.327	Durbin-Watson:	0.024
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2673.564
Skew:	1.077	Prob(JB):	0.00
Kurtosis:	5.438	Cond. No.	4.03

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3y    R-squared:
0.861
Model:                  OLS                            Adj. R-squared:
0.861
Method:                 Least Squares                 F-statistic:
3.592e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:16                     Log-Likelihood:
-4707.3
No. Observations:      5809                          AIC:
9419.
Df Residuals:          5807                          BIC:
9432.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.1527    0.009   -16.369    0.000
=====

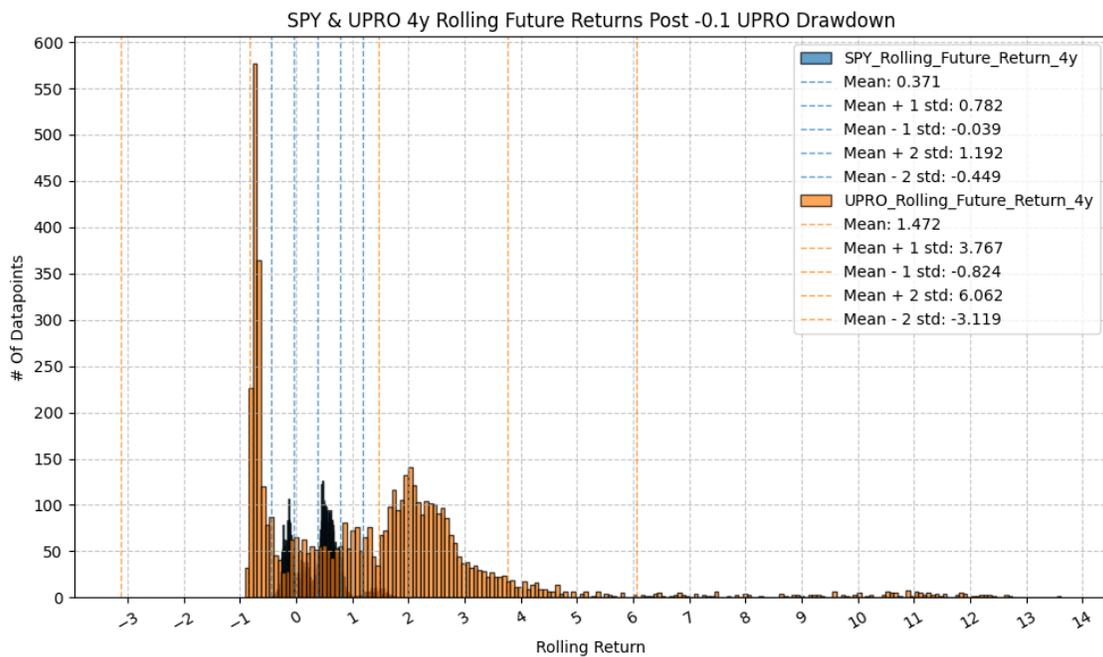
```

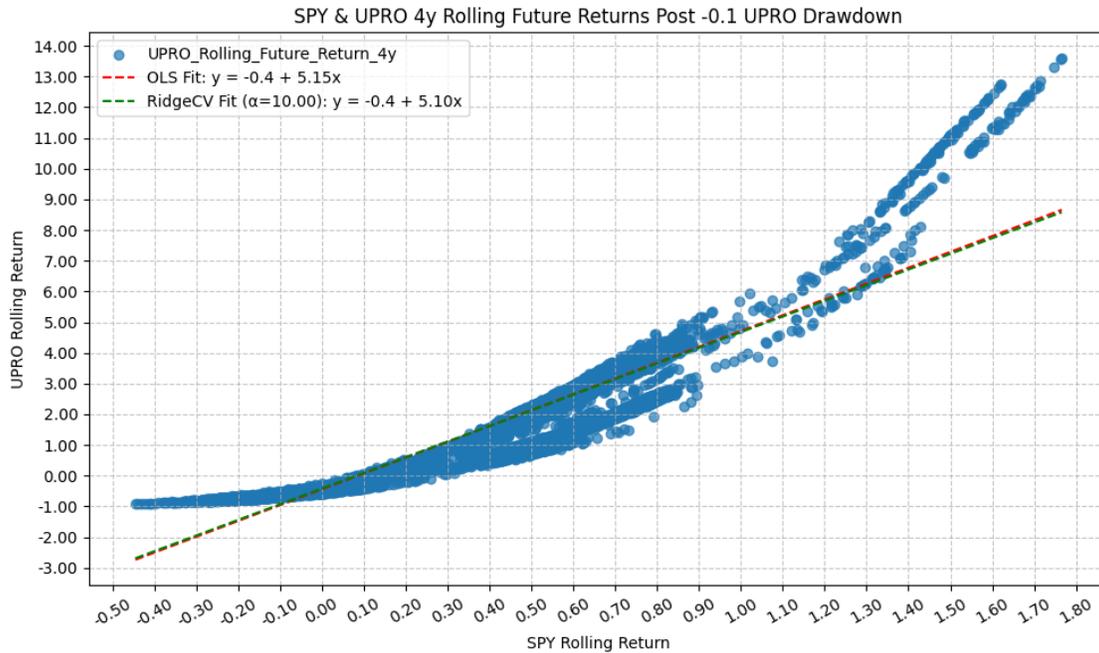
-0.171	-0.134				
SPY_Rolling_Future_Return_3y	4.1206	0.022	189.528	0.000	
4.078	4.163				

Omnibus:	1530.432	Durbin-Watson:	0.011
Prob(Omnibus):	0.000	Jarque-Bera (JB):	4862.520
Skew:	1.335	Prob(JB):	0.00
Kurtosis:	6.601	Cond. No.	3.30

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_4y    R-squared:
0.849
Model:                  OLS                            Adj. R-squared:
0.849
Method:                 Least Squares                 F-statistic:
3.112e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:17                      Log-Likelihood:
-7257.5
No. Observations:      5557                          AIC:
1.452e+04
Df Residuals:          5555                          BIC:
1.453e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.4417    0.016   -27.325    0.000

```

-0.473 -0.410
 SPY_Rolling_Future_Return_4y 5.1530 0.029 176.414 0.000
 5.096 5.210

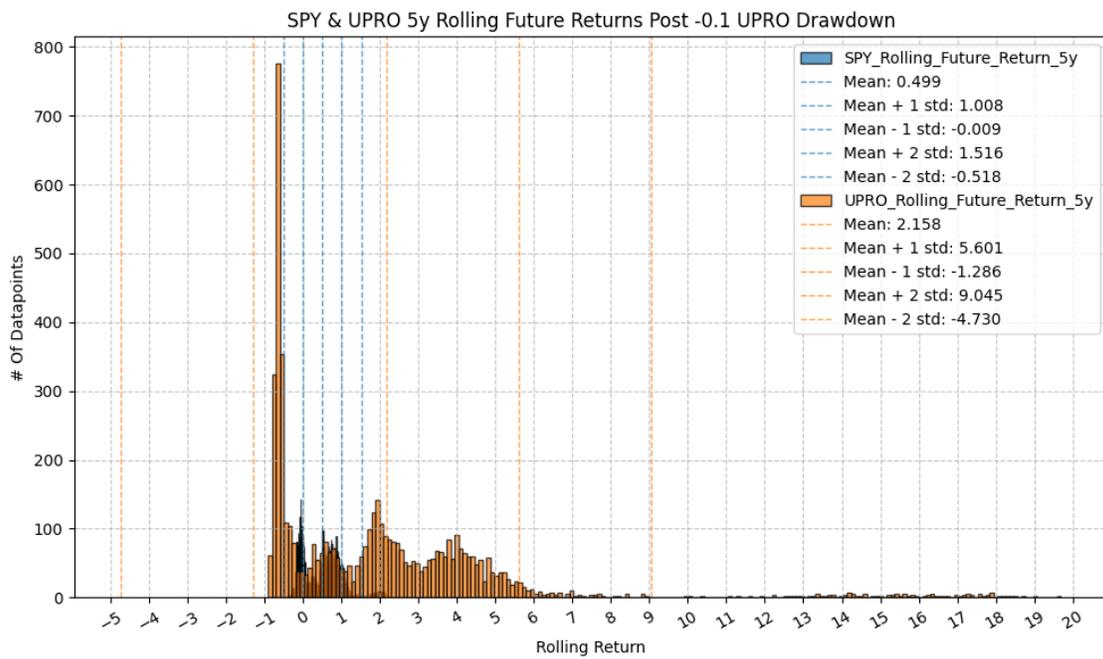
```
=====
```

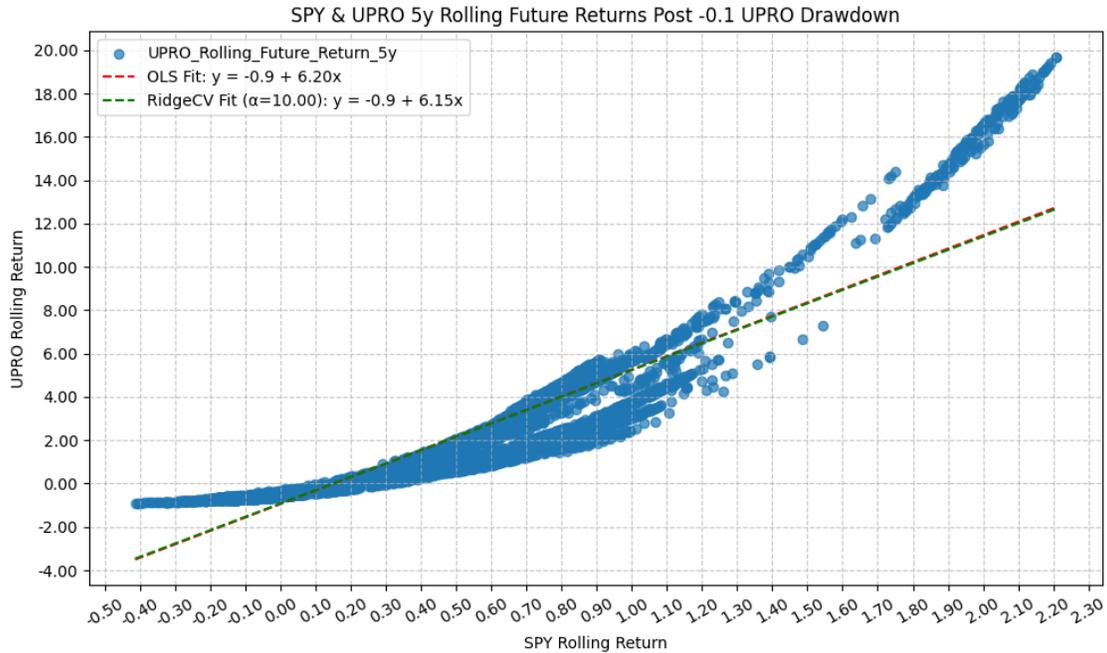
Omnibus:	1907.776	Durbin-Watson:	0.013
Prob(Omnibus):	0.000	Jarque-Bera (JB):	10169.158
Skew:	1.554	Prob(JB):	0.00
Kurtosis:	8.853	Cond. No.	2.83

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_5y    R-squared:
0.838
Model:                  OLS                            Adj. R-squared:
0.838
Method:                 Least Squares                 F-statistic:
2.842e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:18                     Log-Likelihood:
-9617.9
No. Observations:      5508                          AIC:
1.924e+04
Df Residuals:          5506                          BIC:
1.925e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.9357    0.026    -35.724    0.000

```

-0.987	-0.884				
SPY_Rolling_Future_Return_5y	6.1980	0.037	168.589	0.000	
6.126	6.270				

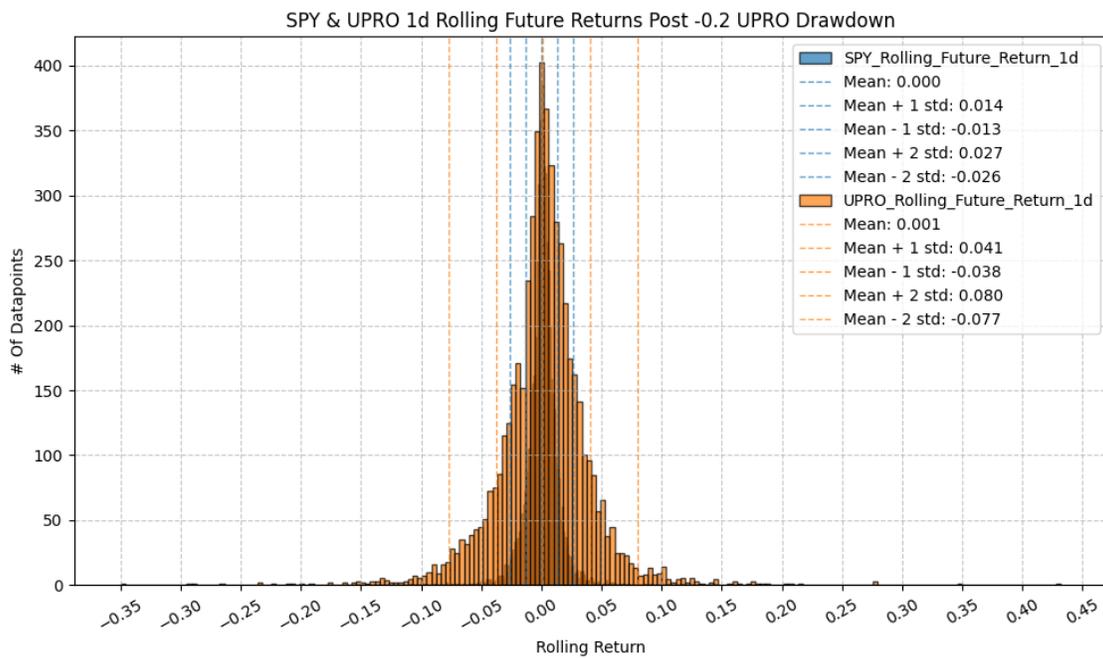
```
=====
```

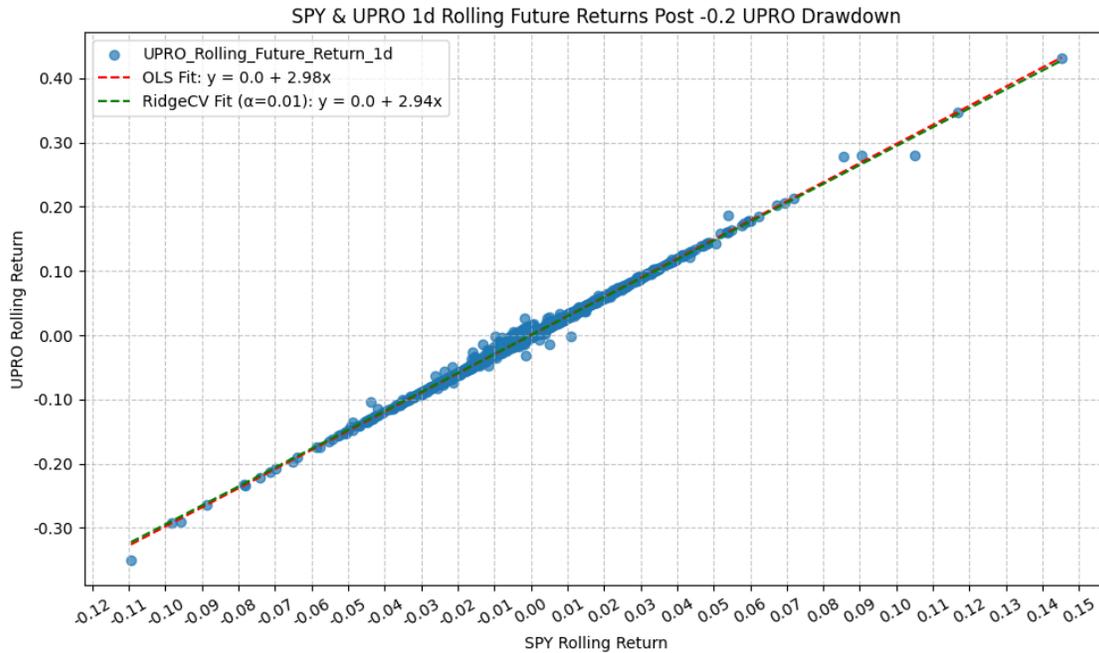
Omnibus:	1244.876	Durbin-Watson:	0.010
Prob(Omnibus):	0.000	Jarque-Bera (JB):	4373.621
Skew:	1.109	Prob(JB):	0.00
Kurtosis:	6.760	Cond. No.	2.58

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1d    R-squared:
0.997
Model:                  OLS                            Adj. R-squared:
0.997
Method:                 Least Squares                 F-statistic:
1.837e+06
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:19                     Log-Likelihood:
25121.
No. Observations:      5293                          AIC:
-5.024e+04
Df Residuals:          5291                          BIC:
-5.023e+04
Df Model:              1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                3.561e-05    2.89e-05     1.232    0.218

```

-2.11e-05 9.23e-05
 SPY_Rolling_Future_Return_1d 2.9772 0.002 1355.226 0.000
 2.973 2.981

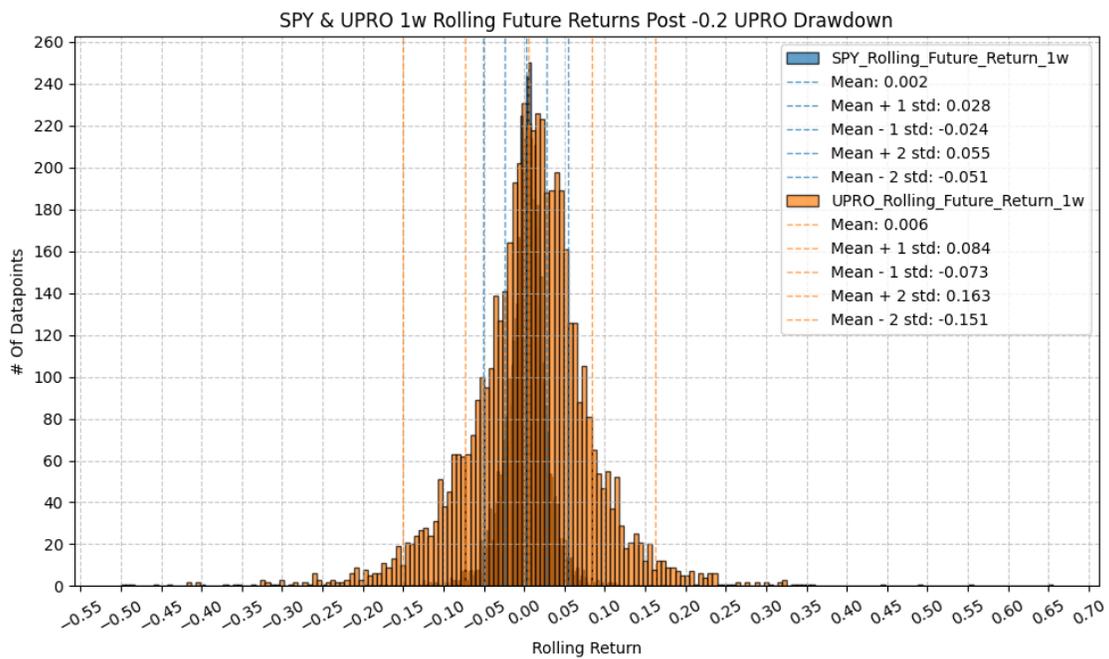
```
=====
```

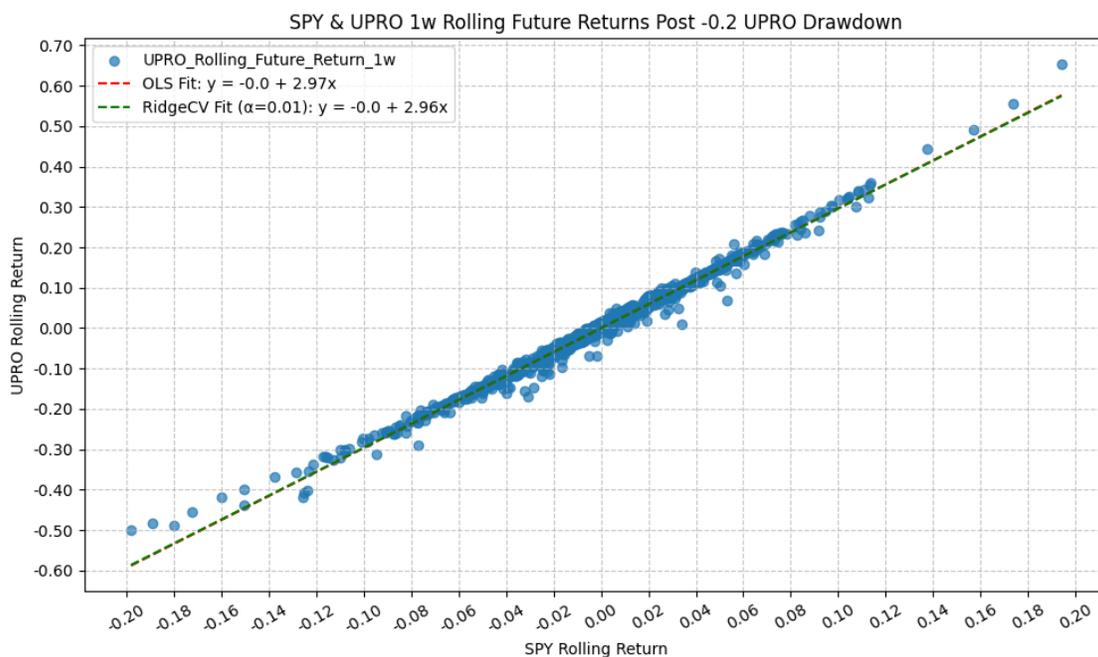
Omnibus:	3682.706	Durbin-Watson:	2.648
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1787435.938
Skew:	2.082	Prob(JB):	0.00
Kurtosis:	92.930	Cond. No.	76.0

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_1w    R-squared:
0.993
Model:              OLS                            Adj. R-squared:
0.993
Method:             Least Squares                  F-statistic:
7.714e+05
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:               14:28:20                        Log-Likelihood:
19160.
No. Observations:  5293                            AIC:
-3.832e+04
Df Residuals:      5291                            BIC:
-3.830e+04
Df Model:           1
Covariance Type:   nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0002    8.94e-05    -2.240    0.025

```

-0.000 -2.5e-05
 SPY_Rolling_Future_Return_1w 2.9708 0.003 878.276 0.000
 2.964 2.977

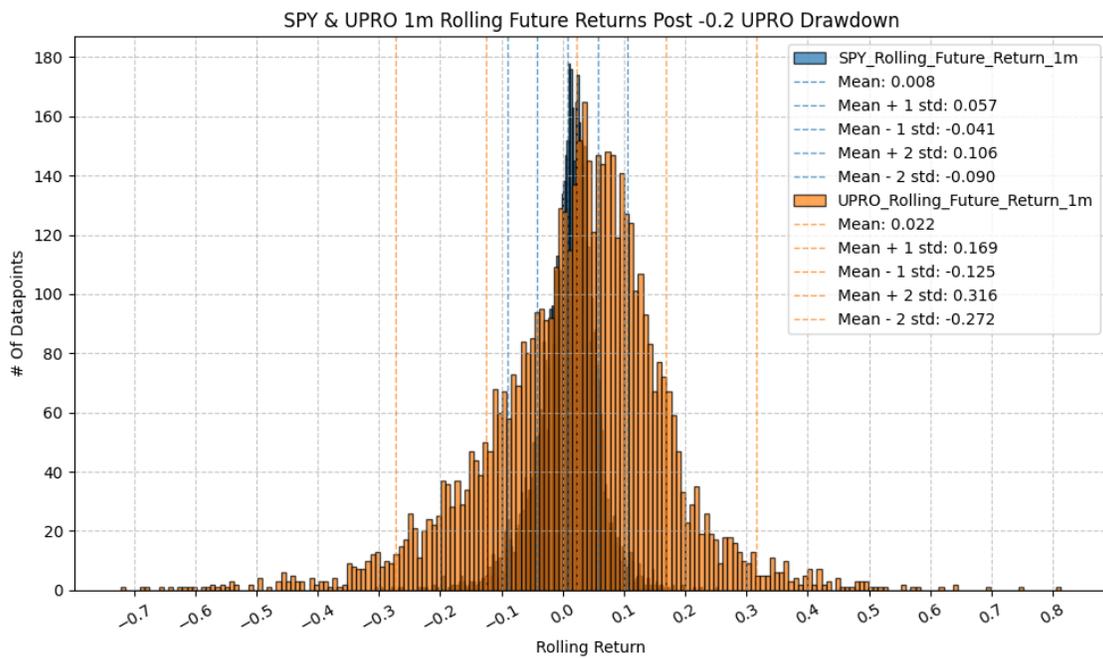
```
=====
```

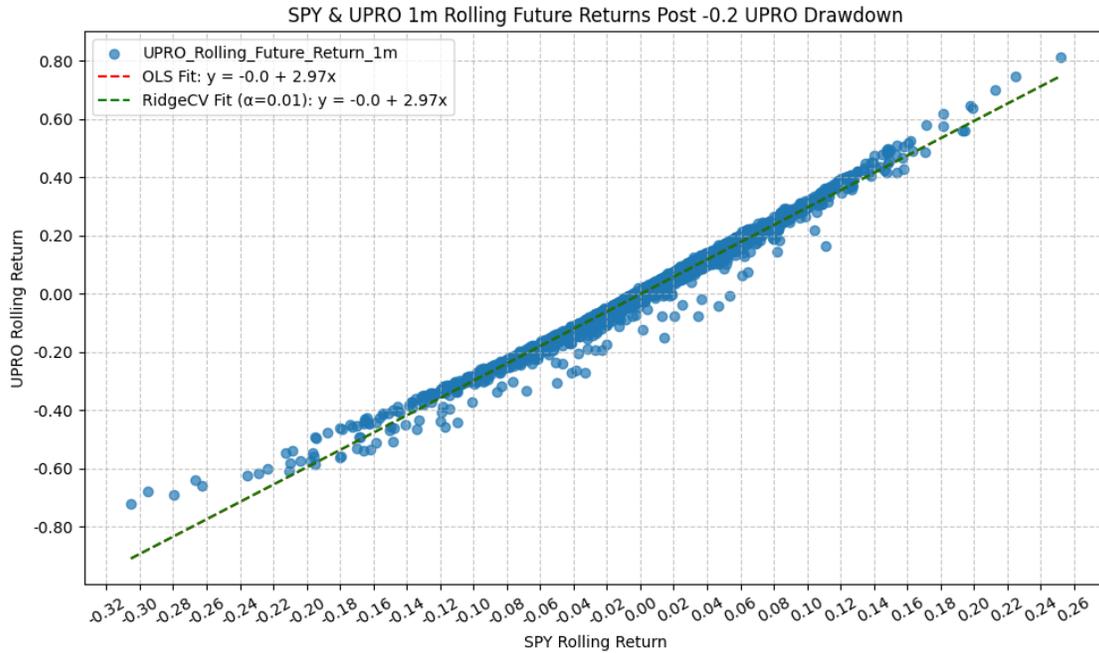
Omnibus:	2333.089	Durbin-Watson:	0.986
Prob(Omnibus):	0.000	Jarque-Bera (JB):	564965.860
Skew:	-0.921	Prob(JB):	0.00
Kurtosis:	53.580	Cond. No.	38.0

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1m    R-squared:
0.987
Model:                  OLS                            Adj. R-squared:
0.987
Method:                 Least Squares                 F-statistic:
4.024e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:21                      Log-Likelihood:
14137.
No. Observations:      5293                          AIC:
-2.827e+04
Df Residuals:          5291                          BIC:
-2.826e+04
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0014    0.000       -6.033    0.000

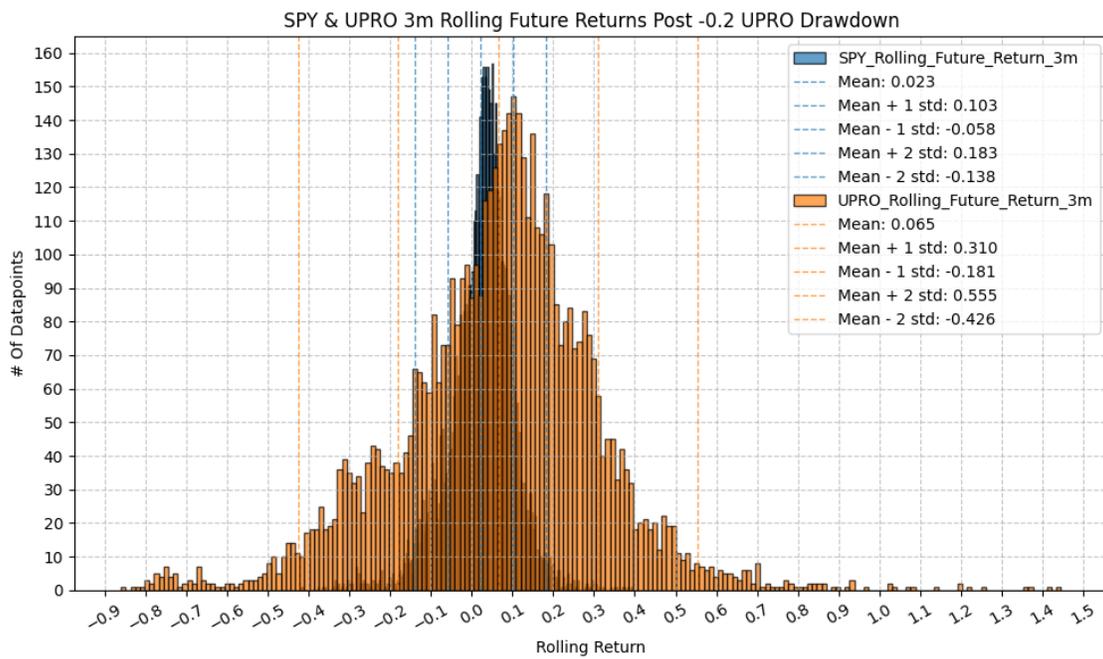
```

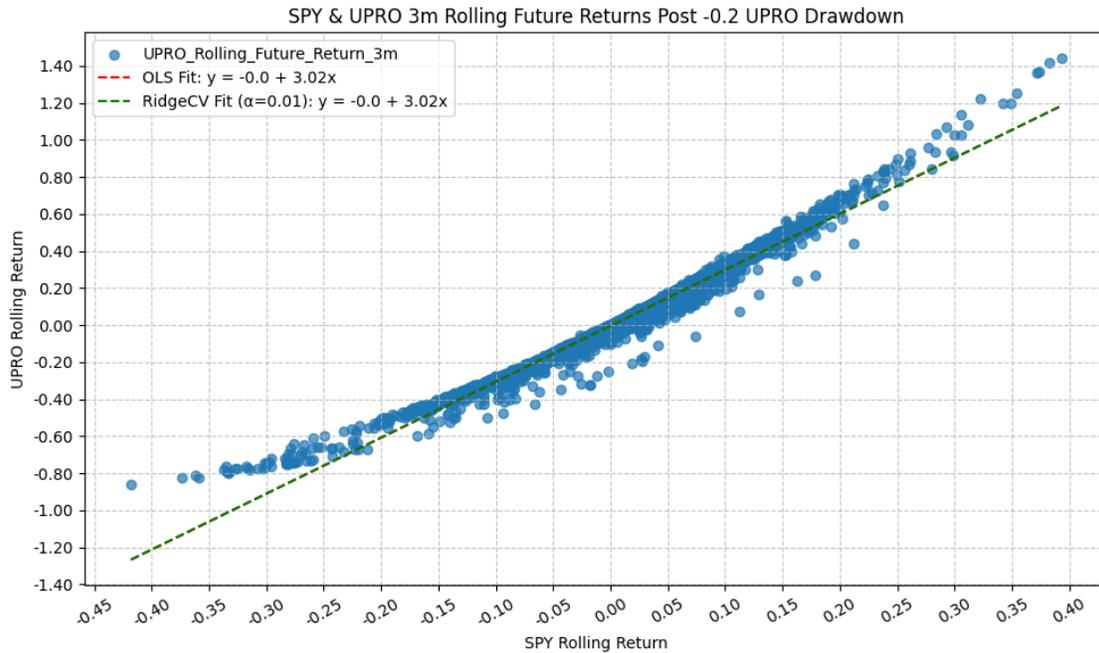
-0.002	-0.001				
SPY_Rolling_Future_Return_1m	2.9716	0.005	634.375	0.000	
2.962	2.981				

```
=====
Omnibus:                2857.215    Durbin-Watson:           0.332
Prob(Omnibus):          0.000    Jarque-Bera (JB):       280080.687
Skew:                   -1.658    Prob(JB):                0.00
Kurtosis:               38.482    Cond. No.                20.4
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3m    R-squared:
0.977
Model:                  OLS                            Adj. R-squared:
0.977
Method:                 Least Squares                 F-statistic:
2.274e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:23                     Log-Likelihood:
9942.2
No. Observations:      5293                          AIC:
-1.988e+04
Df Residuals:          5291                          BIC:
-1.987e+04
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0036    0.001     -6.764    0.000

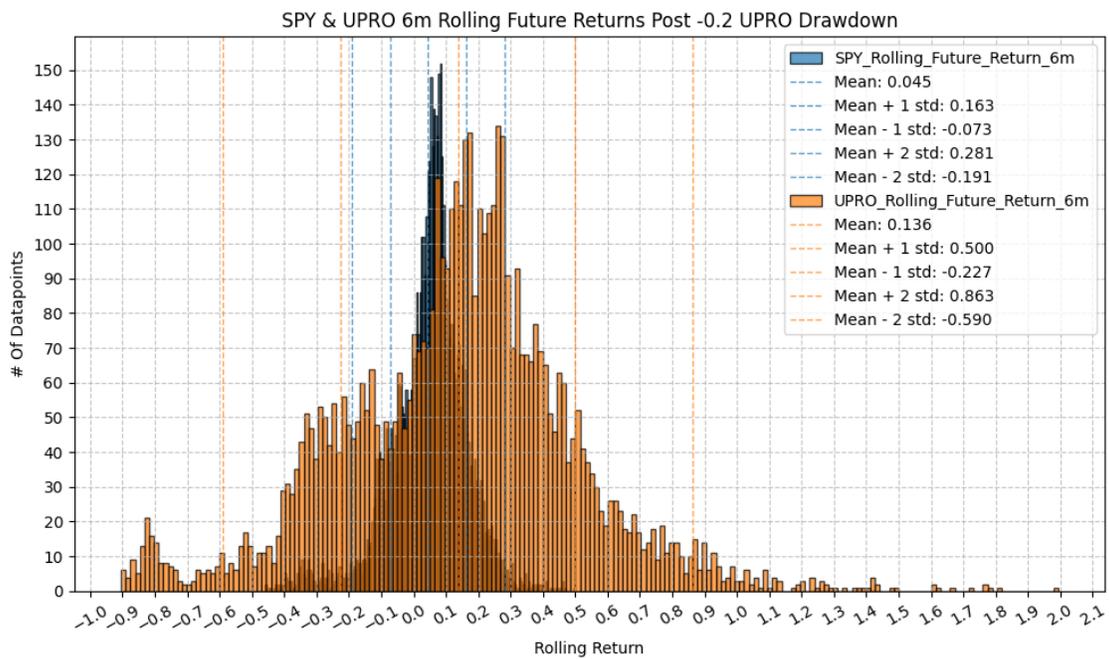
```

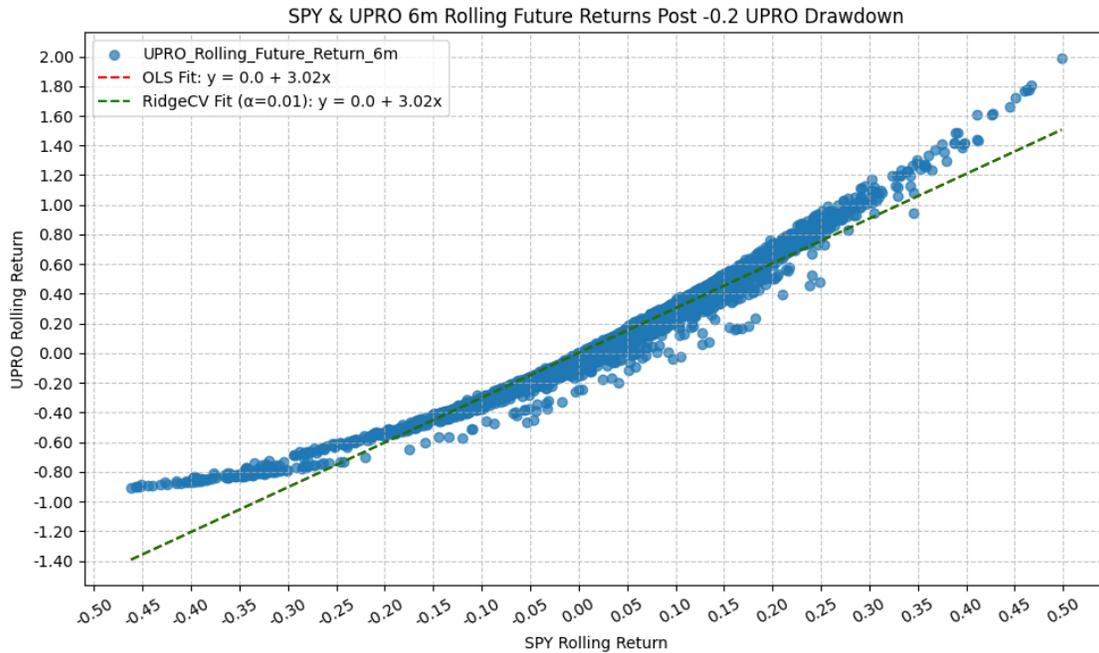
-0.005	-0.003				
SPY_Rolling_Future_Return_3m	3.0230	0.006	476.832	0.000	
3.011	3.035				

```
=====
Omnibus:                1416.233    Durbin-Watson:           0.159
Prob(Omnibus):          0.000    Jarque-Bera (JB):       70537.930
Skew:                   0.467    Prob(JB):                0.00
Kurtosis:               20.860    Cond. No.                12.5
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_6m    R-squared:
0.960
Model:                  OLS                            Adj. R-squared:
0.960
Method:                 Least Squares                 F-statistic:
1.281e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:24                      Log-Likelihood:
6392.3
No. Observations:      5293                          AIC:
-1.278e+04
Df Residuals:          5291                          BIC:
-1.277e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                0.0016    0.001        1.525    0.127
=====

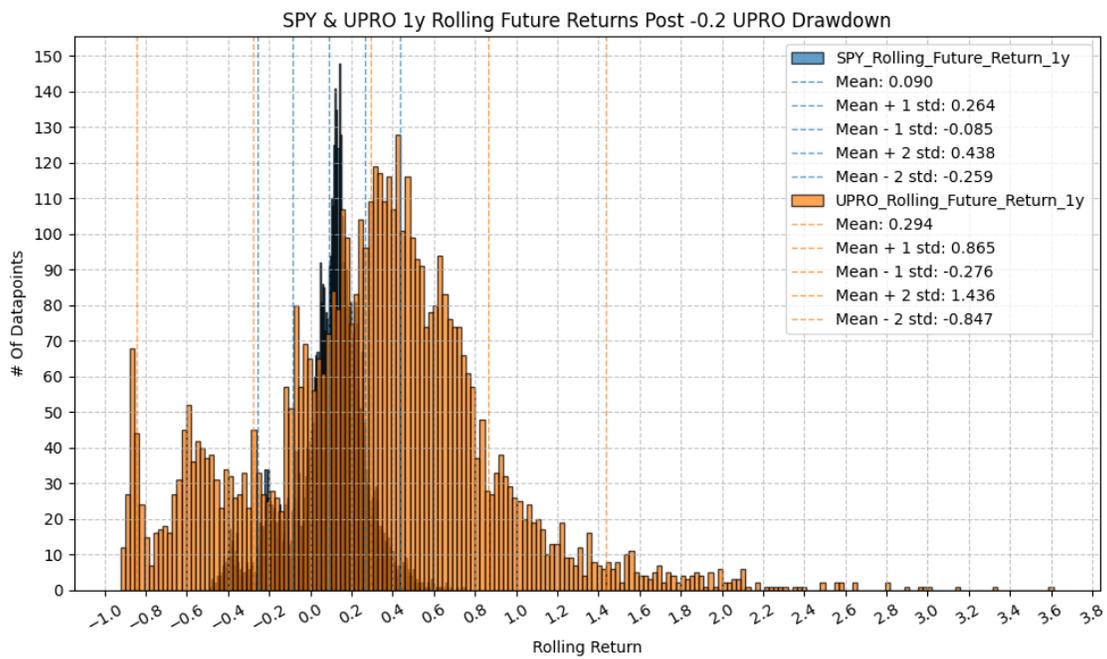
```

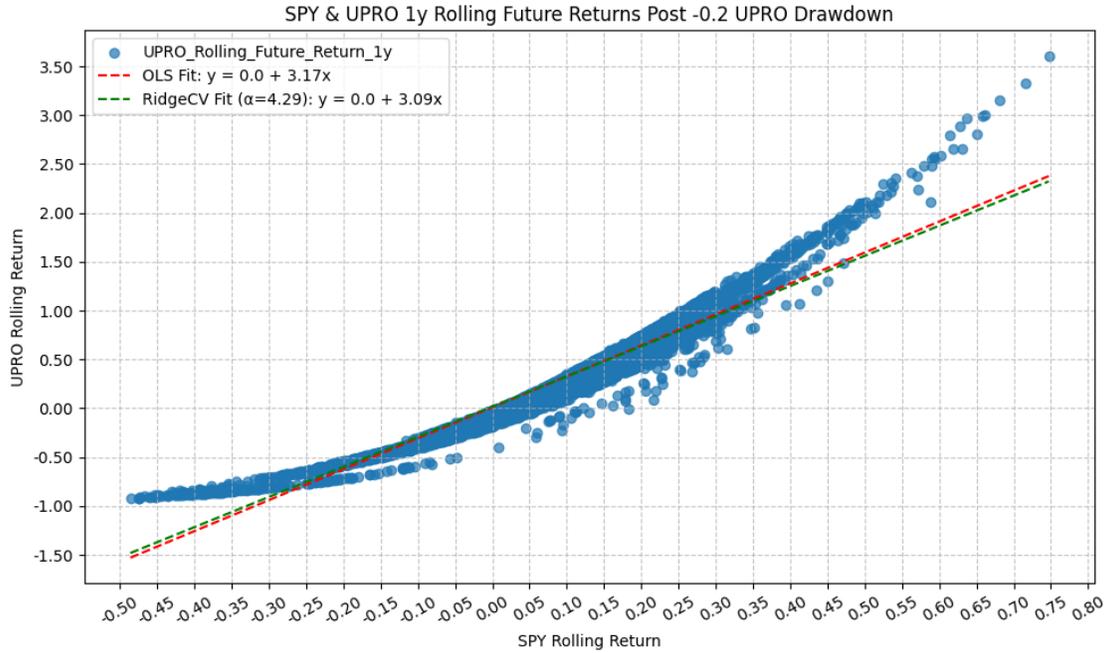
-0.000	0.004				
SPY_Rolling_Future_Return_6m	3.0177	0.008	357.941	0.000	
3.001	3.034				

Omnibus:	1752.103	Durbin-Watson:	0.078
Prob(Omnibus):	0.000	Jarque-Bera (JB):	16365.764
Skew:	1.309	Prob(JB):	0.00
Kurtosis:	11.207	Cond. No.	8.50

Notes:

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





OLS Regression Results

=====

```

Dep. Variable:      UPRO_Rolling_Future_Return_1y    R-squared:
0.937
Model:              OLS                            Adj. R-squared:
0.937
Method:            Least Squares                   F-statistic:
7.757e+04
Date:              Mon, 16 Mar 2026                 Prob (F-statistic):
0.00
Time:              14:28:25                         Log-Likelihood:
2737.3
No. Observations: 5248                             AIC:
-5471.
Df Residuals:     5246                             BIC:
-5457.
Df Model:         1
Covariance Type:  nonrobust

```

=====

	coef	std err	t	P> t
[0.025 0.975]				
const	0.0101	0.002	4.550	0.000

0.006	0.015				
SPY_Rolling_Future_Return_1y	3.1690	0.011	278.518	0.000	
3.147	3.191				

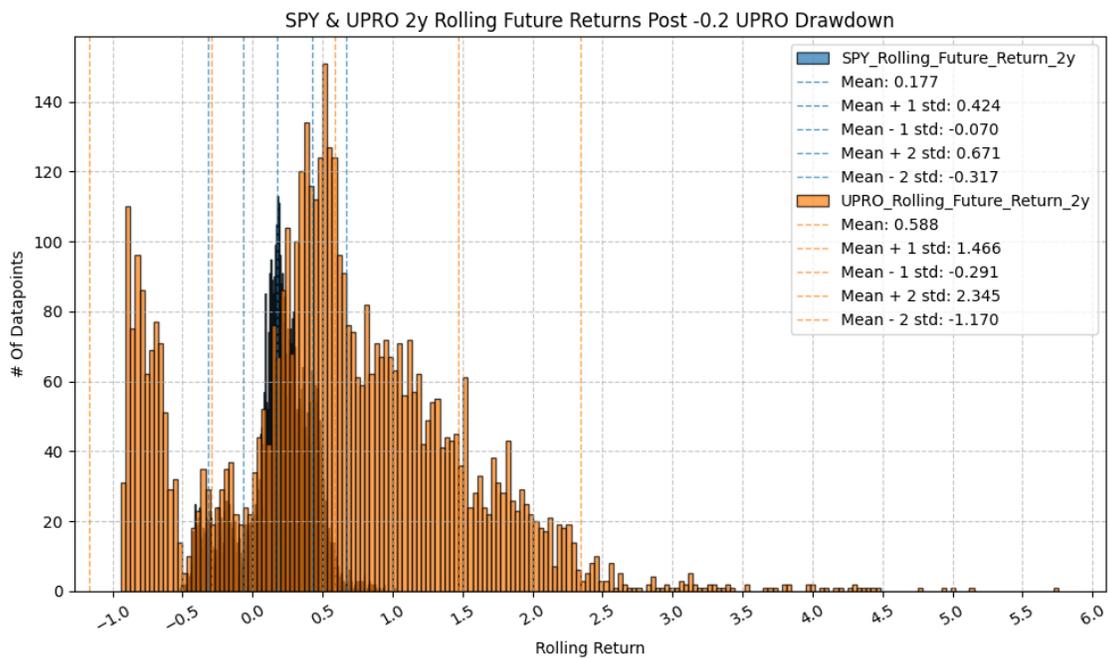
```

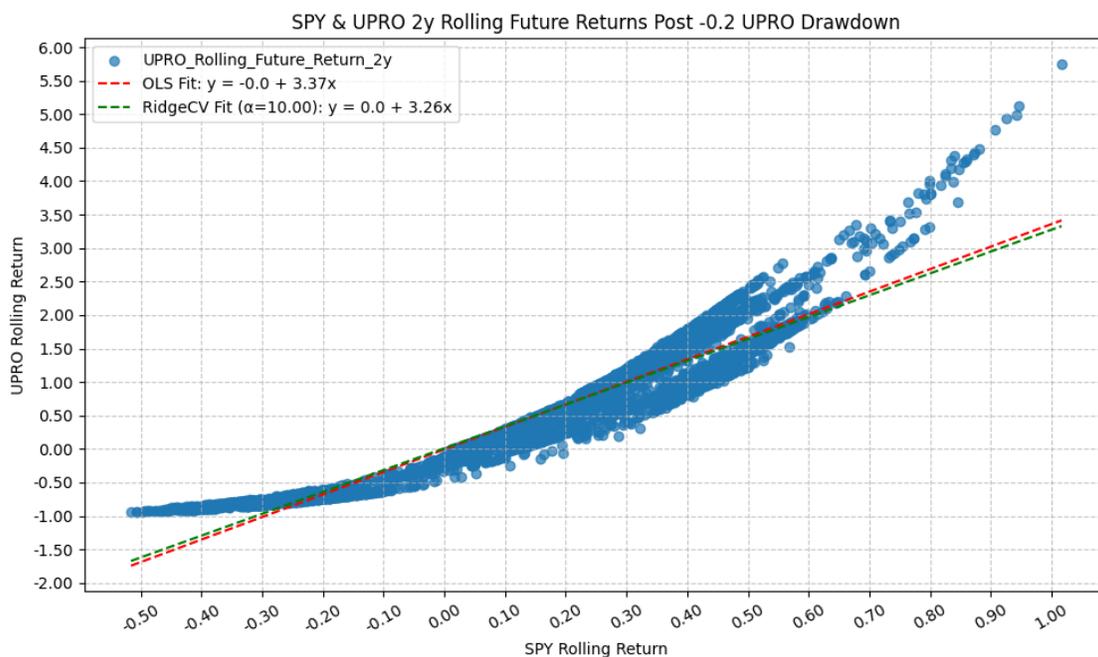
=====
Omnibus:                1724.713    Durbin-Watson:           0.051
Prob(Omnibus):          0.000    Jarque-Bera (JB):       9895.182
Skew:                   1.453    Prob(JB):                0.00
Kurtosis:               9.066    Cond. No.                5.79
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_2y    R-squared:
0.895
Model:                  OLS                            Adj. R-squared:
0.895
Method:                 Least Squares                 F-statistic:
4.481e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:26                     Log-Likelihood:
-840.74
No. Observations:      5235                          AIC:
1685.
Df Residuals:          5233                          BIC:
1699.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0069    0.005      -1.420    0.156

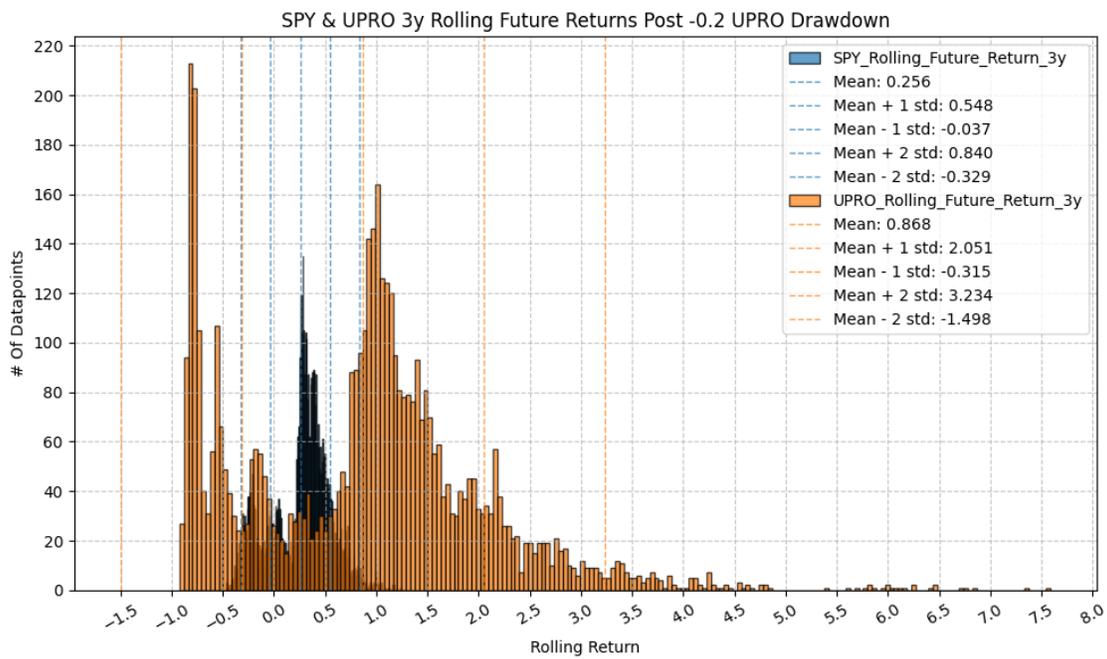
```

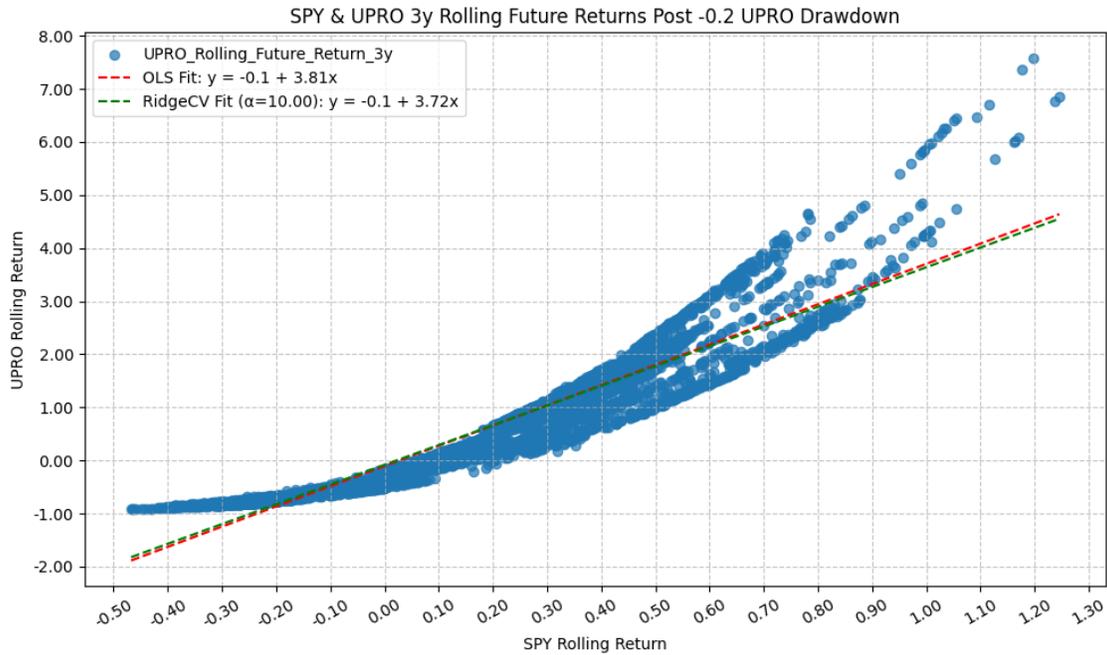
-0.016	0.003				
SPY_Rolling_Future_Return_2y	3.3654	0.016	211.679	0.000	
3.334	3.397				

Omnibus:	1350.050	Durbin-Watson:	0.031
Prob(Omnibus):	0.000	Jarque-Bera (JB):	4692.366
Skew:	1.271	Prob(JB):	0.00
Kurtosis:	6.879	Cond. No.	4.18

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3y    R-squared:
0.885
Model:                  OLS                            Adj. R-squared:
0.885
Method:                 Least Squares                  F-statistic:
3.849e+04
Date:                   Mon, 16 Mar 2026               Prob (F-statistic):
0.00
Time:                   14:28:27                       Log-Likelihood:
-2524.0
No. Observations:      4998                            AIC:
5052.
Df Residuals:          4996                            BIC:
5065.
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

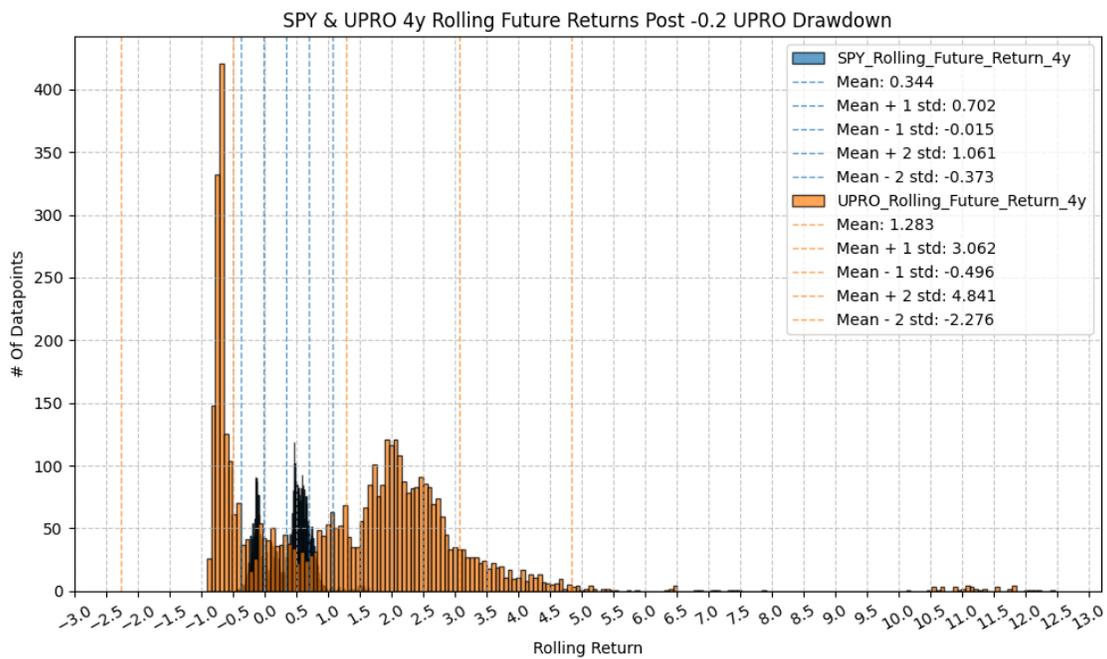
	coef	std err	t	P> t
[0.025 0.975]				
const	-0.1052	0.008	-13.955	0.000

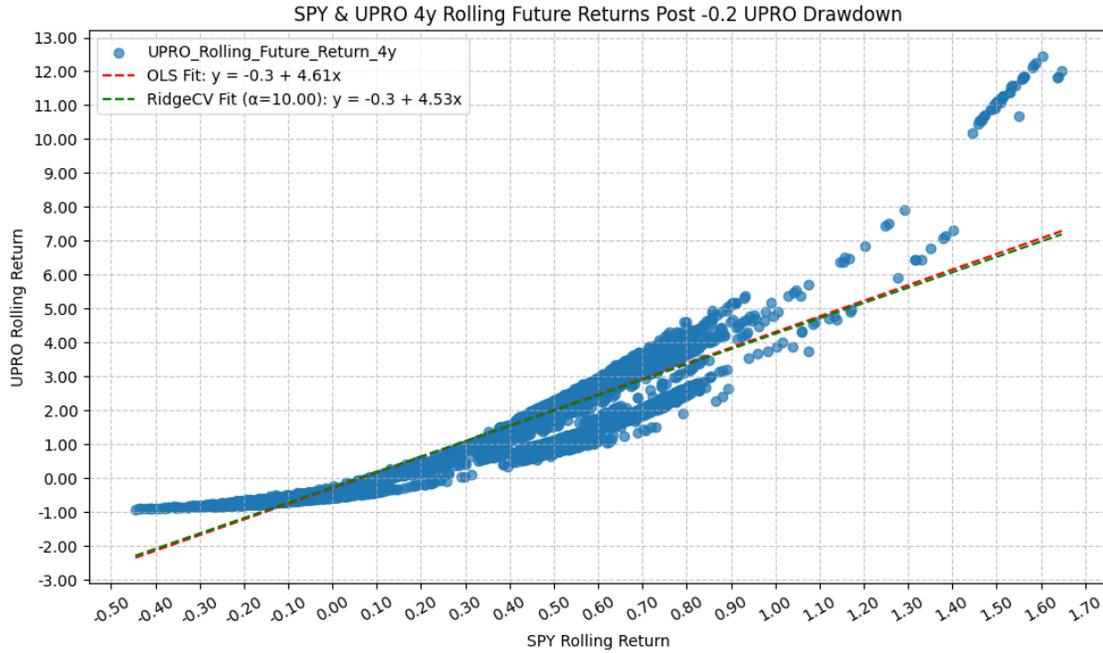
-0.120	-0.090				
SPY_Rolling_Future_Return_3y	3.8081	0.019	196.192	0.000	
3.770	3.846				

```
=====
Omnibus:                1497.695   Durbin-Watson:           0.020
Prob(Omnibus):          0.000     Jarque-Bera (JB):       8214.199
Skew:                   1.324     Prob(JB):                0.00
Kurtosis:               8.695     Cond. No.                3.66
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_4y    R-squared:
0.862
Model:                  OLS                            Adj. R-squared:
0.862
Method:                 Least Squares                 F-statistic:
2.963e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:28                     Log-Likelihood:
-4784.4
No. Observations:      4757                          AIC:
9573.
Df Residuals:          4755                          BIC:
9586.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

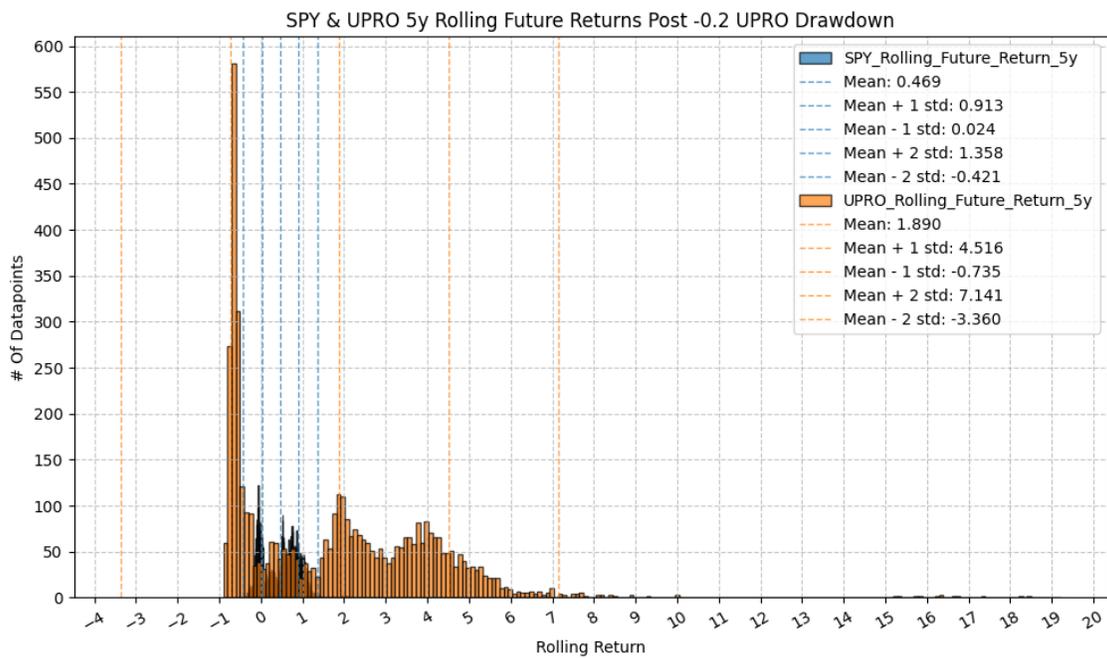
const	-0.3002	0.013	-22.587	0.000

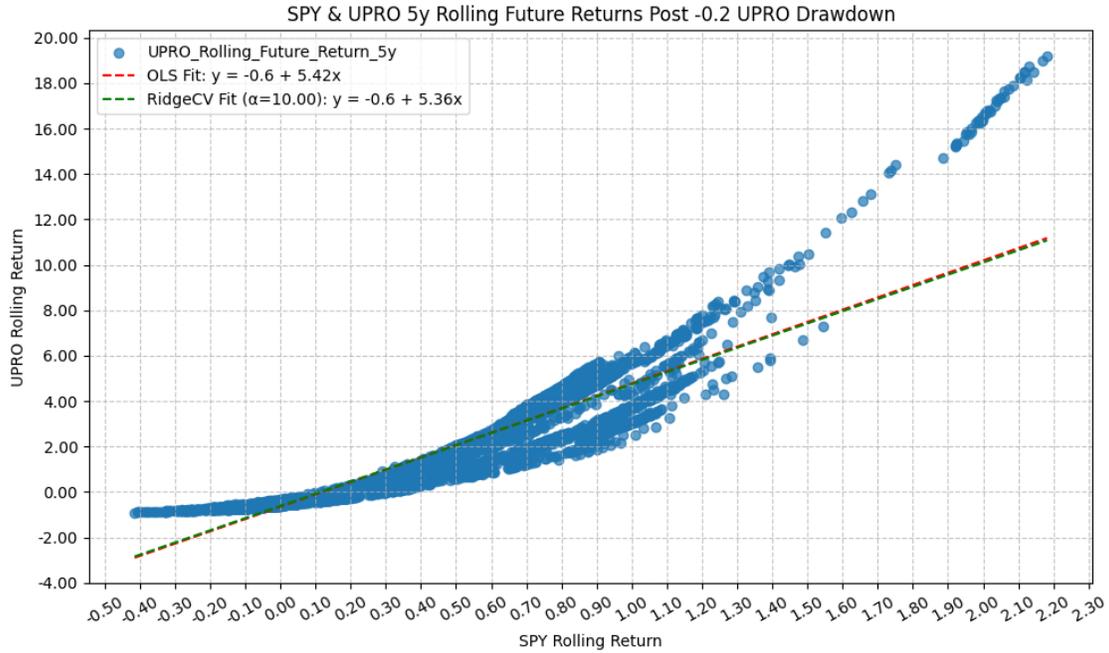
-0.326 -0.274
 SPY_Rolling_Future_Return_4y 4.6068 0.027 172.137 0.000
 4.554 4.659

```
=====
Omnibus:                                    2932.099      Durbin-Watson:                                    0.020
Prob(Omnibus):                              0.000      Jarque-Bera (JB):                                    69932.785
Skew:                                        2.518      Prob(JB):                                            0.00
Kurtosis:                                    21.096      Cond. No.                                            3.16
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_5y    R-squared:
0.842
Model:                  OLS                            Adj. R-squared:
0.842
Method:                 Least Squares                 F-statistic:
2.529e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:30                      Log-Likelihood:
-6916.8
No. Observations:      4736                          AIC:
1.384e+04
Df Residuals:          4734                          BIC:
1.385e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.6492    0.022   -29.490    0.000

```

-0.692 -0.606
 SPY_Rolling_Future_Return_5y 5.4202 0.034 159.020 0.000
 5.353 5.487

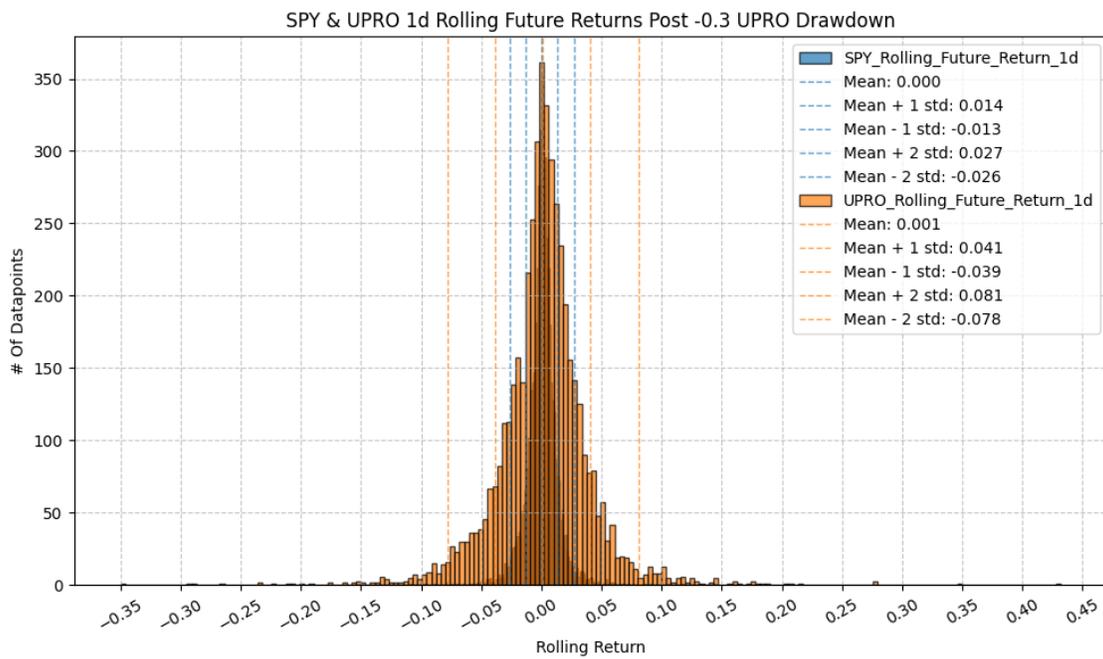
```
=====
```

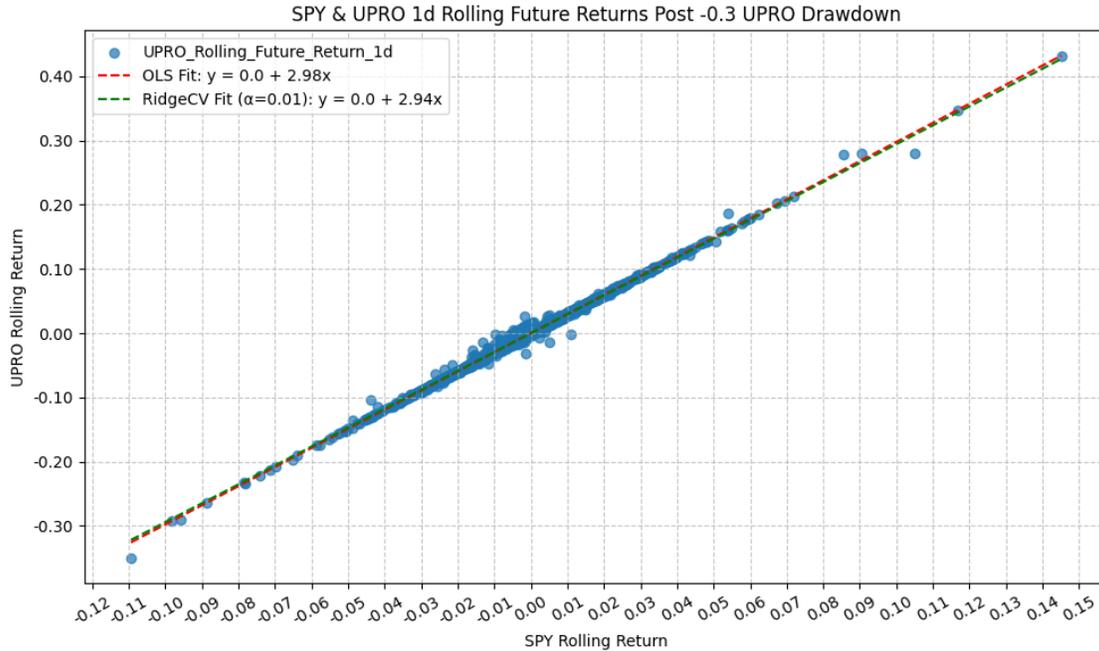
Omnibus:	2512.987	Durbin-Watson:	0.026
Prob(Omnibus):	0.000	Jarque-Bera (JB):	40989.263
Skew:	2.157	Prob(JB):	0.00
Kurtosis:	16.751	Cond. No.	2.84

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1d    R-squared:
0.997
Model:                  OLS                            Adj. R-squared:
0.997
Method:                 Least Squares                 F-statistic:
1.595e+06
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:31                      Log-Likelihood:
22509.
No. Observations:      4774                          AIC:
-4.501e+04
Df Residuals:          4772                          BIC:
-4.500e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

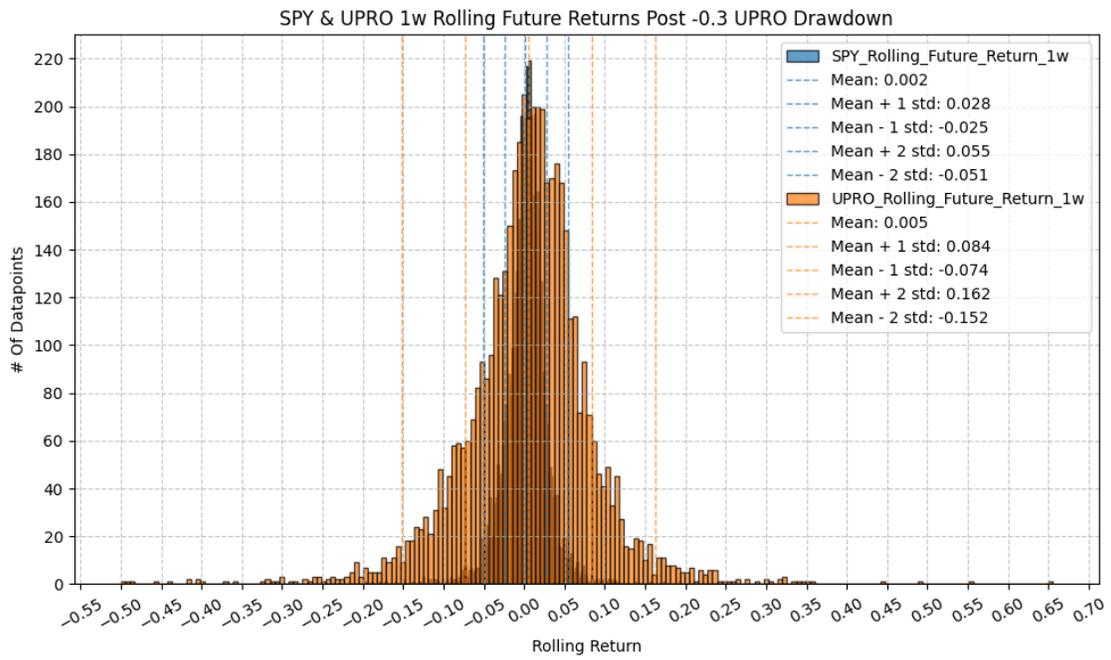
=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                4.7e-05    3.14e-05    1.497    0.135

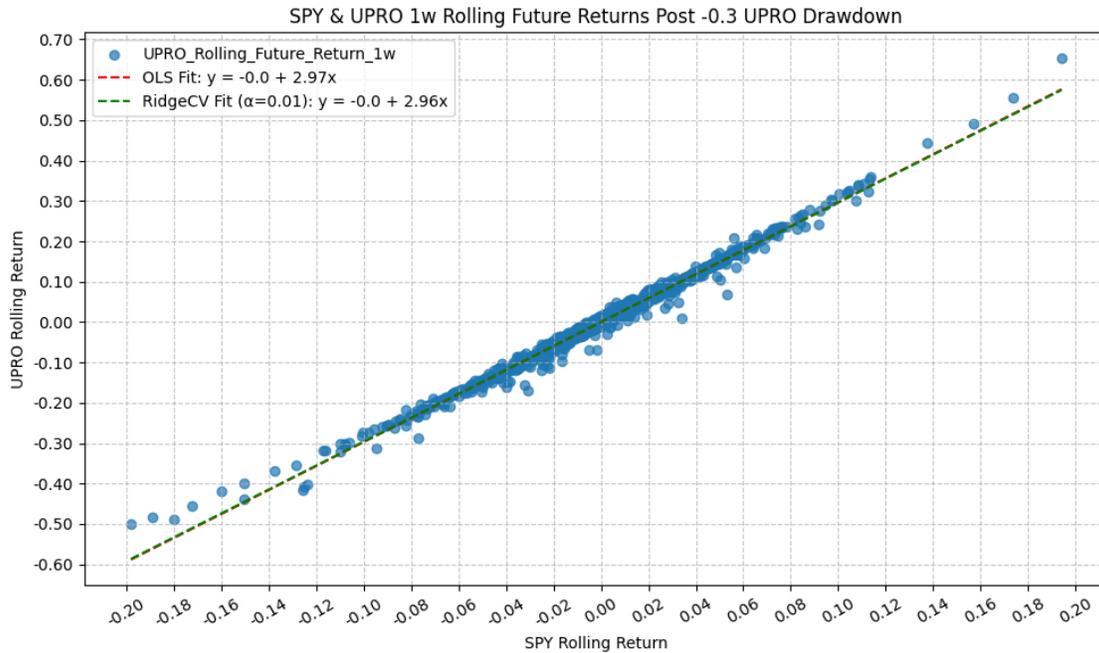
```

-1.46e-05	0.000				
SPY_Rolling_Future_Return_1d	2.9768	0.002	1263.103	0.000	
2.972	2.981				
=====					
Omnibus:	3250.843	Durbin-Watson:		2.668	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		1511414.470	
Skew:	2.004	Prob(JB):		0.00	
Kurtosis:	90.076	Cond. No.		75.1	
=====					

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1w    R-squared:
0.993
Model:                  OLS                            Adj. R-squared:
0.993
Method:                 Least Squares                 F-statistic:
6.655e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:32                      Log-Likelihood:
17170.
No. Observations:      4774                          AIC:
-3.434e+04
Df Residuals:          4772                          BIC:
-3.432e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0002    9.63e-05    -1.929    0.054

```

-0.000 2.99e-06
 SPY_Rolling_Future_Return_1w 2.9716 0.004 815.801 0.000
 2.964 2.979

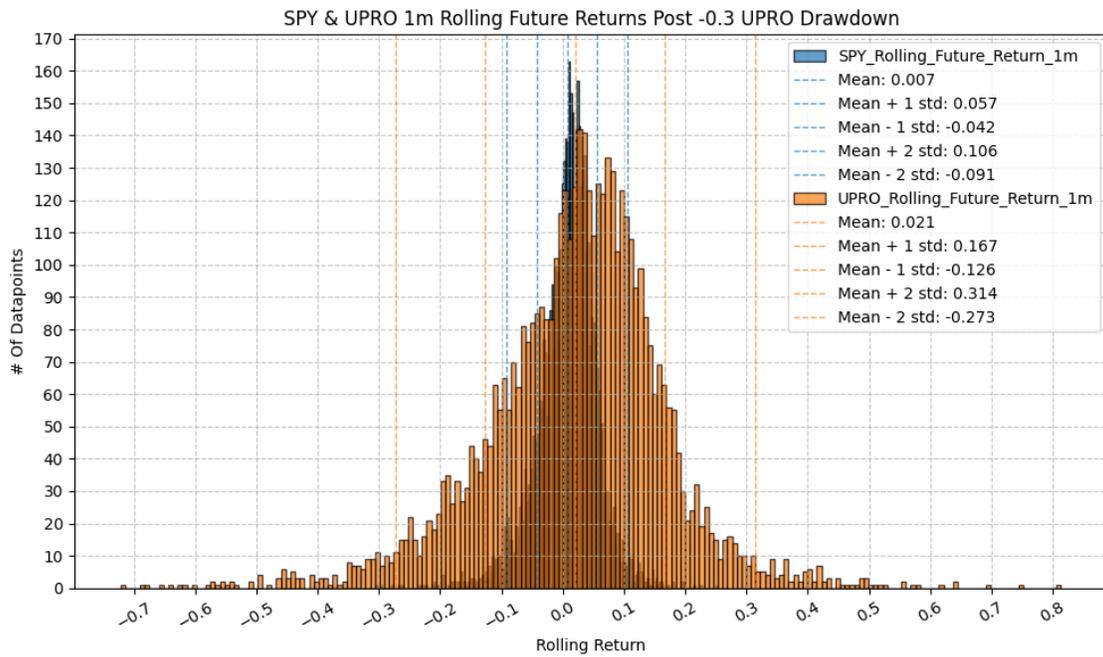
```
=====
```

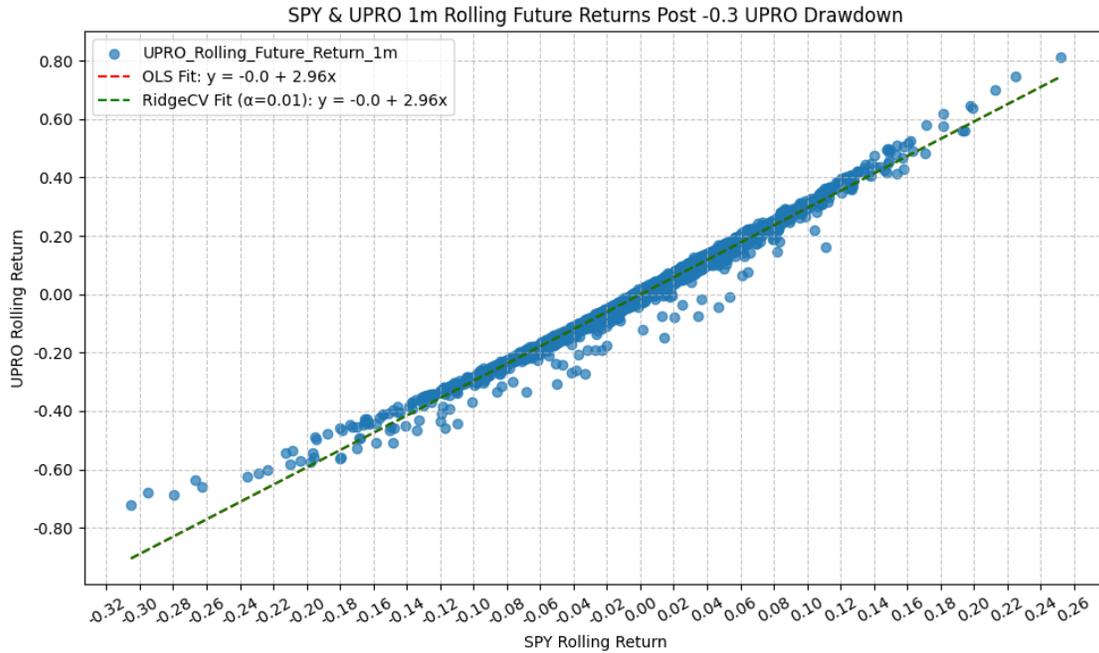
Omnibus:	1997.752	Durbin-Watson:	0.986
Prob(Omnibus):	0.000	Jarque-Bera (JB):	483400.223
Skew:	-0.802	Prob(JB):	0.00
Kurtosis:	52.271	Cond. No.	37.9

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1m    R-squared:
0.987
Model:                  OLS                            Adj. R-squared:
0.987
Method:                 Least Squares                  F-statistic:
3.515e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:33                      Log-Likelihood:
12680.
No. Observations:      4774                          AIC:
-2.536e+04
Df Residuals:          4772                          BIC:
-2.534e+04
Df Model:              1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0011    0.000        -4.428    0.000

```

```

-0.002      -0.001
SPY_Rolling_Future_Return_1m      2.9621      0.005      592.897      0.000
2.952      2.972

```

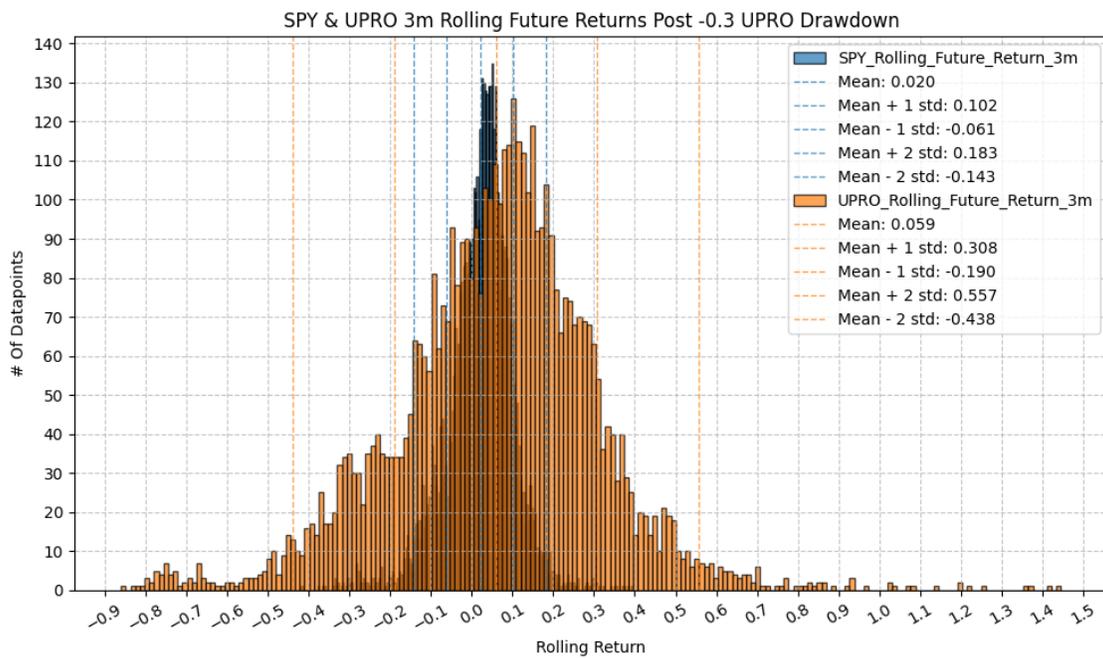
```

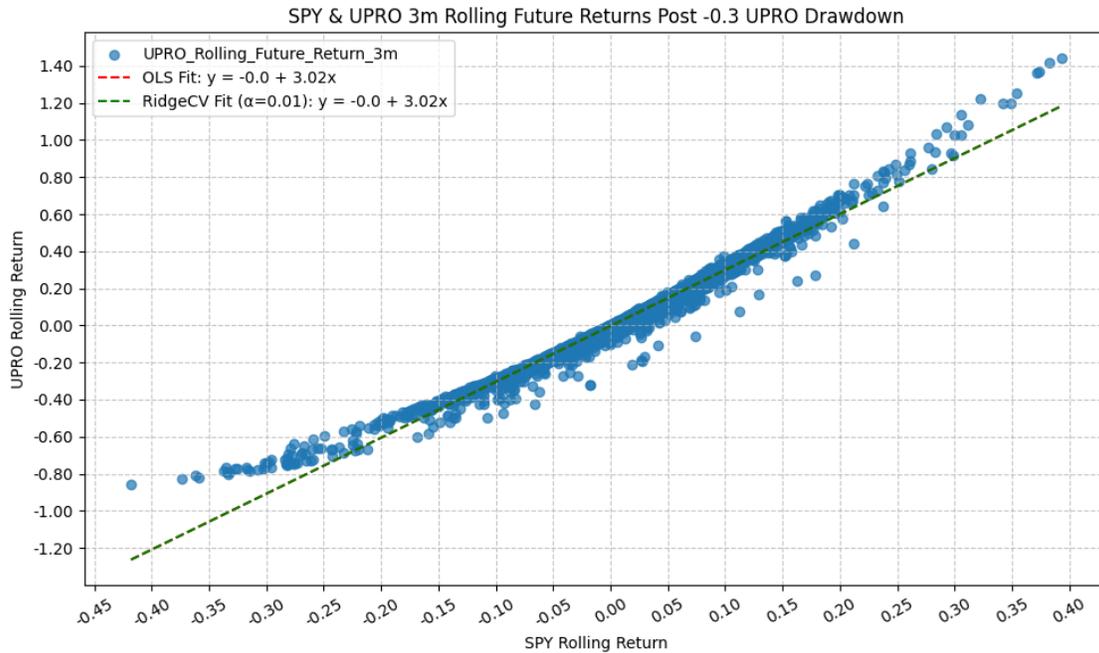
=====
Omnibus:                2677.436      Durbin-Watson:                0.336
Prob(Omnibus):          0.000      Jarque-Bera (JB):            262814.760
Skew:                   -1.764      Prob(JB):                    0.00
Kurtosis:               39.177      Cond. No.                    20.3
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3m    R-squared:
0.978
Model:                  OLS                            Adj. R-squared:
0.978
Method:                 Least Squares                 F-statistic:
2.123e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:34                      Log-Likelihood:
8982.1
No. Observations:      4774                          AIC:
-1.796e+04
Df Residuals:          4772                          BIC:
-1.795e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0024    0.001    -4.439    0.000

```

-0.004	-0.001				
SPY_Rolling_Future_Return_3m	3.0171	0.007	460.794	0.000	
3.004	3.030				

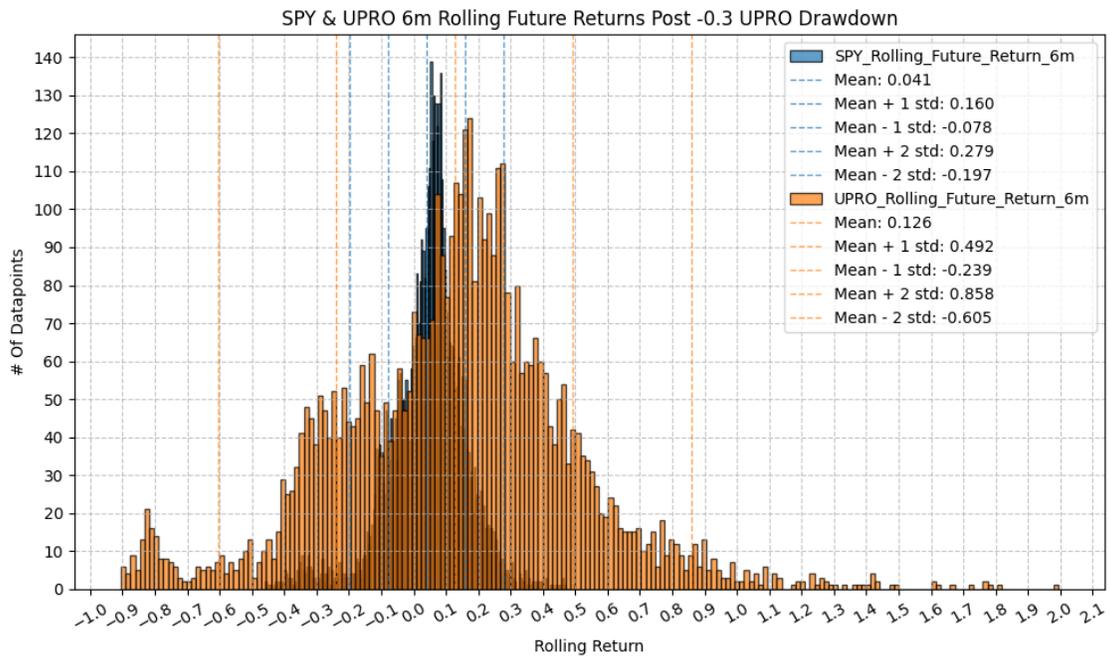
```

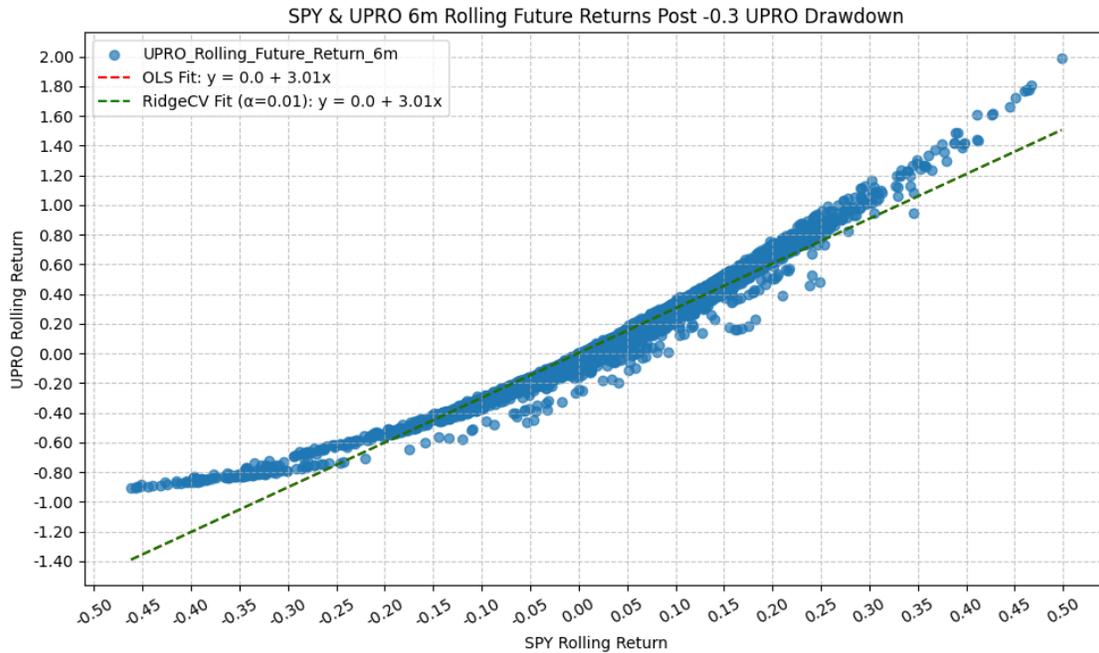
=====
Omnibus:                1429.012    Durbin-Watson:           0.169
Prob(Omnibus):          0.000    Jarque-Bera (JB):       68304.492
Skew:                   0.660    Prob(JB):                0.00
Kurtosis:               21.483    Cond. No.                12.3
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_6m    R-squared:
0.960
Model:                  OLS                            Adj. R-squared:
0.960
Method:                 Least Squares                  F-statistic:
1.138e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:36                      Log-Likelihood:
5697.0
No. Observations:      4774                          AIC:
-1.139e+04
Df Residuals:          4772                          BIC:
-1.138e+04
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                0.0029    0.001    2.542    0.011
=====

```

0.001	0.005				
SPY_Rolling_Future_Return_6m	3.0135	0.009	337.350	0.000	
2.996	3.031				

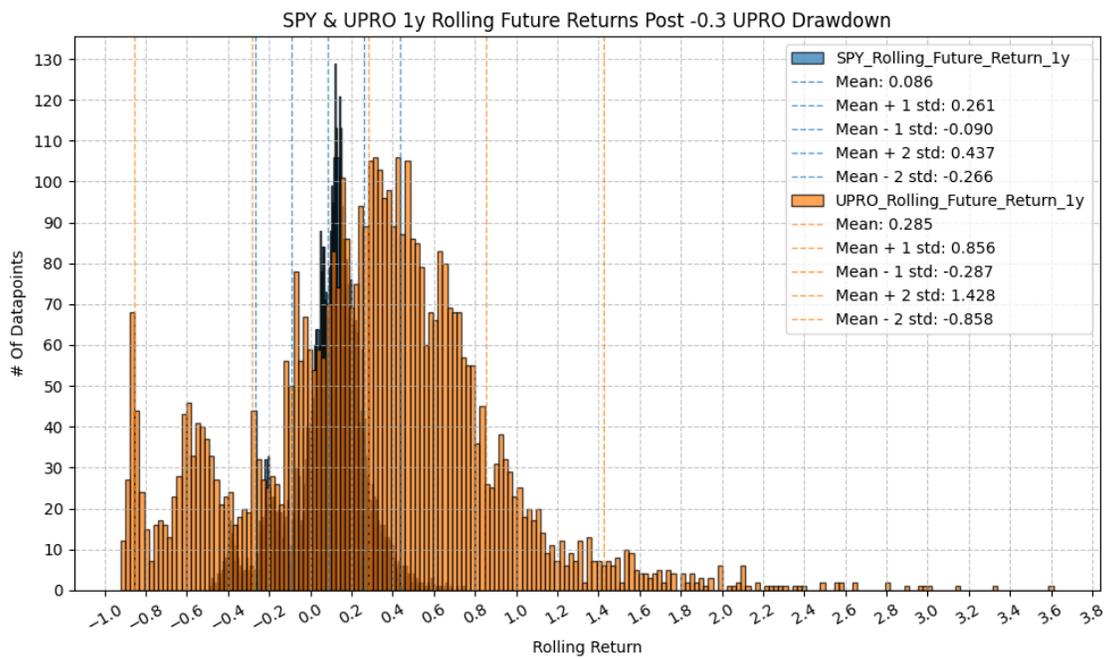
```

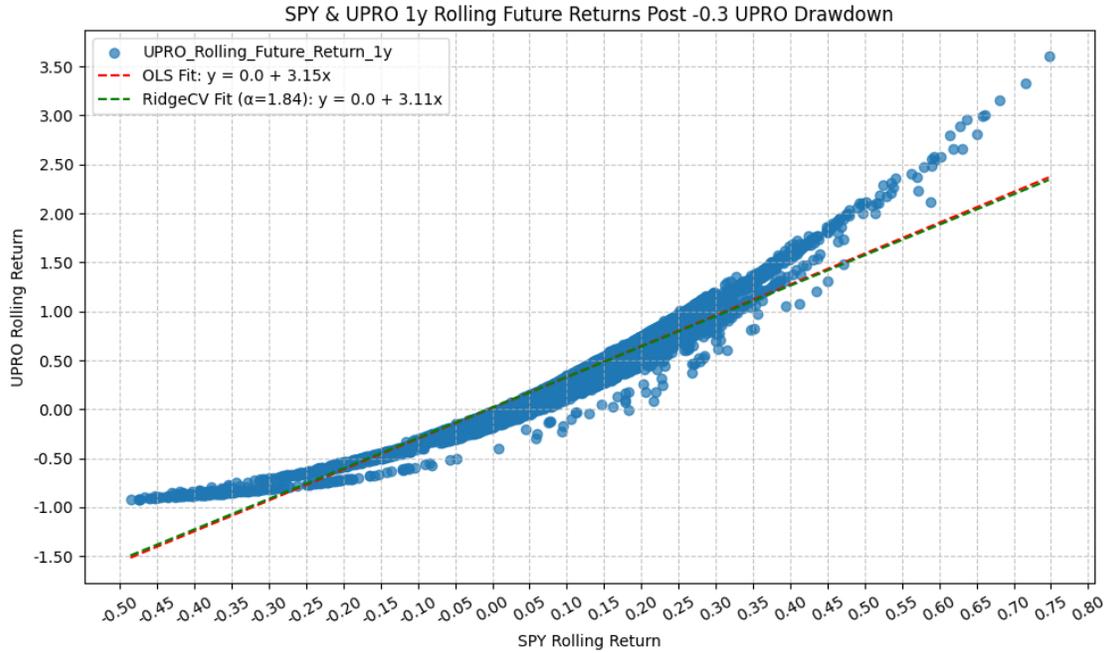
=====
Omnibus:                1652.367   Durbin-Watson:           0.081
Prob(Omnibus):          0.000     Jarque-Bera (JB):       14599.547
Skew:                   1.398     Prob(JB):                0.00
Kurtosis:               11.098    Cond. No.                8.43
=====

```

Notes:

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





OLS Regression Results

=====

```

Dep. Variable:      UPRO_Rolling_Future_Return_1y    R-squared:
0.937
Model:              OLS                            Adj. R-squared:
0.937
Method:             Least Squares                 F-statistic:
7.059e+04
Date:               Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:               14:28:37                      Log-Likelihood:
2483.5
No. Observations:  4753                          AIC:
-4963.
Df Residuals:      4751                          BIC:
-4950.
Df Model:          1
Covariance Type:   nonrobust
  
```

=====

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0150	0.002	6.476	0.000

0.010	0.020				
SPY_Rolling_Future_Return_1y	3.1488	0.012	265.683	0.000	
3.126	3.172				

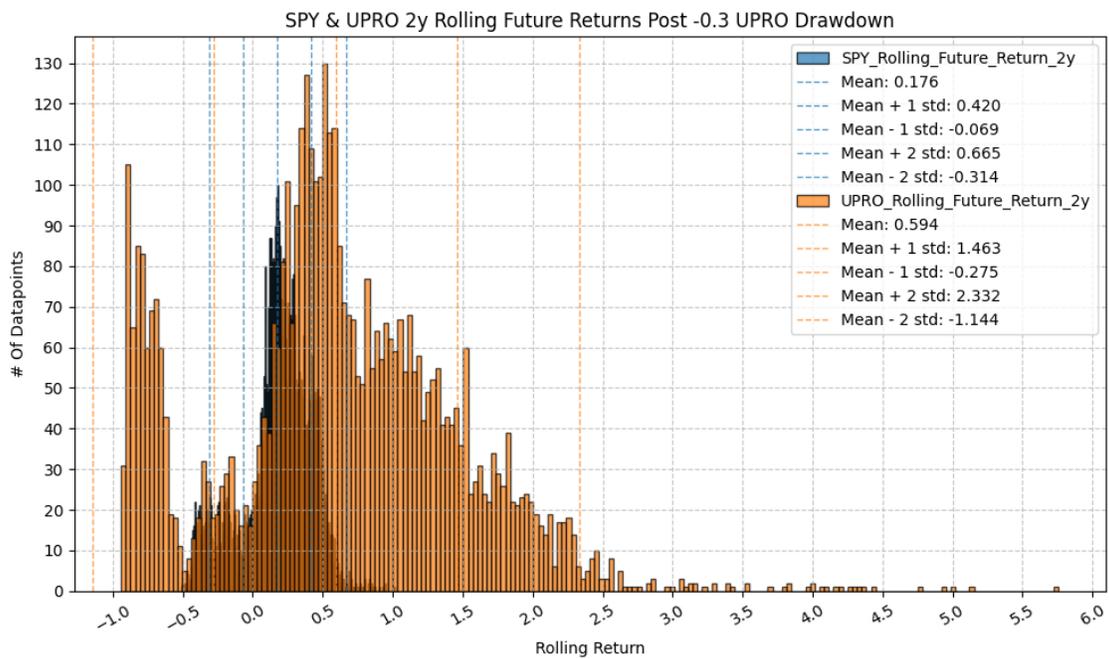
```

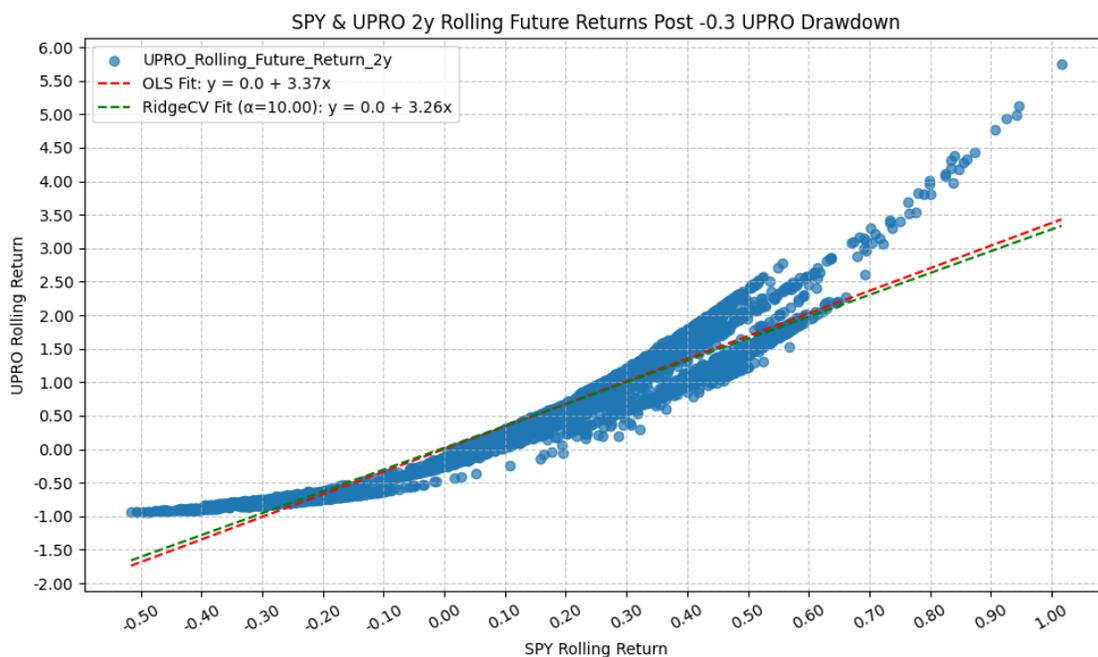
=====
Omnibus:                1666.063    Durbin-Watson:           0.054
Prob(Omnibus):          0.000    Jarque-Bera (JB):       10578.908
Skew:                   1.528    Prob(JB):                0.00
Kurtosis:               9.639    Cond. No.                5.74
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_2y   R-squared:
0.901
Model:              OLS                           Adj. R-squared:
0.901
Method:             Least Squares                 F-statistic:
4.347e+04
Date:               Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:               14:28:38                      Log-Likelihood:
-568.49
No. Observations:  4753                          AIC:
1141.
Df Residuals:      4751                          BIC:
1154.
Df Model:           1
Covariance Type:   nonrobust
=====
=====

```

		coef	std err	t	P> t
[0.025	0.975]				

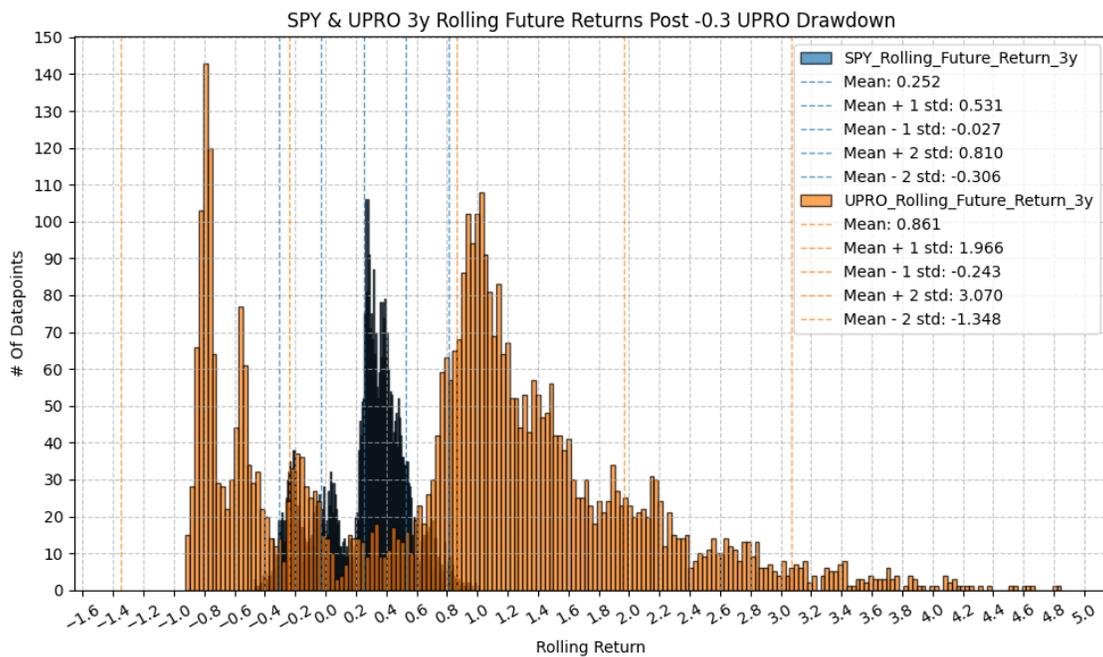
const		0.0020	0.005	0.409	0.683

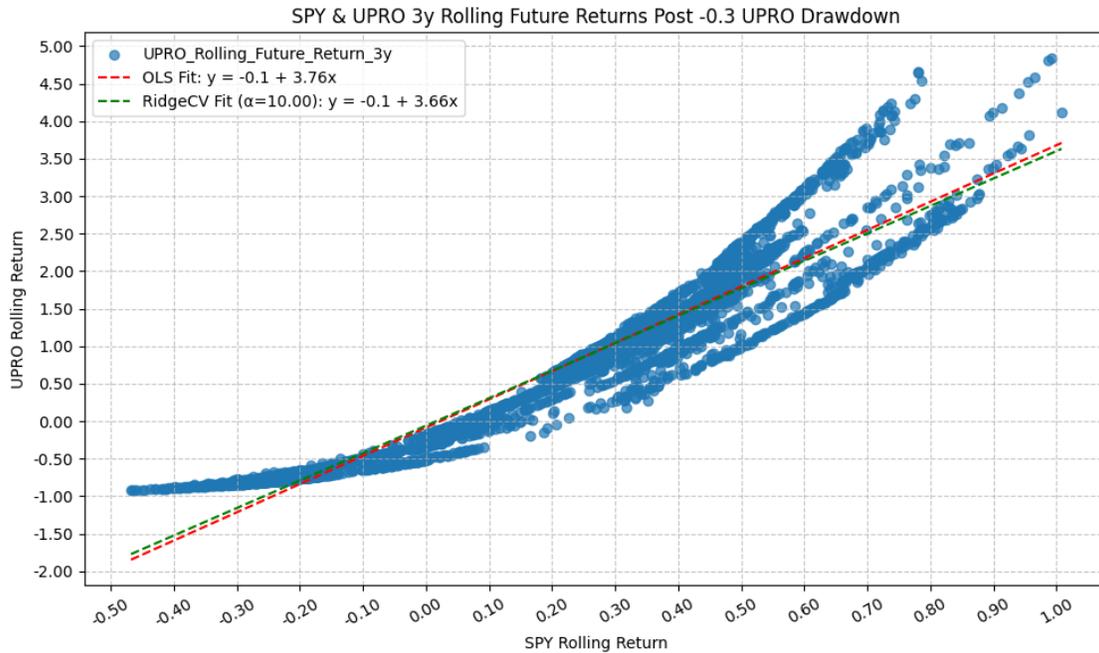
-0.008	0.012				
SPY_Rolling_Future_Return_2y	3.3736	0.016	208.486	0.000	
3.342	3.405				

Omnibus:	1332.905	Durbin-Watson:	0.031
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5113.742
Skew:	1.349	Prob(JB):	0.00
Kurtosis:	7.306	Cond. No.	4.22

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3y    R-squared:
0.904
Model:                  OLS                            Adj. R-squared:
0.904
Method:                 Least Squares                 F-statistic:
4.265e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:39                     Log-Likelihood:
-1581.0
No. Observations:      4545                          AIC:
3166.
Df Residuals:          4543                          BIC:
3179.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -0.0865    0.007    -12.630    0.000

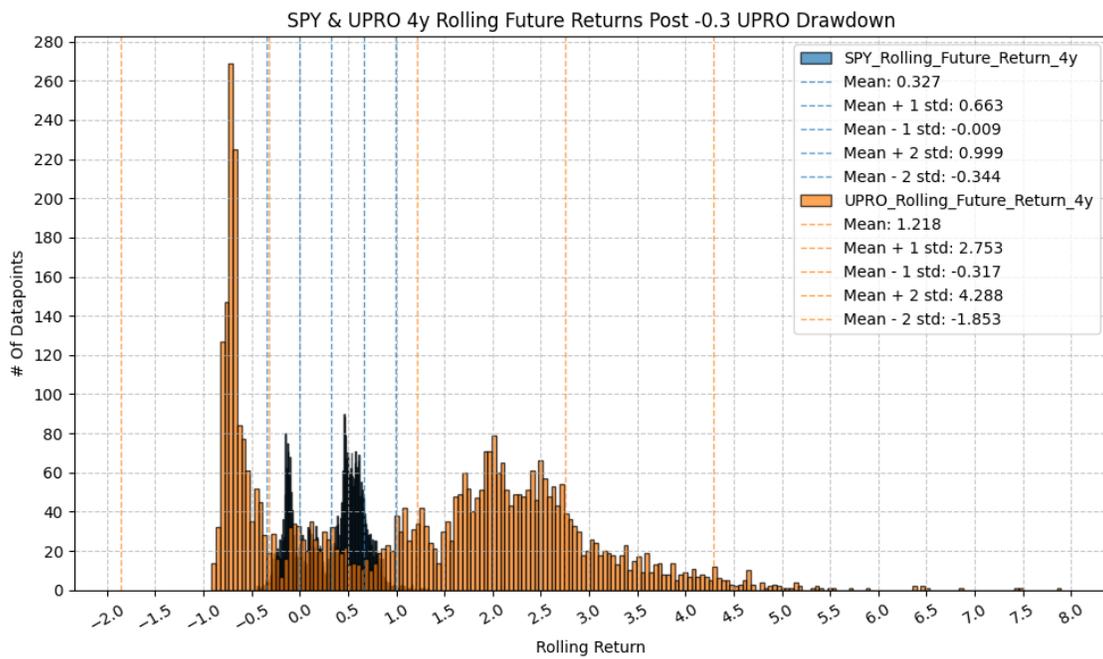
```

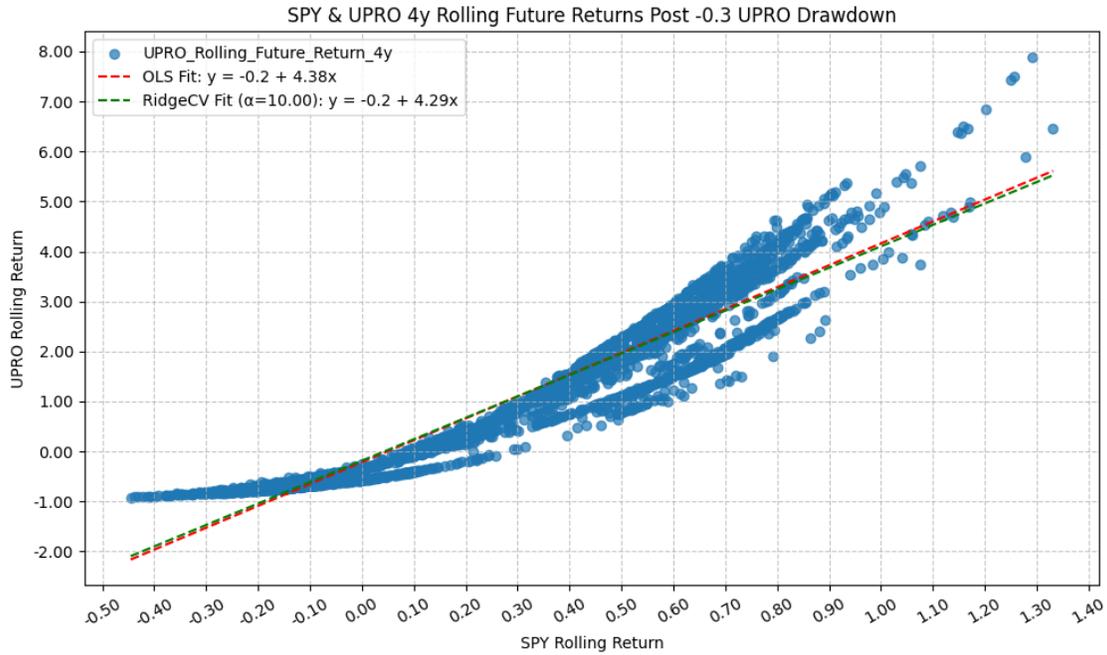
-0.100	-0.073				
SPY_Rolling_Future_Return_3y	3.7644	0.018	206.520	0.000	
3.729	3.800				

Omnibus:	685.599	Durbin-Watson:	0.019
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1776.838
Skew:	0.833	Prob(JB):	0.00
Kurtosis:	5.571	Cond. No.	3.83

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_4y    R-squared:
0.916
Model:                  OLS                            Adj. R-squared:
0.916
Method:                 Least Squares                 F-statistic:
4.728e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:40                      Log-Likelihood:
-2622.0
No. Observations:      4319                          AIC:
5248.
Df Residuals:          4317                          BIC:
5261.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.2143    0.009    -22.712    0.000

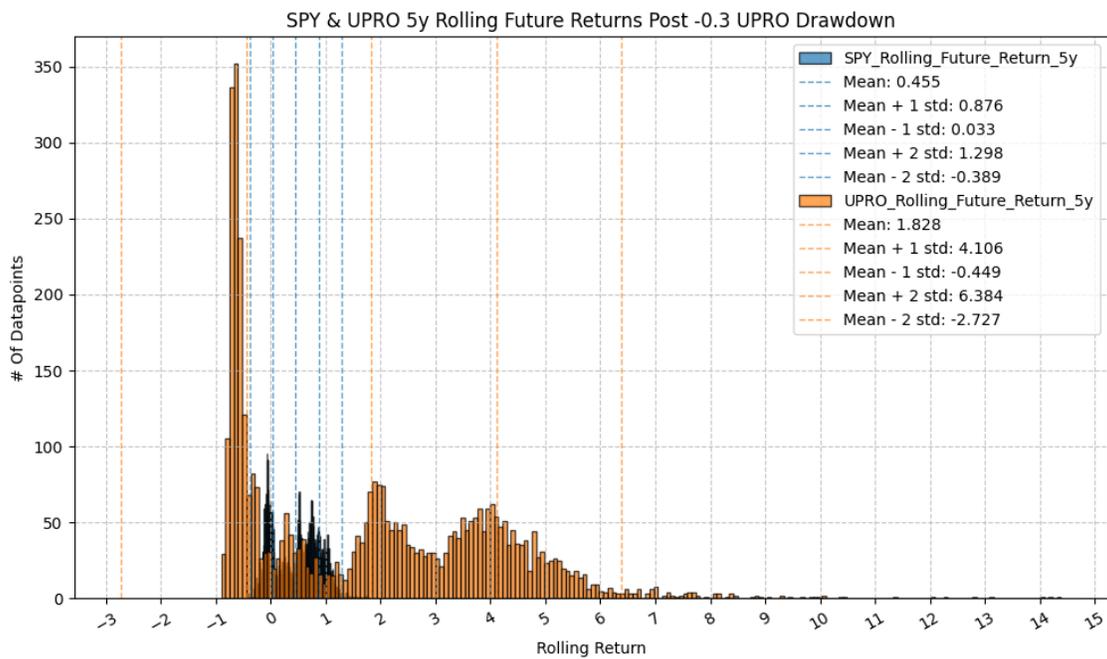
```

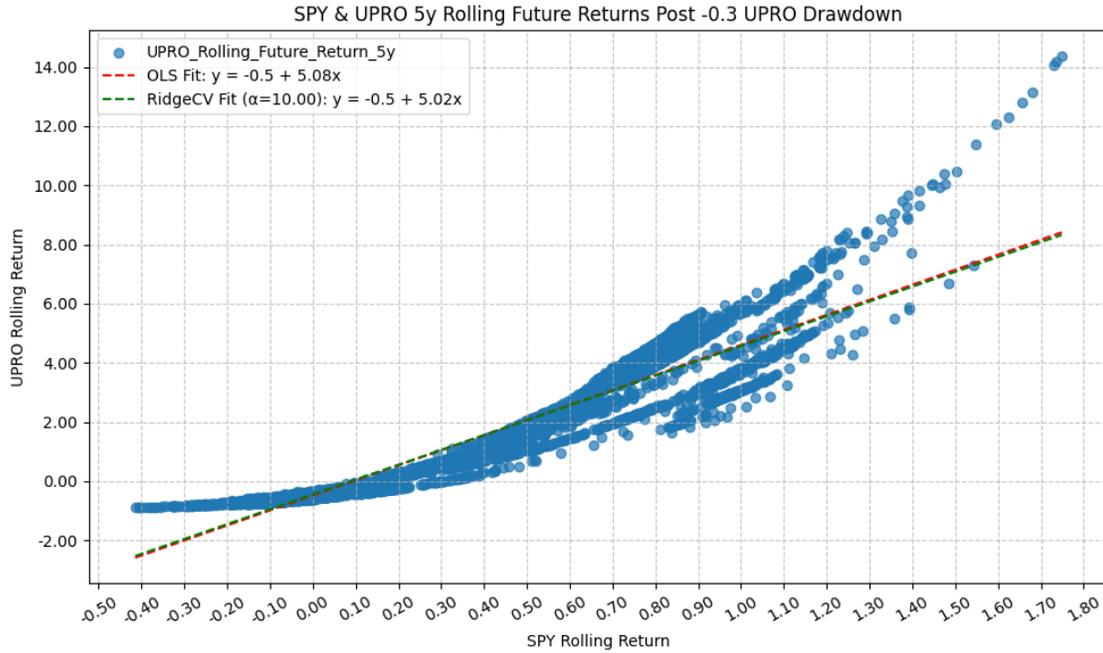
-0.233	-0.196				
SPY_Rolling_Future_Return_4y	4.3762	0.020	217.433	0.000	
4.337	4.416				

Omnibus:	112.708	Durbin-Watson:	0.023
Prob(Omnibus):	0.000	Jarque-Bera (JB):	238.544
Skew:	-0.138	Prob(JB):	1.59e-52
Kurtosis:	4.118	Cond. No.	3.33

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_5y    R-squared:
0.887
Model:                  OLS                            Adj. R-squared:
0.887
Method:                 Least Squares                  F-statistic:
3.391e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:42                      Log-Likelihood:
-4969.9
No. Observations:      4317                            AIC:
9944.
Df Residuals:          4315                            BIC:
9957.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.4824    0.017   -28.176    0.000

```

-0.516 -0.449
 SPY_Rolling_Future_Return_5y 5.0841 0.028 184.147 0.000
 5.030 5.138

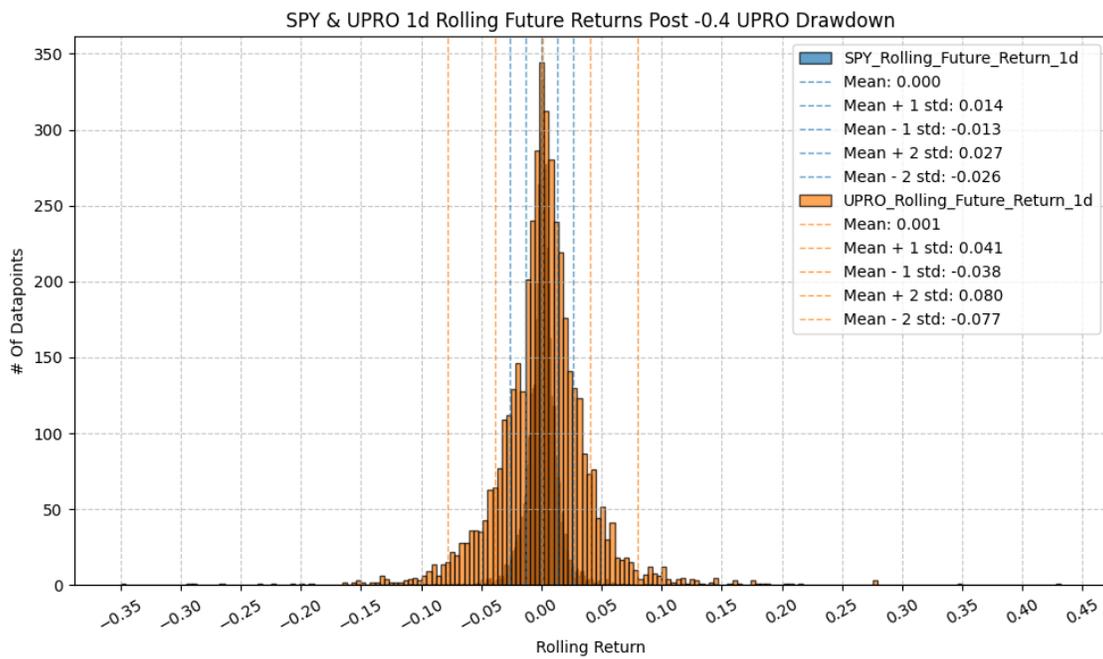
```
=====
```

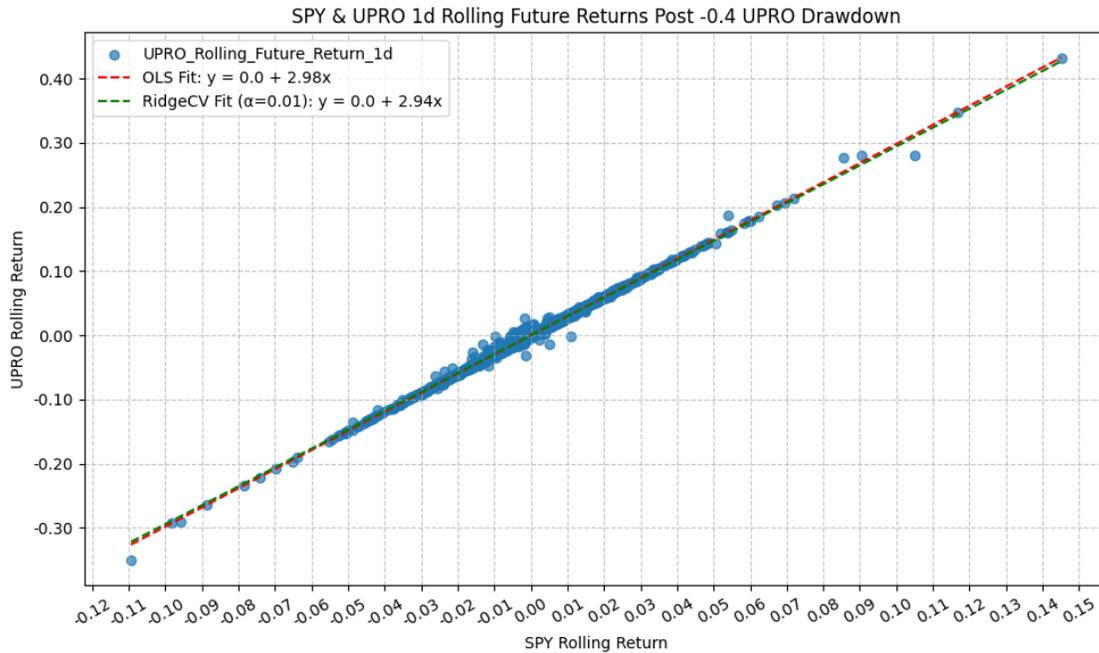
Omnibus:	712.799	Durbin-Watson:	0.017
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3463.389
Skew:	0.712	Prob(JB):	0.00
Kurtosis:	7.150	Cond. No.	2.94

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1d    R-squared:
0.997
Model:                  OLS                            Adj. R-squared:
0.997
Method:                 Least Squares                 F-statistic:
1.488e+06
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:43                      Log-Likelihood:
21081.
No. Observations:      4464                          AIC:
-4.216e+04
Df Residuals:          4462                          BIC:
-4.214e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                4.396e-05    3.22e-05     1.364    0.173
=====

```

-1.92e-05 0.000
 SPY_Rolling_Future_Return_1d 2.9793 0.002 1219.664 0.000
 2.974 2.984

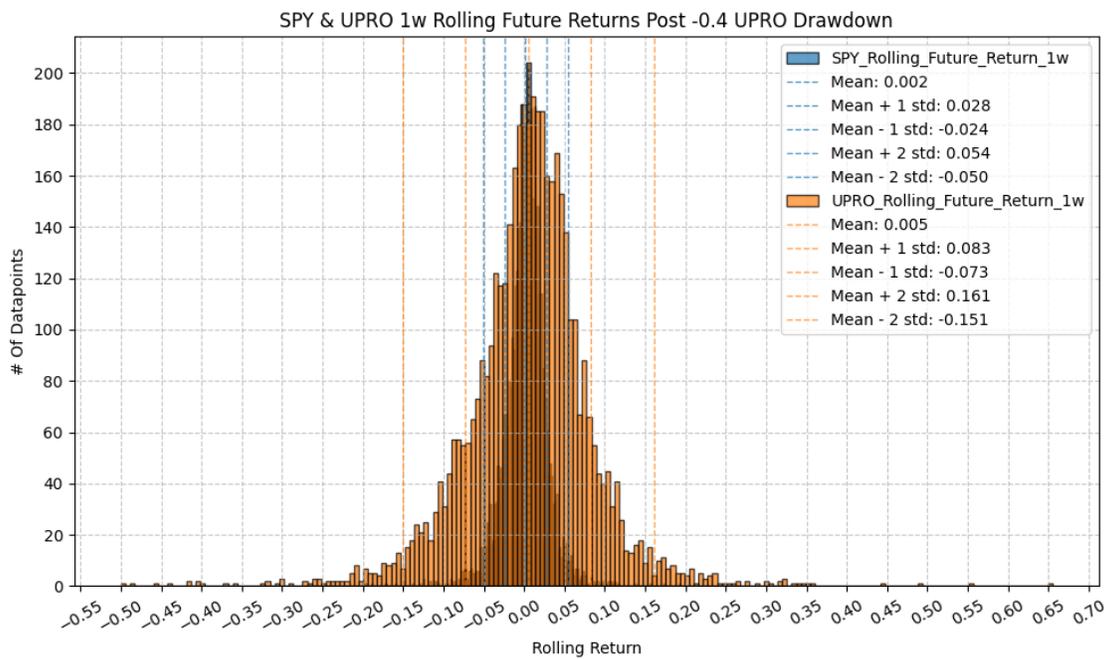
```
=====
```

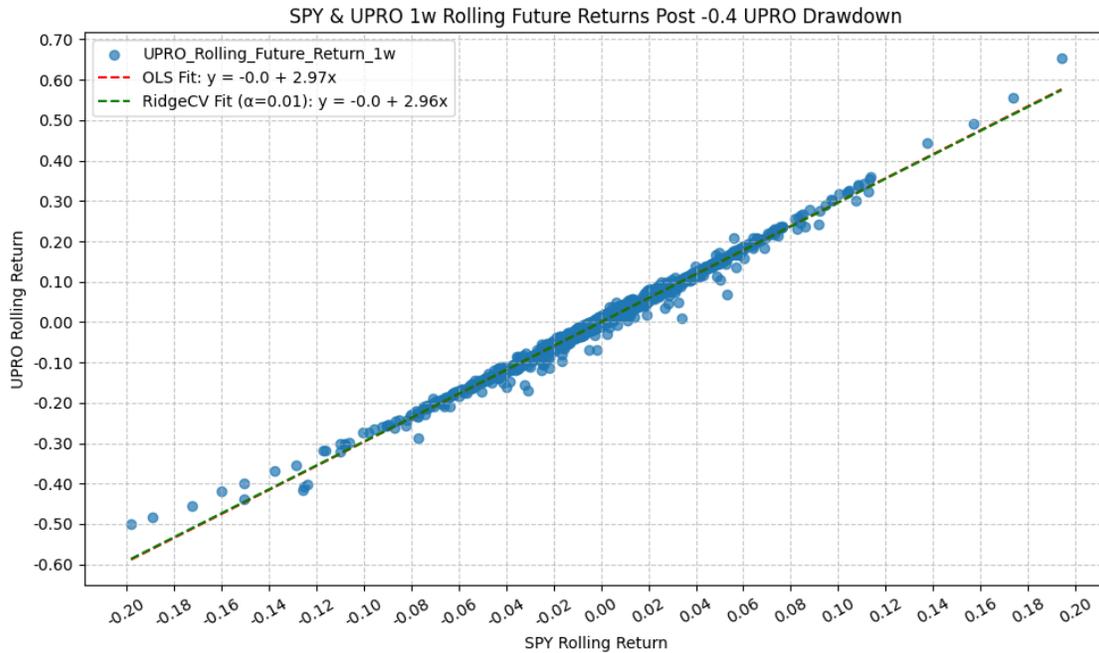
Omnibus:	2686.077	Durbin-Watson:	2.618
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1503196.947
Skew:	1.531	Prob(JB):	0.00
Kurtosis:	92.846	Cond. No.	75.8

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1w    R-squared:
0.993
Model:                  OLS                            Adj. R-squared:
0.993
Method:                 Least Squares                  F-statistic:
6.179e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:44                      Log-Likelihood:
16080.
No. Observations:      4464                            AIC:
-3.216e+04
Df Residuals:          4462                            BIC:
-3.214e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0002    9.9e-05    -1.778    0.075

```

-0.000 1.8e-05
 SPY_Rolling_Future_Return_1w 2.9718 0.004 786.075 0.000
 2.964 2.979

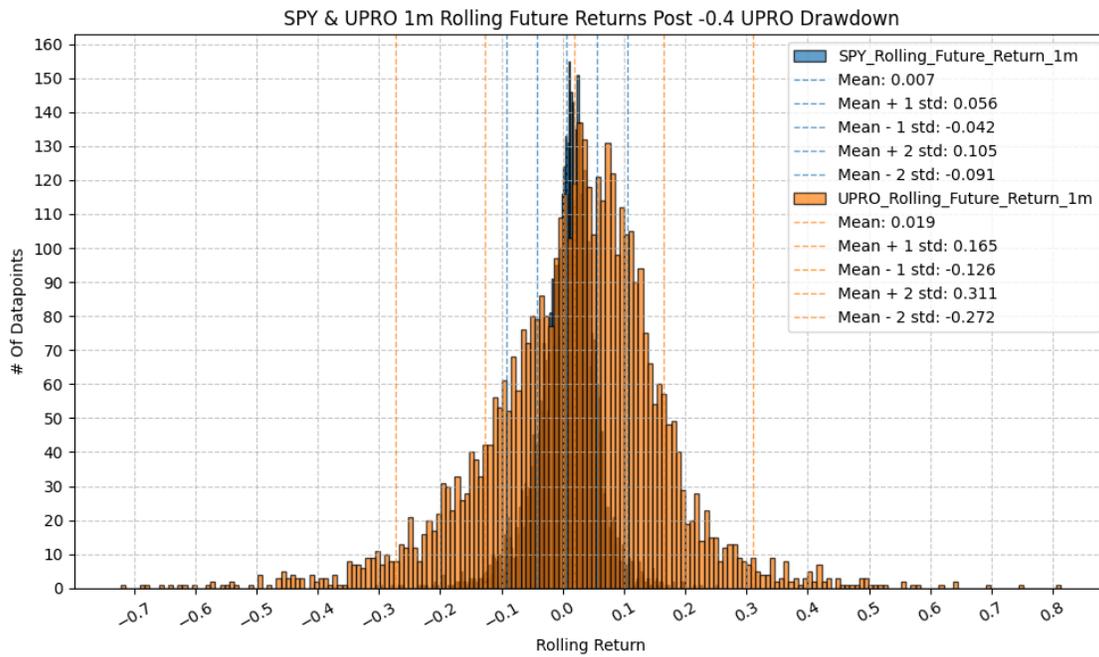
```
=====
```

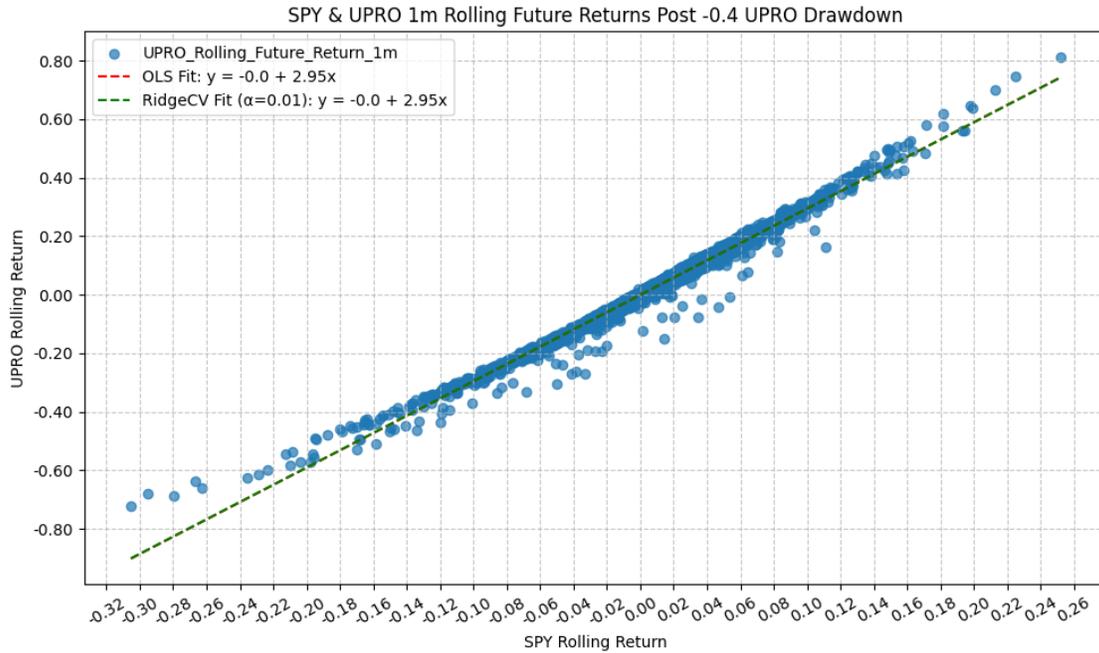
Omnibus:	1978.267	Durbin-Watson:	0.971
Prob(Omnibus):	0.000	Jarque-Bera (JB):	519572.475
Skew:	-0.906	Prob(JB):	0.00
Kurtosis:	55.822	Cond. No.	38.3

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1m    R-squared:
0.986
Model:                  OLS                            Adj. R-squared:
0.986
Method:                 Least Squares                 F-statistic:
3.225e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:45                      Log-Likelihood:
11851.
No. Observations:      4464                          AIC:
-2.370e+04
Df Residuals:          4462                          BIC:
-2.368e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -0.0009    0.000   -3.423    0.001
=====

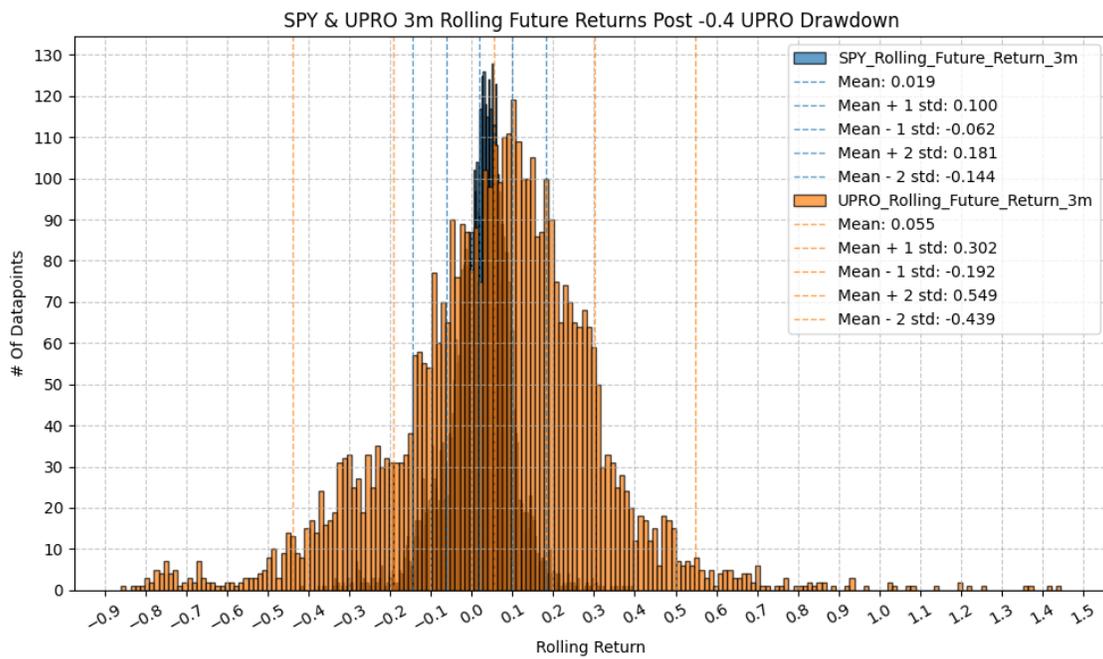
```

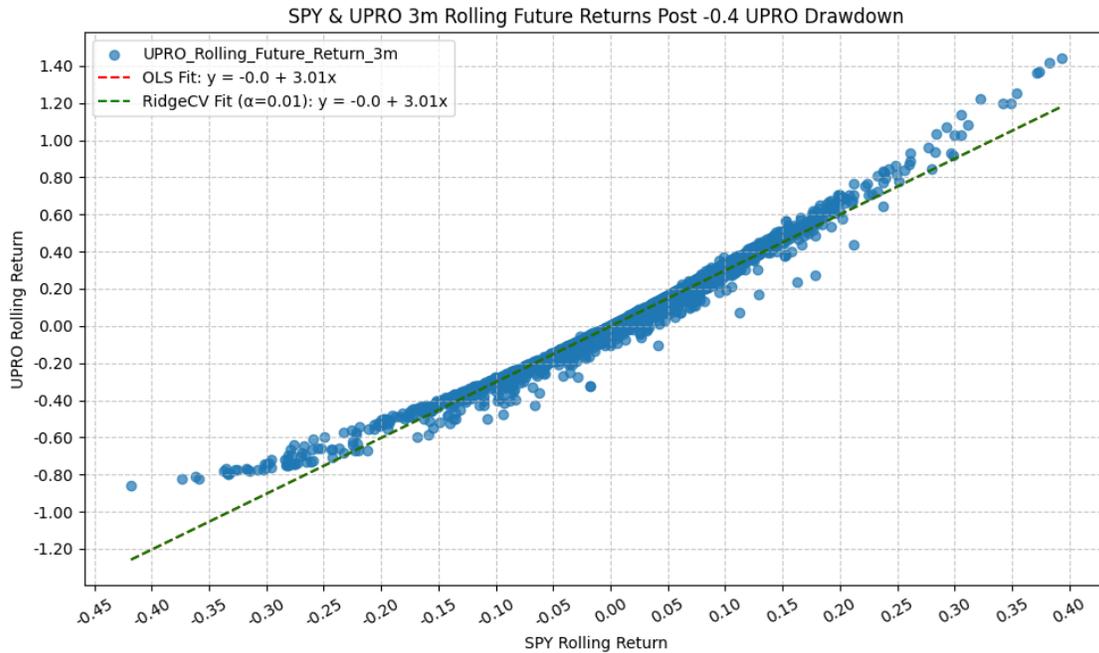
-0.001	-0.000				
SPY_Rolling_Future_Return_1m	2.9521	0.005	567.899	0.000	
2.942	2.962				

```
=====
Omnibus:                2550.504    Durbin-Watson:                0.358
Prob(Omnibus):          0.000    Jarque-Bera (JB):            256191.593
Skew:                   -1.811    Prob(JB):                     0.00
Kurtosis:               39.936    Cond. No.                     20.4
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3m    R-squared:
0.978
Model:                  OLS                            Adj. R-squared:
0.978
Method:                 Least Squares                  F-statistic:
2.007e+05
Date:                   Mon, 16 Mar 2026               Prob (F-statistic):
0.00
Time:                   14:28:46                       Log-Likelihood:
8451.5
No. Observations:      4464                            AIC:
-1.690e+04
Df Residuals:          4462                            BIC:
-1.689e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -0.0018    0.001    -3.149    0.002
=====

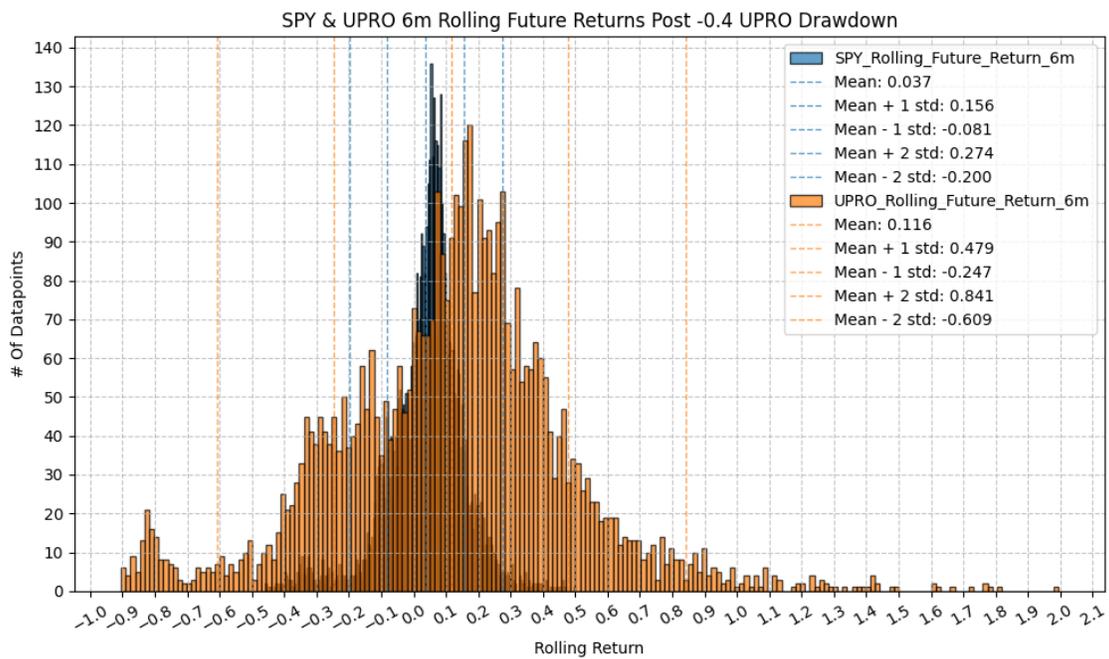
```

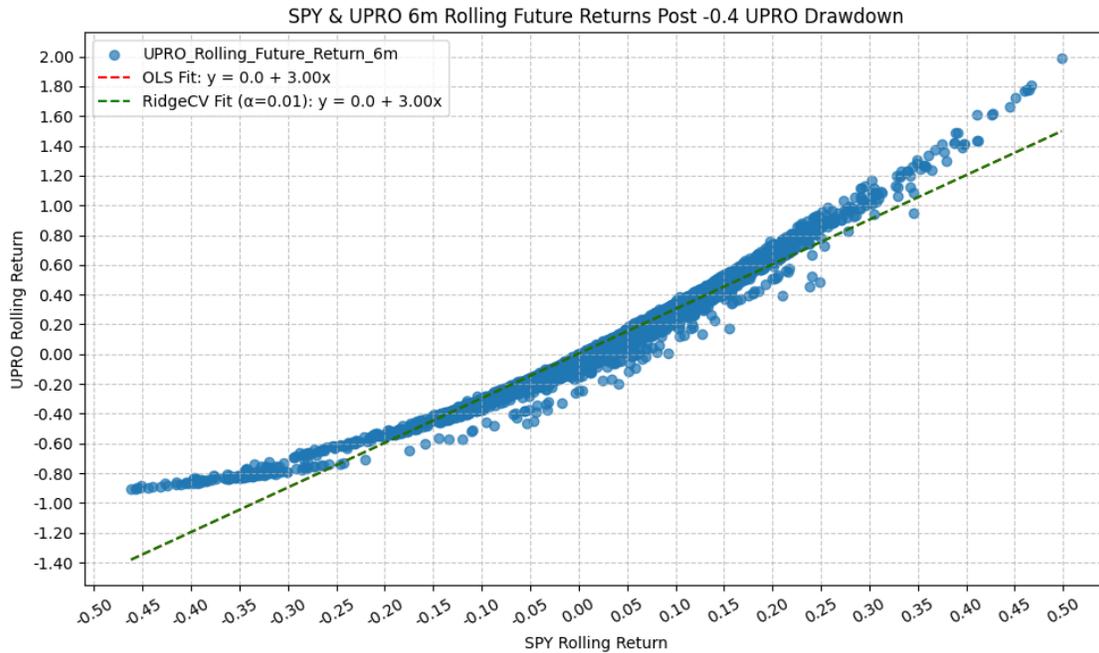
-0.003	-0.001				
SPY_Rolling_Future_Return_3m	3.0075	0.007	448.019	0.000	
2.994	3.021				

```
=====
Omnibus:                1648.790    Durbin-Watson:           0.182
Prob(Omnibus):          0.000    Jarque-Bera (JB):       57107.468
Skew:                   1.101    Prob(JB):                0.00
Kurtosis:               20.383    Cond. No.                12.3
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_6m    R-squared:
0.959
Model:                  OLS                            Adj. R-squared:
0.959
Method:                 Least Squares                 F-statistic:
1.039e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:48                     Log-Likelihood:
5314.4
No. Observations:      4464                          AIC:
-1.062e+04
Df Residuals:          4462                          BIC:
-1.061e+04
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                0.0040    0.001      3.492    0.000

```

0.002	0.006				
SPY_Rolling_Future_Return_6m	2.9974	0.009	322.290	0.000	
2.979	3.016				

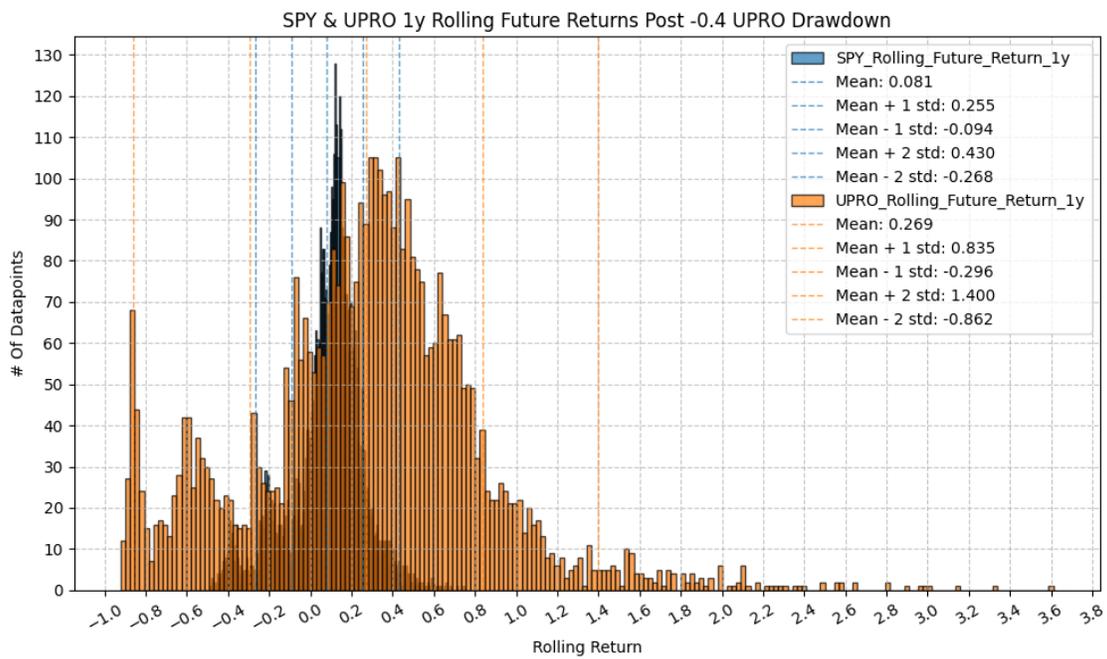
```

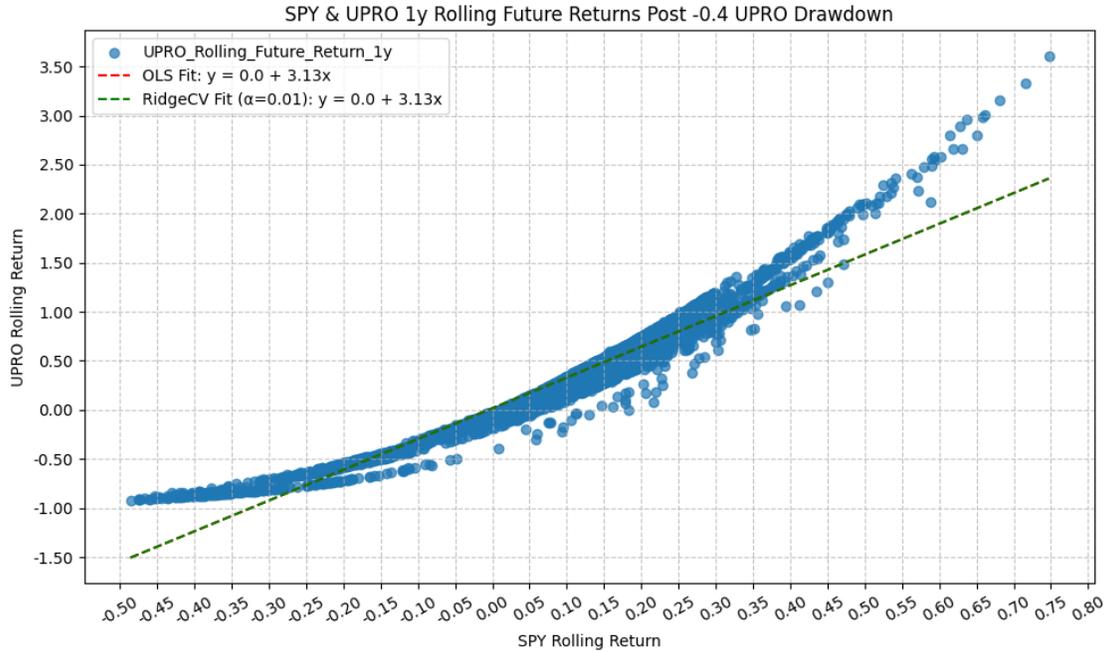
=====
Omnibus:                1611.795   Durbin-Watson:           0.081
Prob(Omnibus):          0.000     Jarque-Bera (JB):       13016.420
Skew:                   1.500     Prob(JB):                0.00
Kurtosis:               10.809    Cond. No.                8.46
=====

```

Notes:

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





OLS Regression Results

=====

```

Dep. Variable:      UPRO_Rolling_Future_Return_1y      R-squared:
0.936
Model:              OLS                               Adj. R-squared:
0.936
Method:             Least Squares                    F-statistic:
6.492e+04
Date:               Mon, 16 Mar 2026                 Prob (F-statistic):
0.00
Time:               14:28:49                         Log-Likelihood:
2334.7
No. Observations:  4456                             AIC:
-4665.
Df Residuals:      4454                             BIC:
-4653.
Df Model:          1
Covariance Type:   nonrobust
  
```

=====

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0162	0.002	6.861	0.000

0.012	0.021				
SPY_Rolling_Future_Return_1y	3.1341	0.012	254.788	0.000	
3.110	3.158				

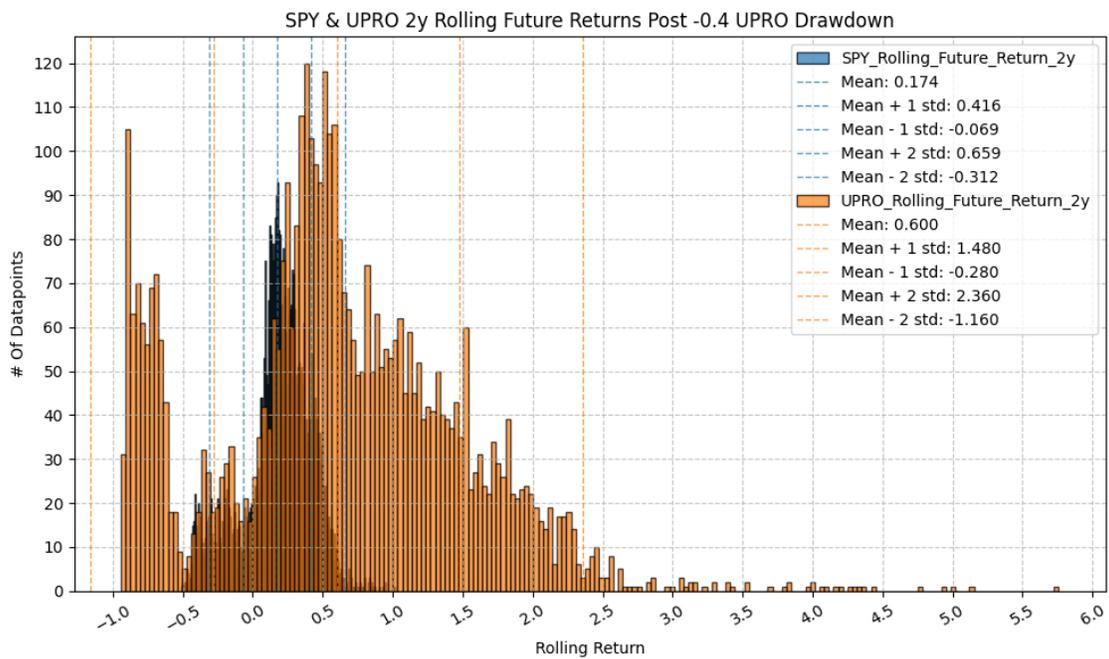
```

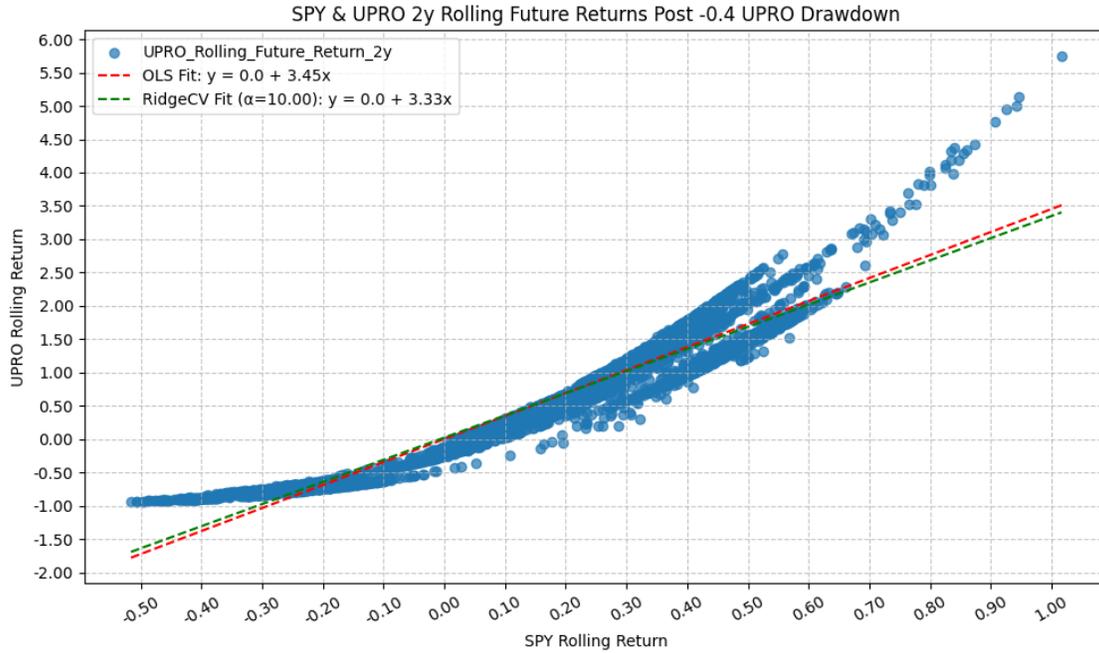
=====
Omnibus:                1684.542    Durbin-Watson:          0.054
Prob(Omnibus):          0.000    Jarque-Bera (JB):      11773.004
Skew:                   1.634    Prob(JB):              0.00
Kurtosis:               10.262    Cond. No.              5.77
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_2y    R-squared:
0.907
Model:                  OLS                            Adj. R-squared:
0.907
Method:                 Least Squares                 F-statistic:
4.354e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:50                      Log-Likelihood:
-457.07
No. Observations:      4456                          AIC:
918.1
Df Residuals:          4454                          BIC:
930.9
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                0.0011    0.005      0.221    0.825

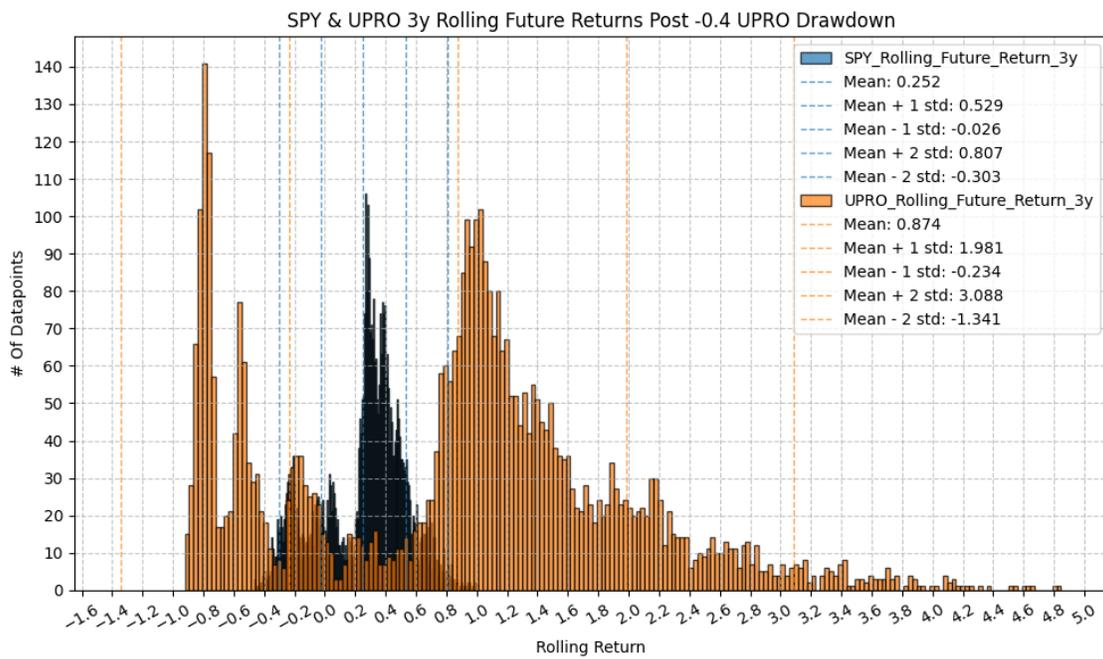
```

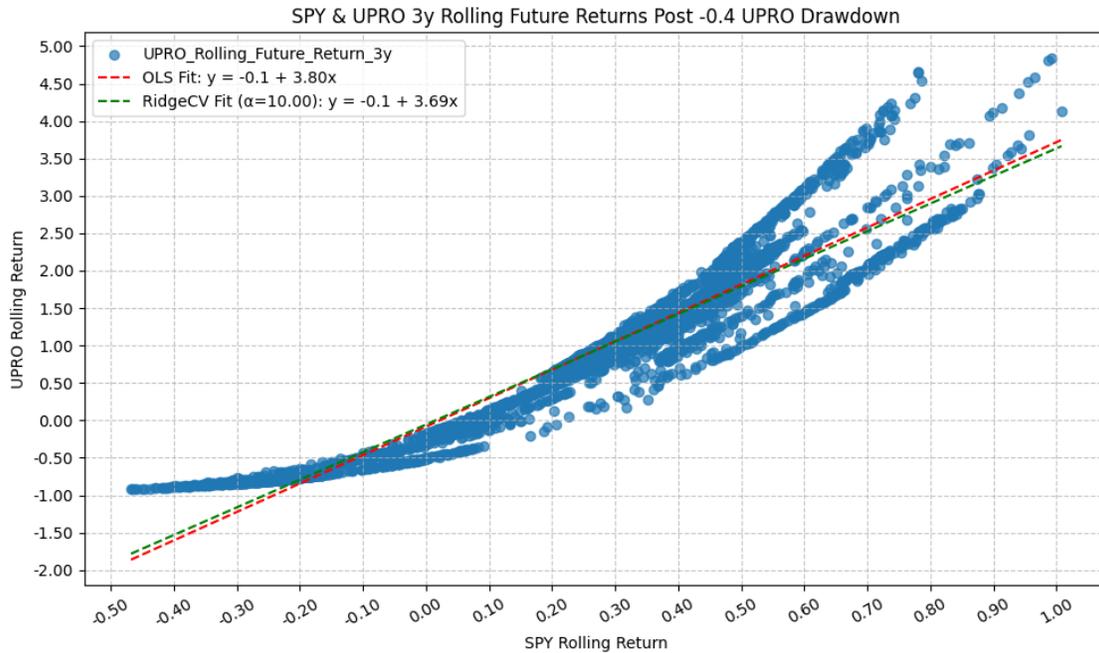
-0.009	0.011				
SPY_Rolling_Future_Return_2y	3.4517	0.017	208.652	0.000	
3.419	3.484				

Omnibus:	1243.361	Durbin-Watson:	0.033
Prob(Omnibus):	0.000	Jarque-Bera (JB):	4602.615
Skew:	1.354	Prob(JB):	0.00
Kurtosis:	7.179	Cond. No.	4.25

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_3y    R-squared:
0.907
Model:              OLS                            Adj. R-squared:
0.907
Method:             Least Squares                  F-statistic:
4.210e+04
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:               14:28:51                        Log-Likelihood:
-1442.5
No. Observations:  4323                            AIC:
2889.
Df Residuals:      4321                            BIC:
2902.
Df Model:           1
Covariance Type:   nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -0.0838    0.007    -12.068    0.000

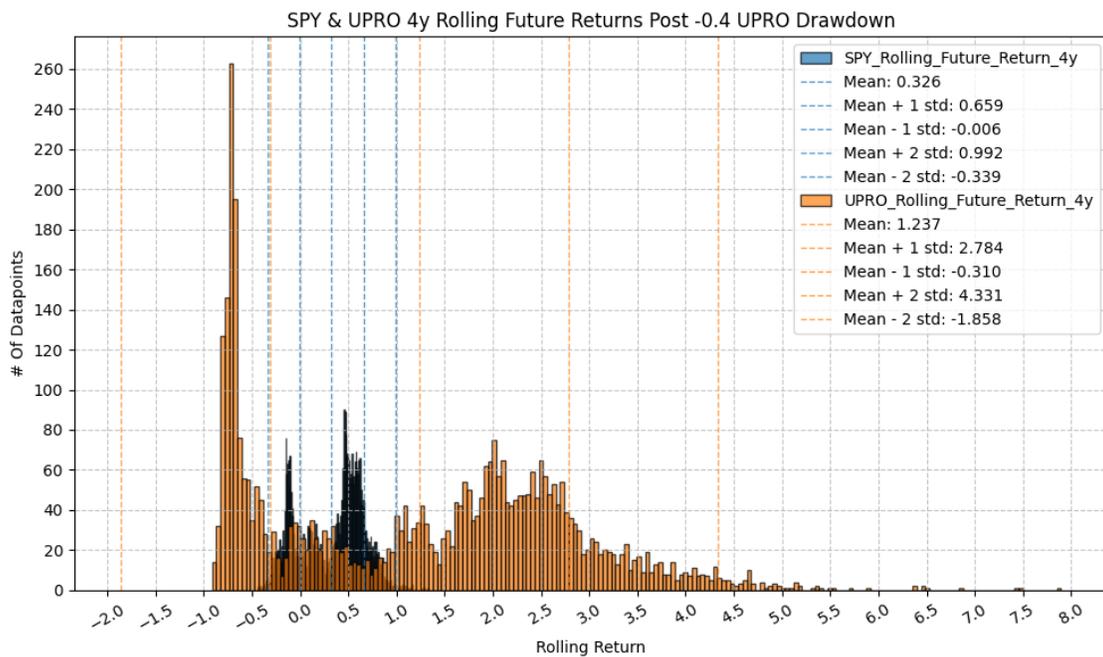
```

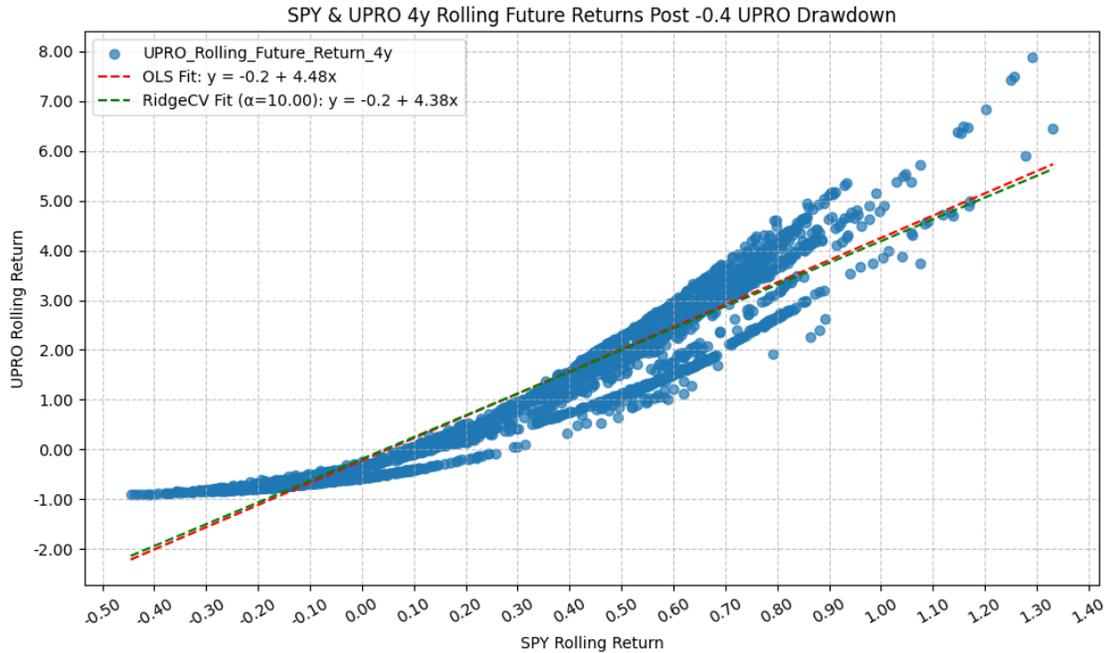
-0.097	-0.070				
SPY_Rolling_Future_Return_3y	3.8006	0.019	205.187	0.000	
3.764	3.837				

Omnibus:	700.473	Durbin-Watson:	0.022
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1800.061
Skew:	0.891	Prob(JB):	0.00
Kurtosis:	5.611	Cond. No.	3.85

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_4y    R-squared:
0.926
Model:                  OLS                            Adj. R-squared:
0.926
Method:                 Least Squares                 F-statistic:
5.187e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:52                      Log-Likelihood:
-2273.5
No. Observations:      4126                            AIC:
4551.
Df Residuals:          4124                            BIC:
4564.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.2233    0.009   -24.385    0.000

```

-0.241	-0.205				
SPY_Rolling_Future_Return_4y	4.4751	0.020	227.751	0.000	
4.437	4.514				

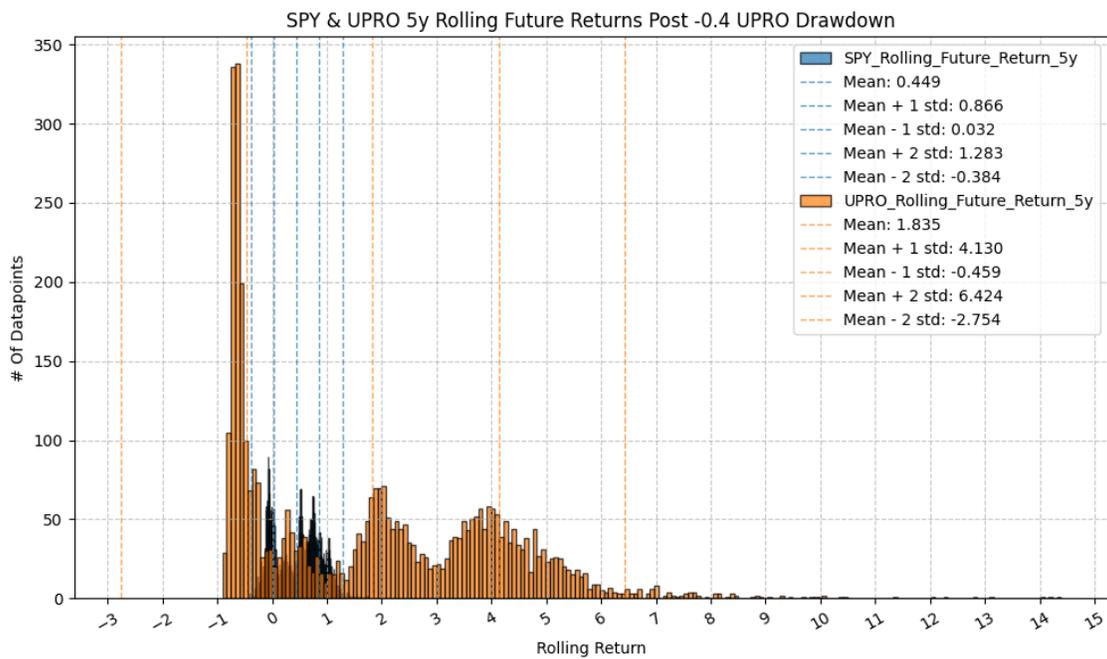
```

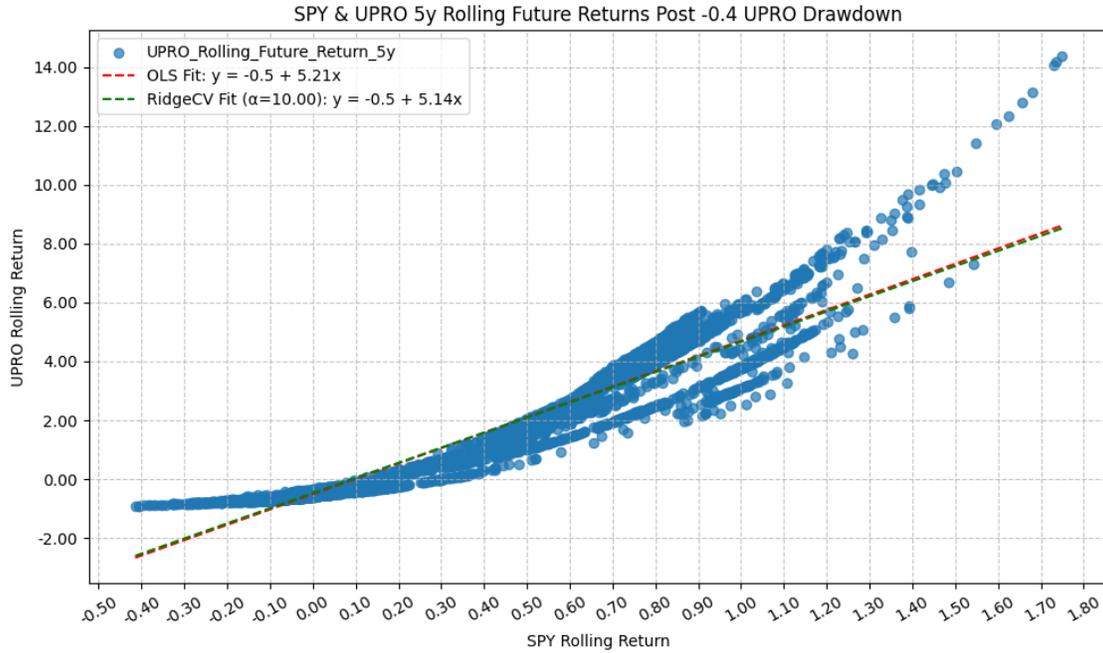
=====
Omnibus:                119.525   Durbin-Watson:           0.024
Prob(Omnibus):          0.000   Jarque-Bera (JB):       294.806
Skew:                   -0.074   Prob(JB):                9.63e-65
Kurtosis:               4.301   Cond. No.                3.36
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_5y    R-squared:
0.896
Model:                  OLS                            Adj. R-squared:
0.896
Method:                 Least Squares                 F-statistic:
3.555e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:54                      Log-Likelihood:
-4610.6
No. Observations:      4126                          AIC:
9225.
Df Residuals:          4124                          BIC:
9238.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.5058    0.017    -29.867    0.000

```

-0.539 -0.473
 SPY_Rolling_Future_Return_5y 5.2122 0.028 188.534 0.000
 5.158 5.266

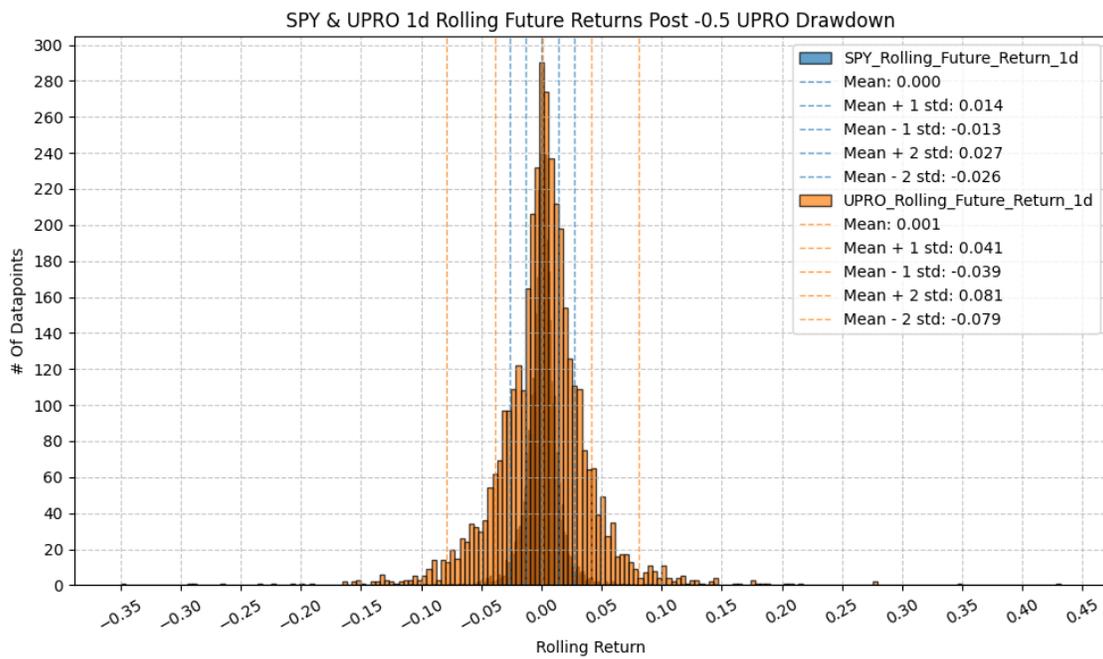
```
=====
```

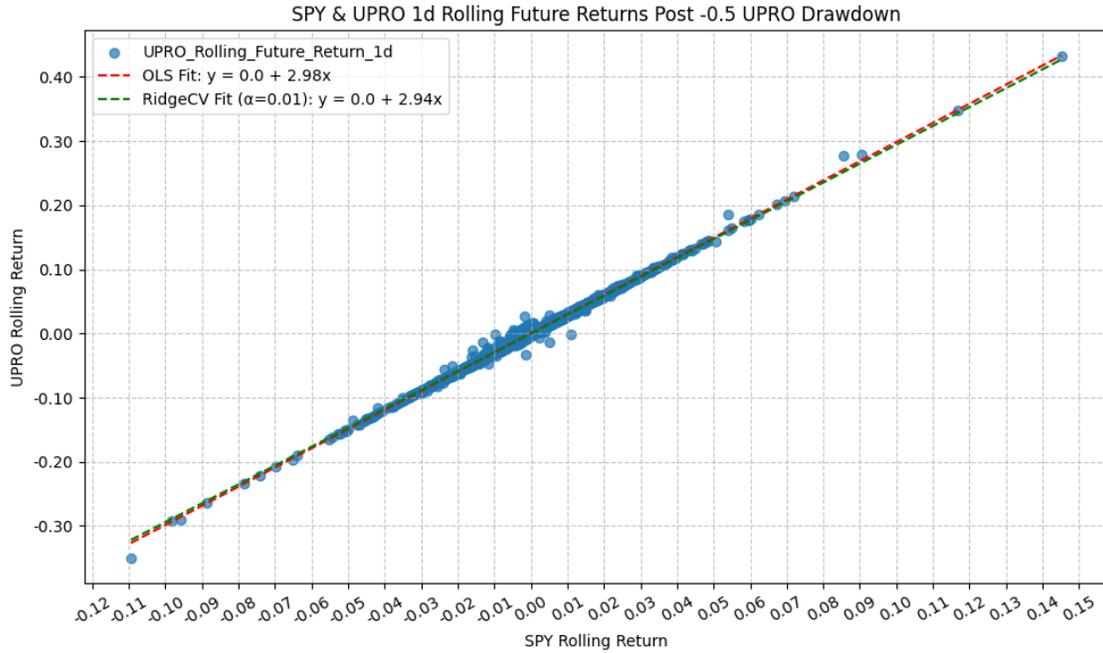
Omnibus:	688.588	Durbin-Watson:	0.019
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3306.754
Skew:	0.724	Prob(JB):	0.00
Kurtosis:	7.140	Cond. No.	2.96

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1d    R-squared:
0.997
Model:                  OLS                            Adj. R-squared:
0.997
Method:                 Least Squares                 F-statistic:
1.317e+06
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:55                     Log-Likelihood:
18256.
No. Observations:      3871                          AIC:
-3.651e+04
Df Residuals:          3869                          BIC:
-3.650e+04
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                6.221e-05   3.48e-05     1.786    0.074

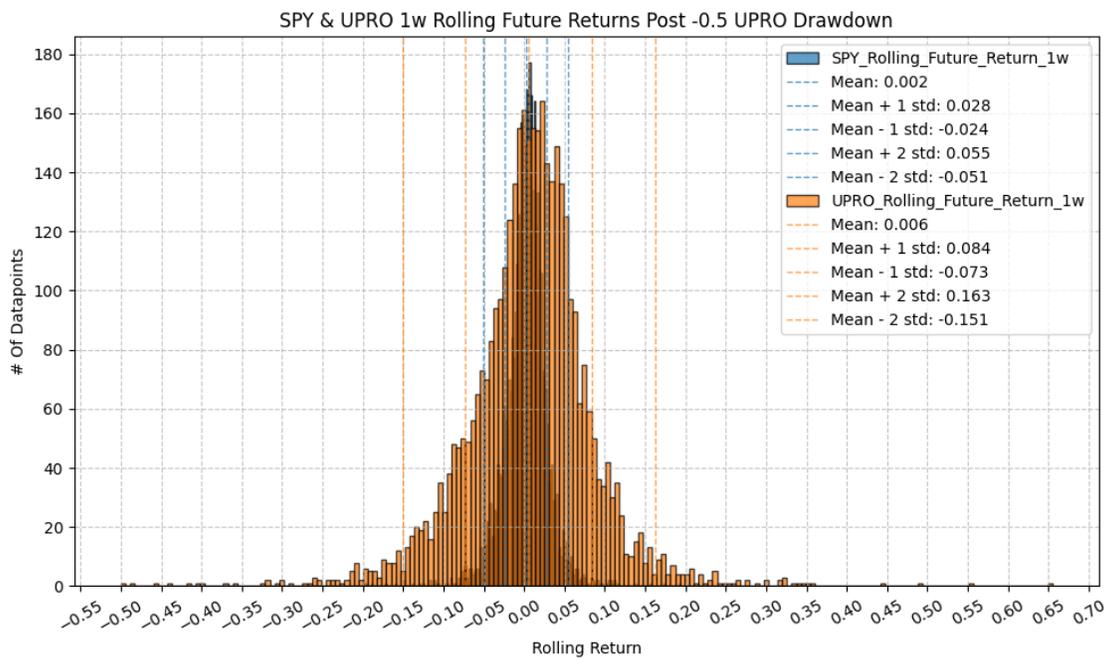
```

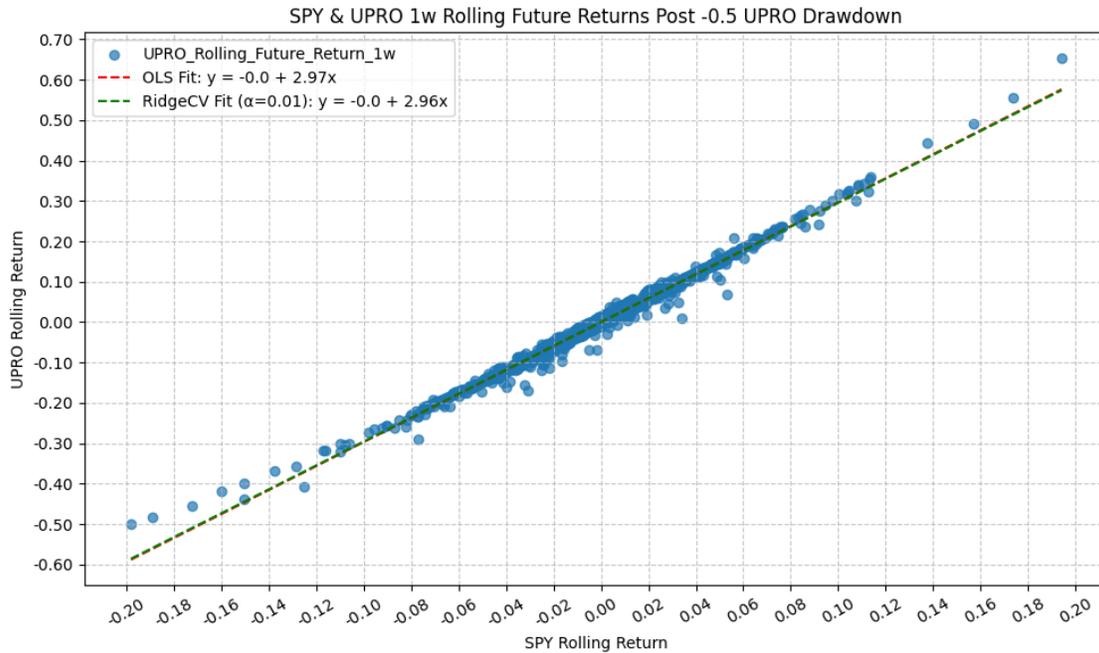
-6.08e-06	0.000				
SPY_Rolling_Future_Return_1d	2.9842	0.003	1147.793	0.000	
2.979	2.989				

```
=====
Omnibus:                2862.865    Durbin-Watson:                2.686
Prob(Omnibus):          0.000    Jarque-Bera (JB):            1149210.351
Skew:                   2.367    Prob(JB):                     0.00
Kurtosis:               87.277    Cond. No.                     74.7
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1w    R-squared:
0.992
Model:                  OLS                            Adj. R-squared:
0.992
Method:                 Least Squares                 F-statistic:
5.116e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:56                      Log-Likelihood:
13825.
No. Observations:      3871                          AIC:
-2.765e+04
Df Residuals:          3869                          BIC:
-2.763e+04
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0001    0.000      -0.958    0.338

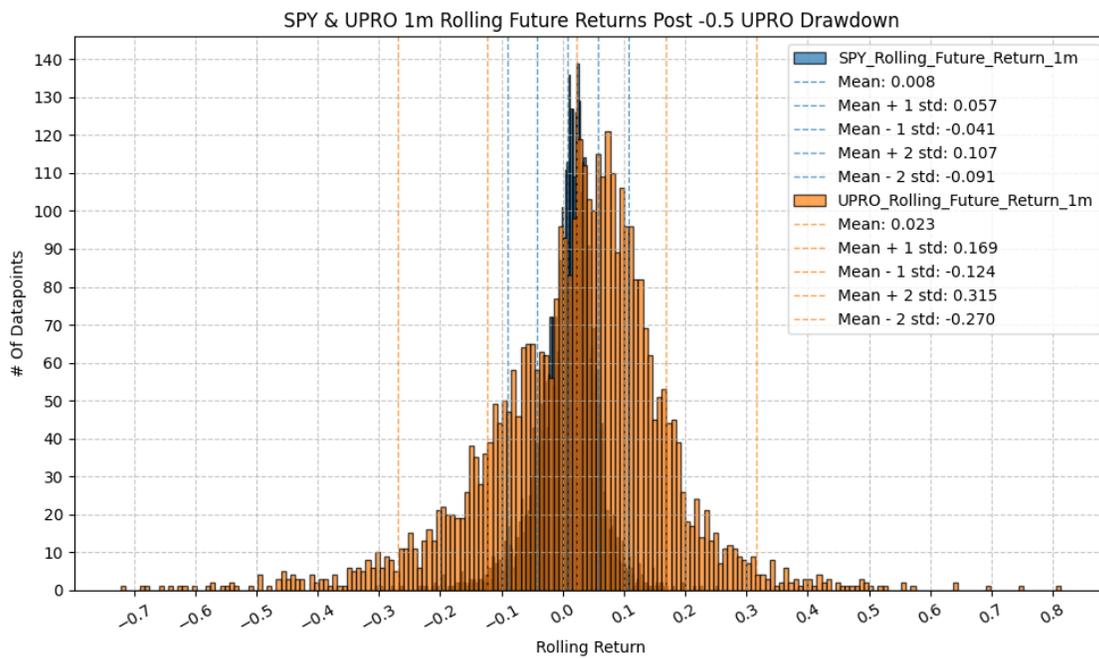
```

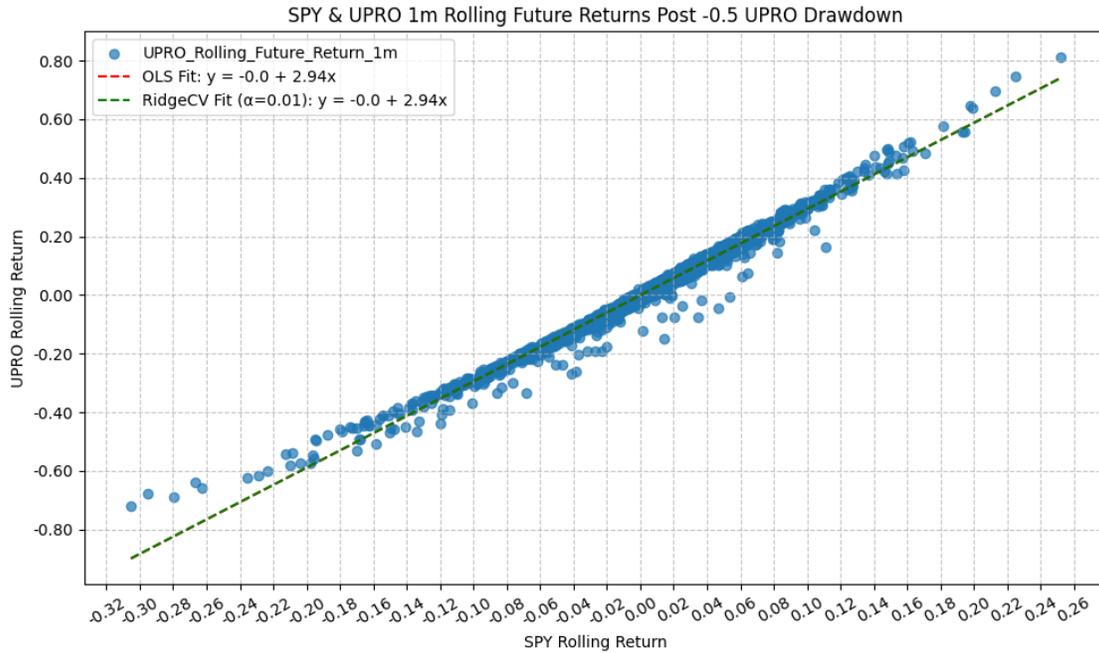
-0.000	0.000				
SPY_Rolling_Future_Return_1w	2.9704	0.004	715.239	0.000	
2.962	2.979				

```
=====
Omnibus:                1716.538   Durbin-Watson:           1.002
Prob(Omnibus):          0.000     Jarque-Bera (JB):       449887.905
Skew:                   -0.903     Prob(JB):                0.00
Kurtosis:               55.783     Cond. No.                38.0
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1m    R-squared:
0.986
Model:                  OLS                            Adj. R-squared:
0.986
Method:                 Least Squares                 F-statistic:
2.738e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:57                      Log-Likelihood:
10219.
No. Observations:      3871                          AIC:
-2.043e+04
Df Residuals:          3869                          BIC:
-2.042e+04
Df Model:              1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0008    0.000    -2.717    0.007
=====

```

-0.001	-0.000				
SPY_Rolling_Future_Return_1m	2.9439	0.006	523.305	0.000	
2.933	2.955				

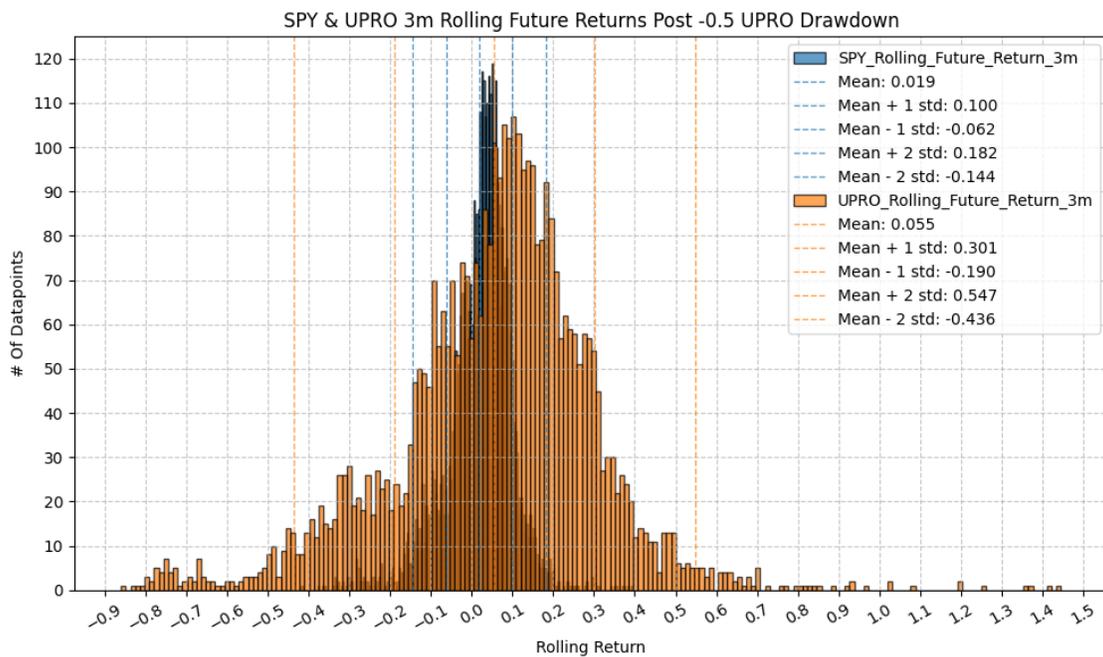
```

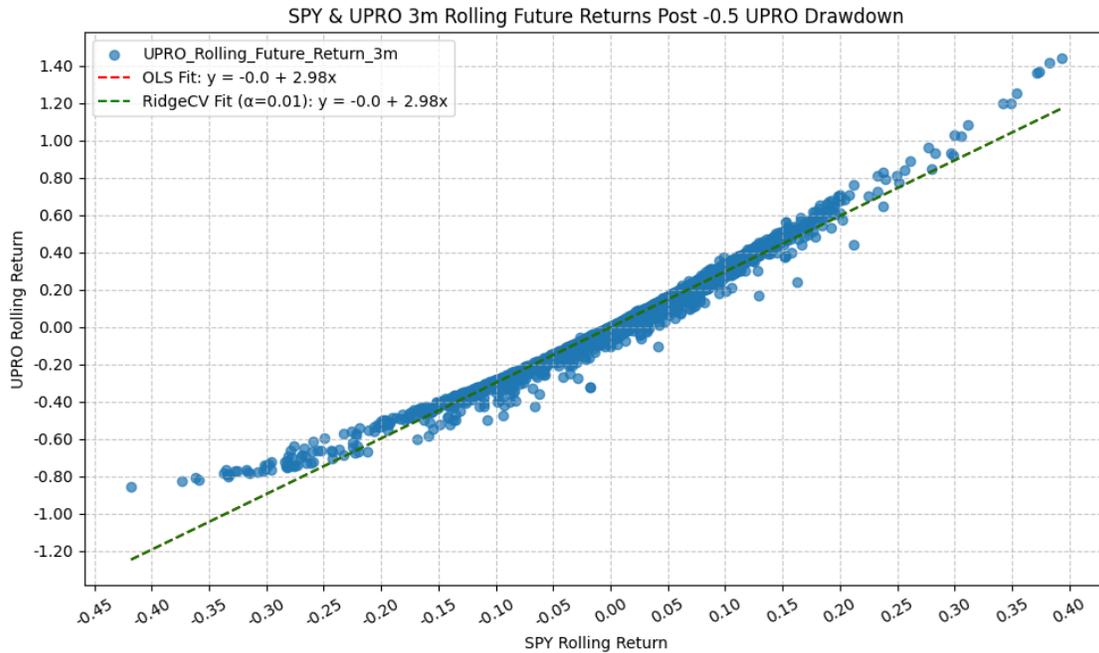
=====
Omnibus:                2107.631    Durbin-Watson:           0.385
Prob(Omnibus):          0.000    Jarque-Bera (JB):       199364.230
Skew:                   -1.681    Prob(JB):                0.00
Kurtosis:               37.996    Cond. No.                20.3
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3m    R-squared:
0.978
Model:                  OLS                            Adj. R-squared:
0.978
Method:                 Least Squares                 F-statistic:
1.701e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:28:58                     Log-Likelihood:
7306.6
No. Observations:      3871                          AIC:
-1.461e+04
Df Residuals:          3869                          BIC:
-1.460e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -0.0011    0.001    -1.901    0.057
=====

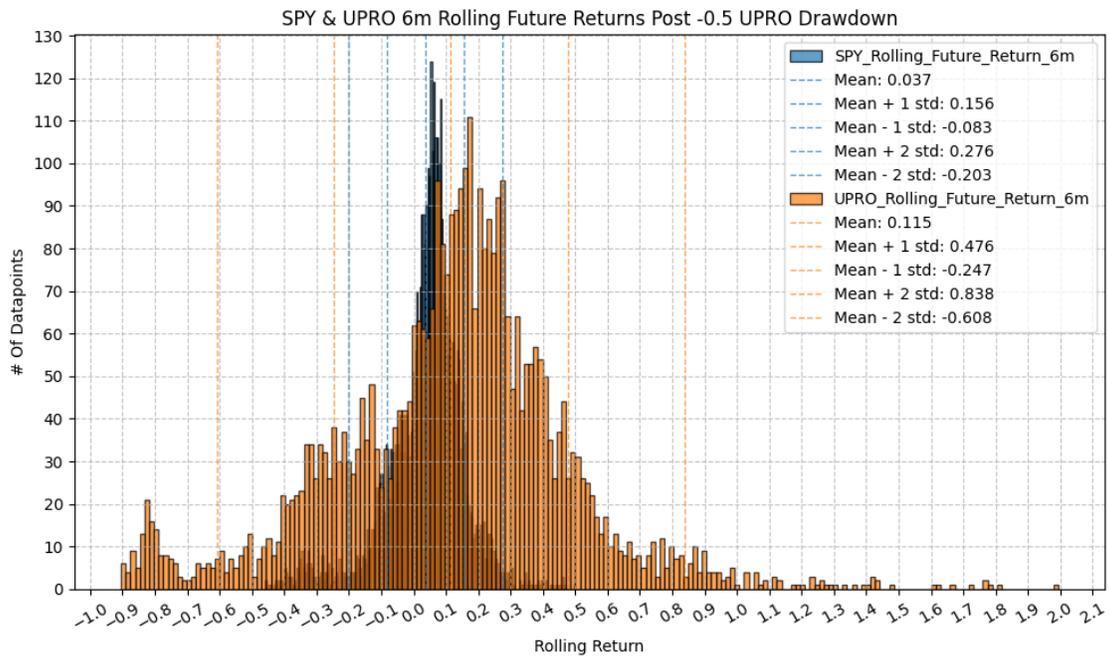
```

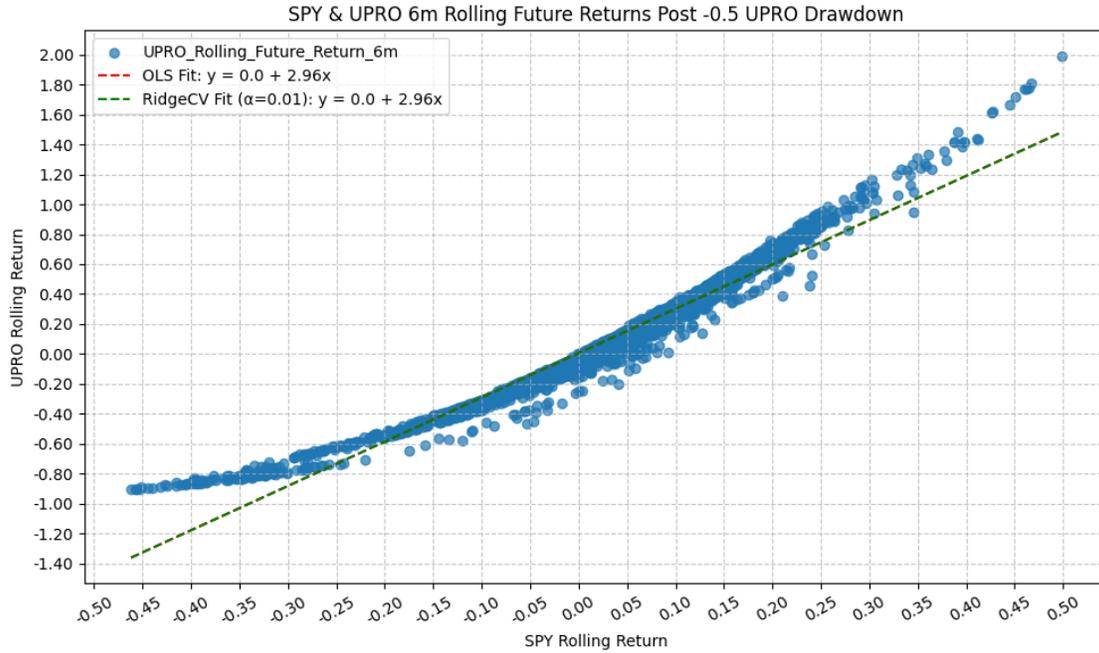
-0.002 3.63e-05
 SPY_Rolling_Future_Return_3m 2.9840 0.007 412.439 0.000
 2.970 2.998

```
=====
Omnibus:                    1375.125    Durbin-Watson:                    0.193
Prob(Omnibus):             0.000    Jarque-Bera (JB):                43082.229
Skew:                      1.059    Prob(JB):                         0.00
Kurtosis:                  19.206    Cond. No.                         12.3
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_6m    R-squared:
0.957
Model:                  OLS                            Adj. R-squared:
0.957
Method:                 Least Squares                 F-statistic:
8.590e+04
Date:                   Mon, 16 Mar 2026               Prob (F-statistic):
0.00
Time:                   14:29:00                      Log-Likelihood:
4532.3
No. Observations:      3871                            AIC:
-9061.
Df Residuals:          3869                            BIC:
-9048.
Df Model:              1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                0.0067    0.001     5.300    0.000

```

0.004	0.009				
SPY_Rolling_Future_Return_6m	2.9569	0.010	293.089	0.000	
2.937	2.977				

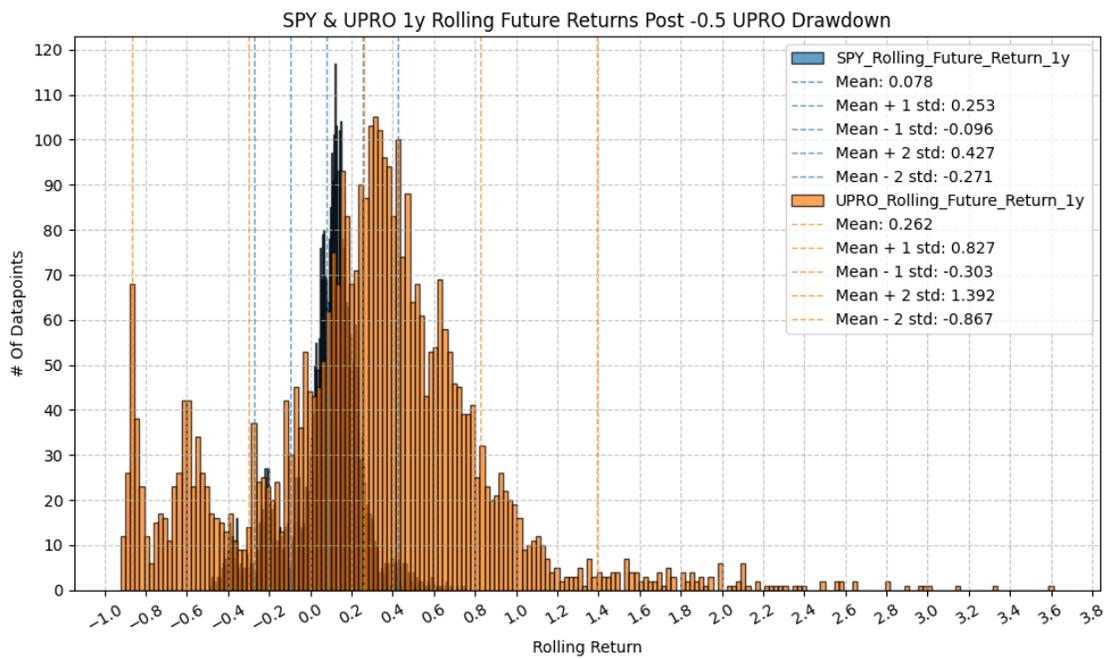
```

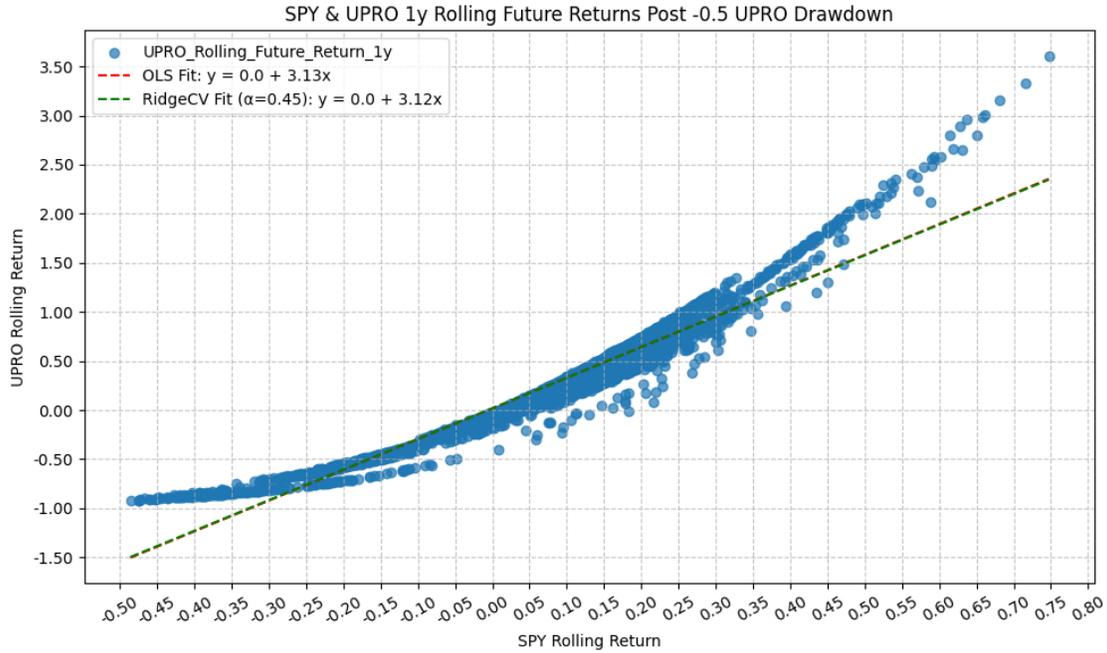
=====
Omnibus:                1292.768    Durbin-Watson:           0.081
Prob(Omnibus):          0.000    Jarque-Bera (JB):       9397.773
Skew:                   1.396    Prob(JB):               0.00
Kurtosis:               10.104    Cond. No.               8.37
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1y    R-squared:
0.933
Model:                  OLS                            Adj. R-squared:
0.933
Method:                 Least Squares                 F-statistic:
5.409e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:01                      Log-Likelihood:
1958.2
No. Observations:      3871                          AIC:
-3912.
Df Residuals:          3869                          BIC:
-3900.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0174	0.003	6.787	0.000

0.012 0.022
 SPY_Rolling_Future_Return_1y 3.1291 0.013 232.562 0.000
 3.103 3.155

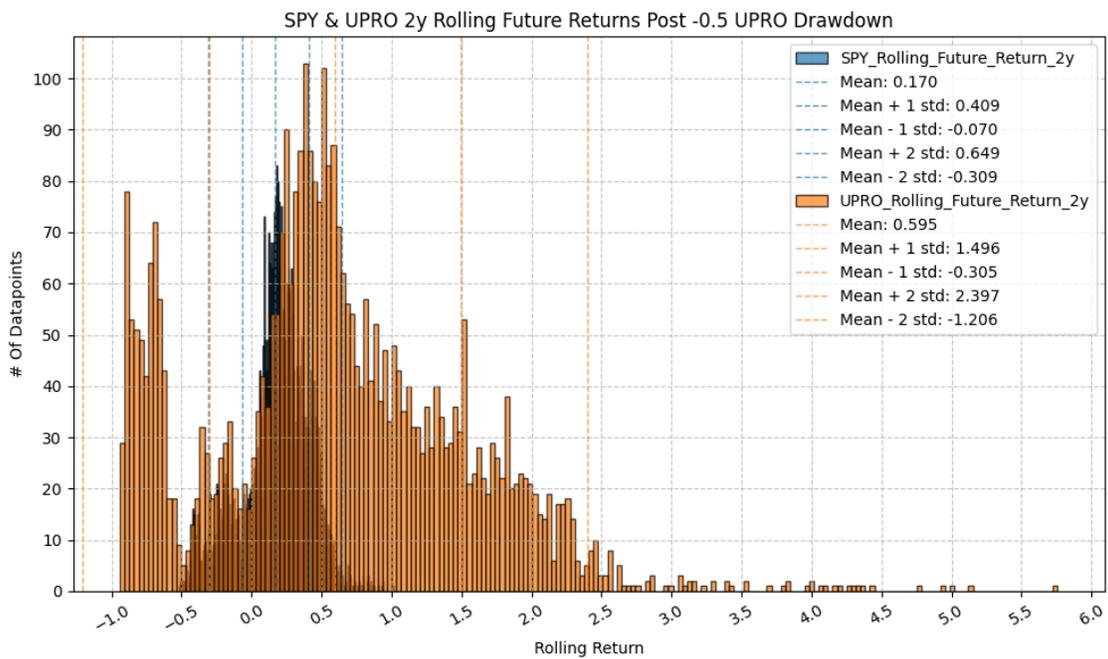
```
=====
```

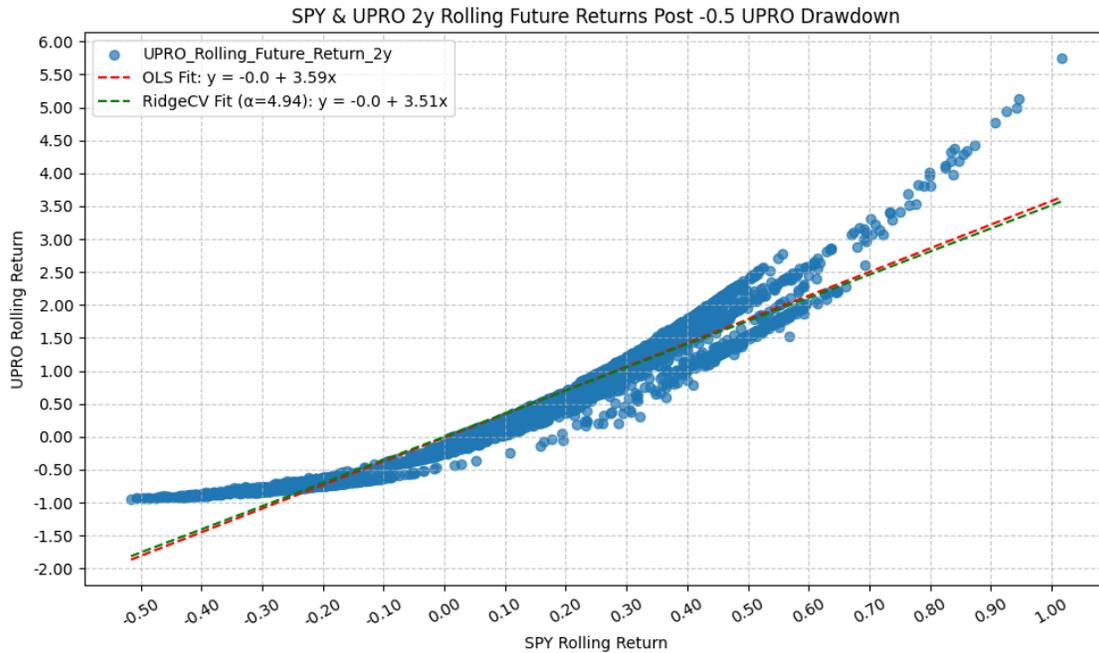
Omnibus:	1514.882	Durbin-Watson:	0.057
Prob(Omnibus):	0.000	Jarque-Bera (JB):	11136.976
Skew:	1.682	Prob(JB):	0.00
Kurtosis:	10.598	Cond. No.	5.77

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_2y    R-squared:
0.912
Model:                  OLS                            Adj. R-squared:
0.912
Method:                 Least Squares                  F-statistic:
4.022e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:02                      Log-Likelihood:
-377.53
No. Observations:      3871                          AIC:
759.1
Df Residuals:          3869                          BIC:
771.6
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0141    0.005     -2.685    0.007
=====

```

-0.024	-0.004				
SPY_Rolling_Future_Return_2y	3.5921	0.018	200.550	0.000	
3.557	3.627				

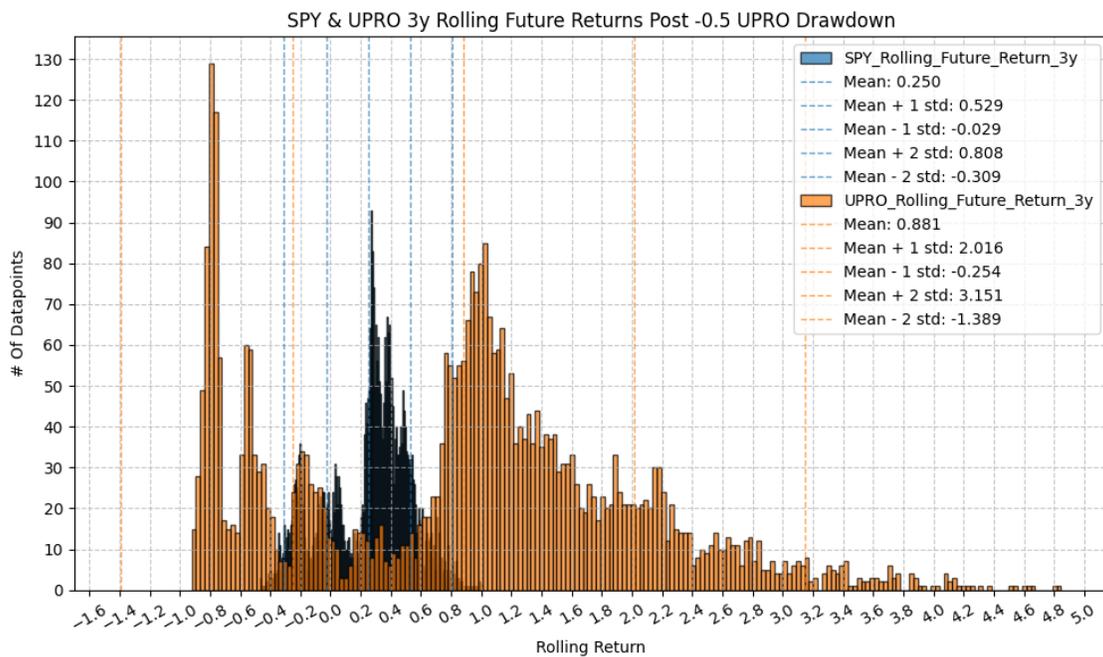
```

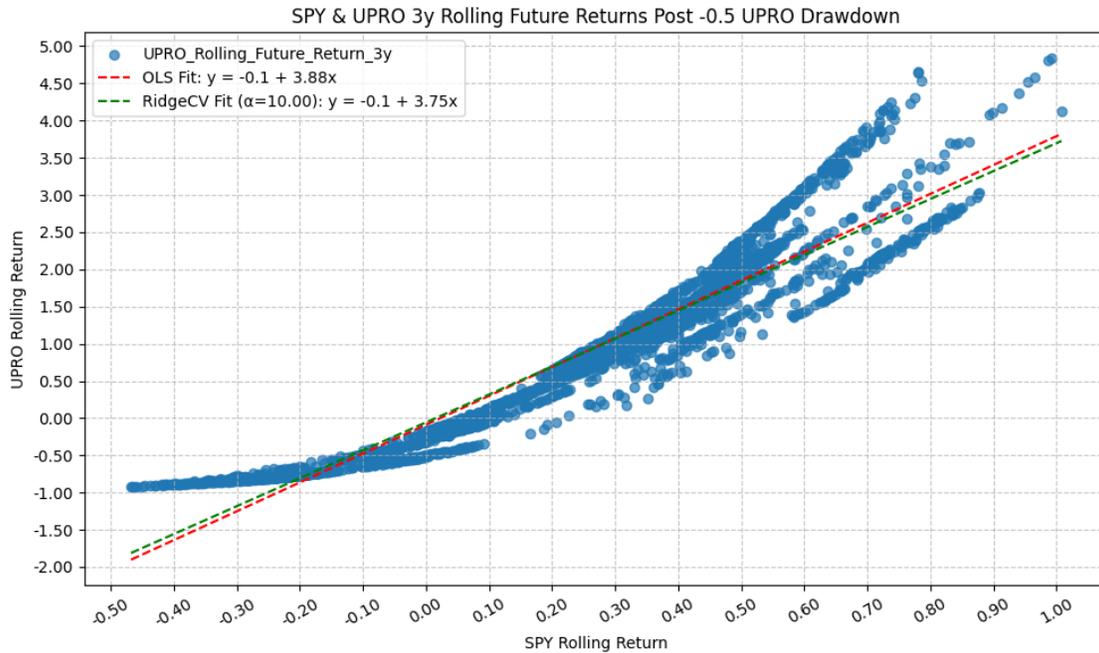
=====
Omnibus:                1084.267   Durbin-Watson:          0.036
Prob(Omnibus):          0.000     Jarque-Bera (JB):      3631.483
Skew:                   1.395     Prob(JB):               0.00
Kurtosis:               6.839     Cond. No.               4.30
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_3y    R-squared:
0.911
Model:              OLS                            Adj. R-squared:
0.911
Method:             Least Squares                  F-statistic:
3.909e+04
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:               14:29:03                       Log-Likelihood:
-1292.1
No. Observations:  3832                            AIC:
2588.
Df Residuals:      3830                            BIC:
2601.
Df Model:           1
Covariance Type:   nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0884    0.007    -12.033    0.000

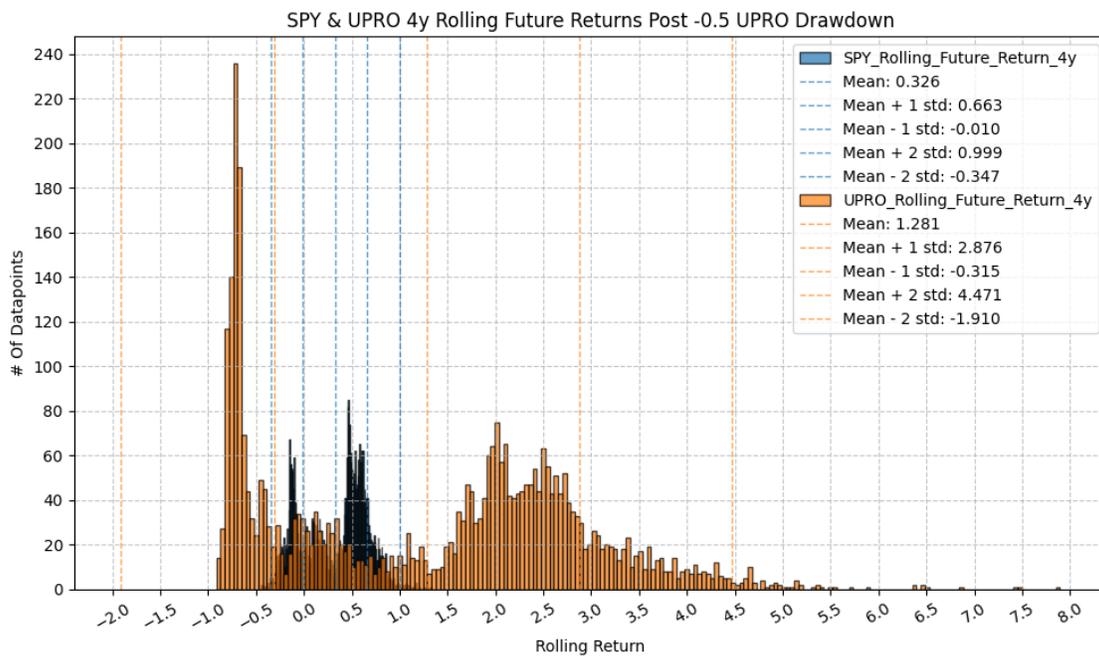
```

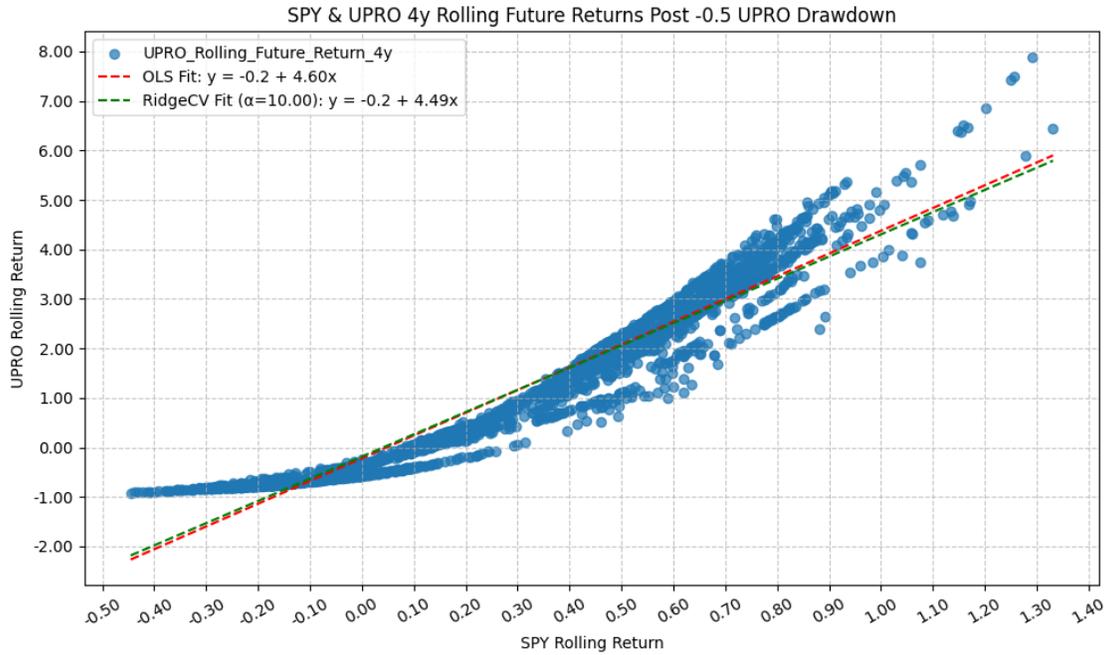
-0.103 -0.074
 SPY_Rolling_Future_Return_3y 3.8786 0.020 197.723 0.000
 3.840 3.917

```
=====
Omnibus:                              631.089      Durbin-Watson:                              0.022
Prob(Omnibus):                        0.000      Jarque-Bera (JB):                        1399.356
Skew:                                  0.954      Prob(JB):                                  1.36e-304
Kurtosis:                              5.263      Cond. No.                                  3.82
=====
```

Notes:

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





OLS Regression Results

=====

```

Dep. Variable:      UPRO_Rolling_Future_Return_4y      R-squared:
0.940
Model:              OLS                               Adj. R-squared:
0.940
Method:             Least Squares                    F-statistic:
5.811e+04
Date:               Mon, 16 Mar 2026                 Prob (F-statistic):
0.00
Time:               14:29:04                          Log-Likelihood:
-1764.0
No. Observations:  3696                               AIC:
3532.
Df Residuals:      3694                               BIC:
3544.
Df Model:           1
Covariance Type:   nonrobust

```

=====

	coef	std err	t	P> t
[0.025 0.975]				
const	-0.2199	0.009	-24.595	0.000

-0.237	-0.202				
SPY_Rolling_Future_Return_4y	4.5978	0.019	241.056	0.000	
4.560	4.635				

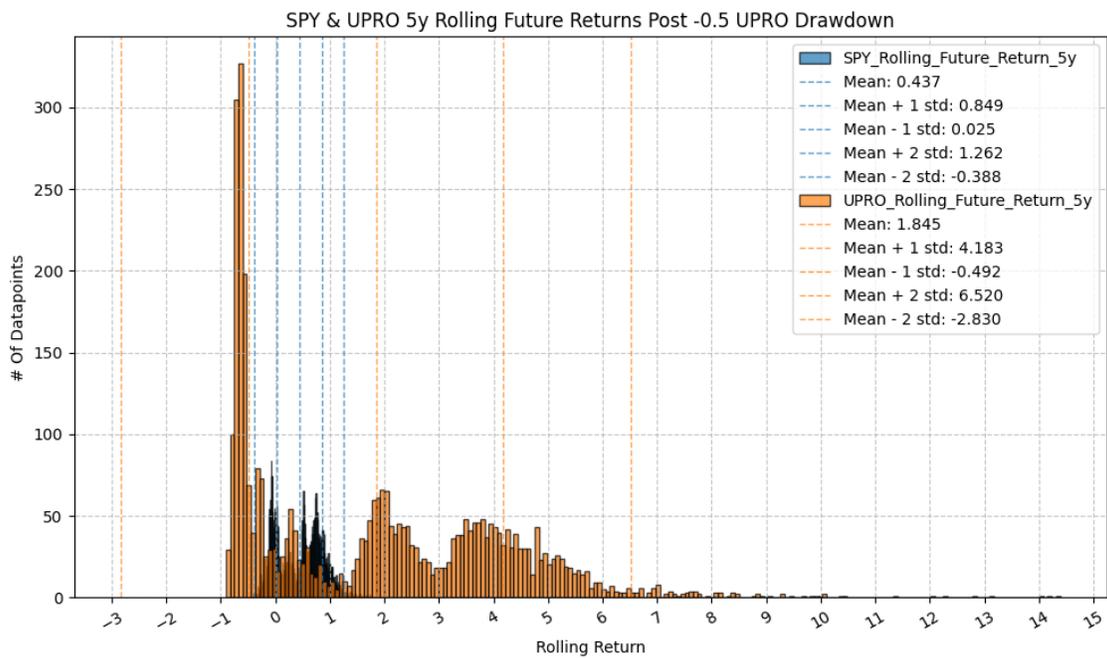
```

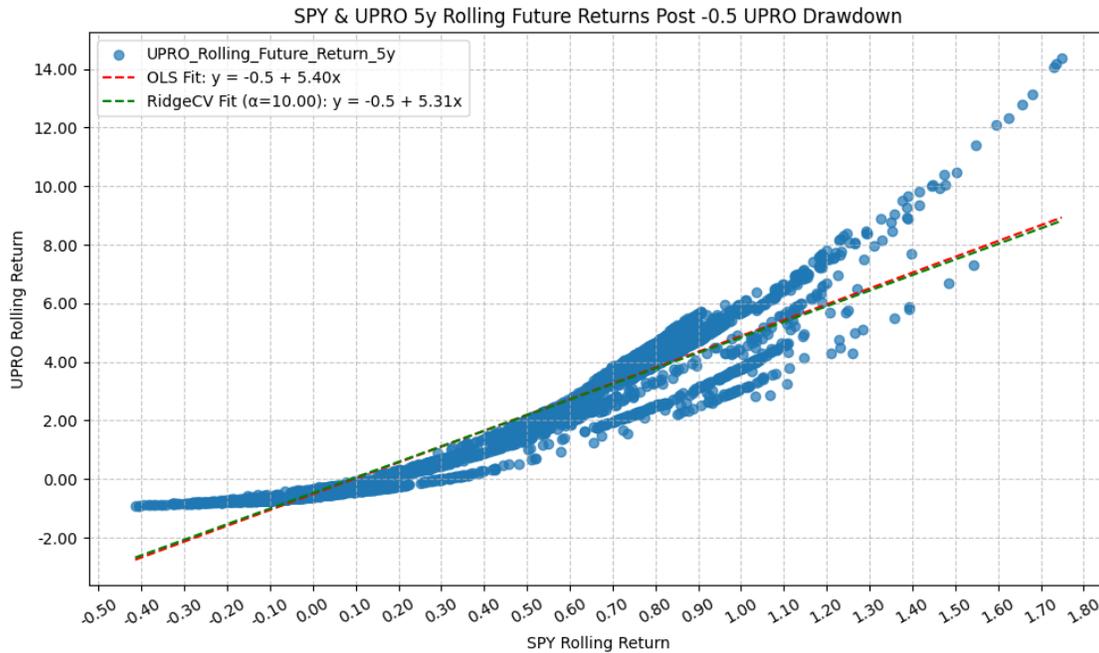
=====
Omnibus:                141.094   Durbin-Watson:           0.030
Prob(Omnibus):          0.000   Jarque-Bera (JB):       415.728
Skew:                   0.068   Prob(JB):                5.32e-91
Kurtosis:               4.637   Cond. No.                3.32
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_5y    R-squared:
0.907
Model:                  OLS                            Adj. R-squared:
0.907
Method:                 Least Squares                 F-statistic:
3.594e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:05                     Log-Likelihood:
-3996.6
No. Observations:      3696                          AIC:
7997.
Df Residuals:          3694                          BIC:
8010.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.5139    0.017    -30.042    0.000

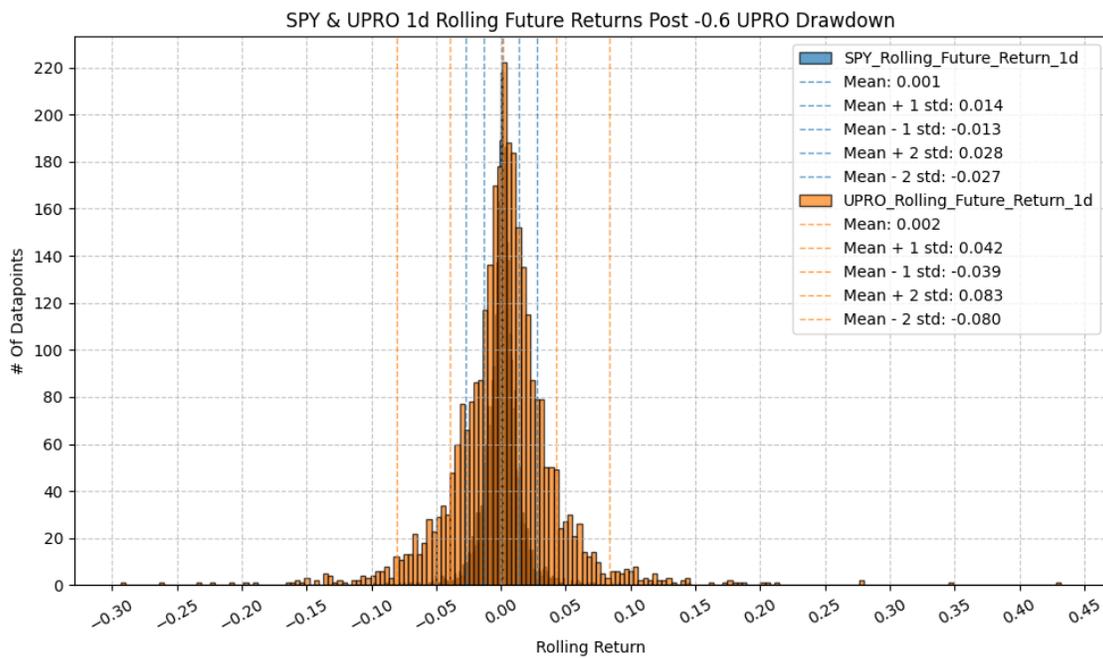
```

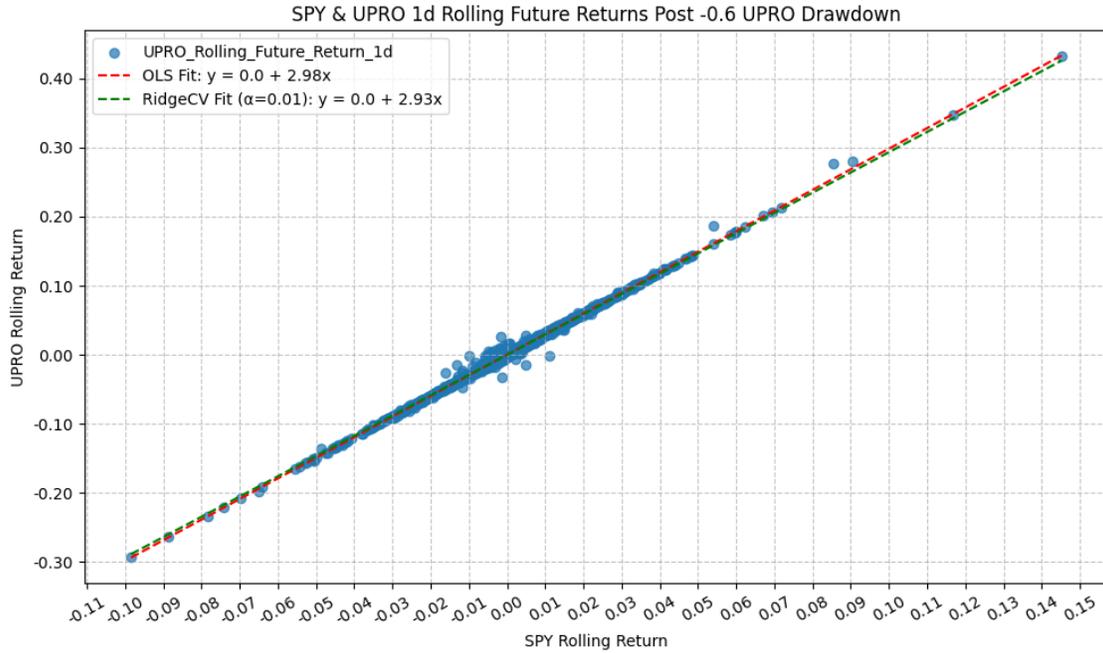
-0.547 -0.480
 SPY_Rolling_Future_Return_5y 5.3991 0.028 189.589 0.000
 5.343 5.455

```
=====
Omnibus:                                    551.159      Durbin-Watson:                                    0.022
Prob(Omnibus):                              0.000      Jarque-Bera (JB):                                    2881.358
Skew:                                        0.609      Prob(JB):                                            0.00
Kurtosis:                                    7.151      Cond. No.                                            2.96
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1d    R-squared:
0.997
Model:                  OLS                            Adj. R-squared:
0.997
Method:                 Least Squares                 F-statistic:
1.059e+06
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:07                     Log-Likelihood:
14432.
No. Observations:      3070                          AIC:
-2.886e+04
Df Residuals:          3068                          BIC:
-2.885e+04
Df Model:              1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                7.42e-05   3.97e-05     1.868    0.062
=====

```

-3.69e-06 0.000
 SPY_Rolling_Future_Return_1d 2.9825 0.003 1028.945 0.000
 2.977 2.988

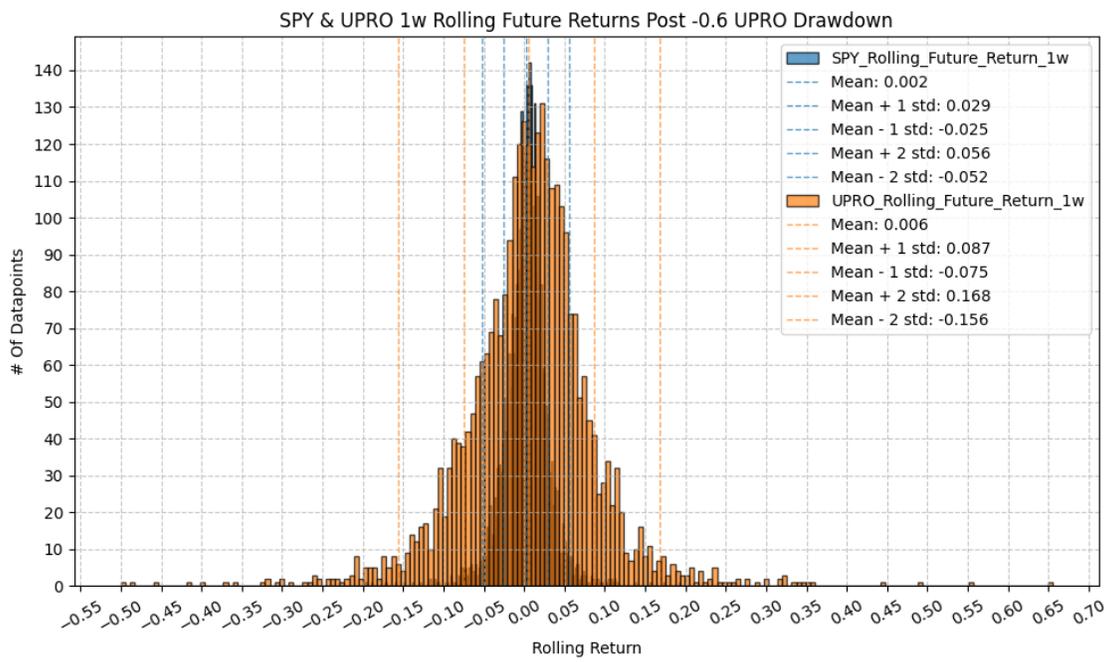
```
=====
```

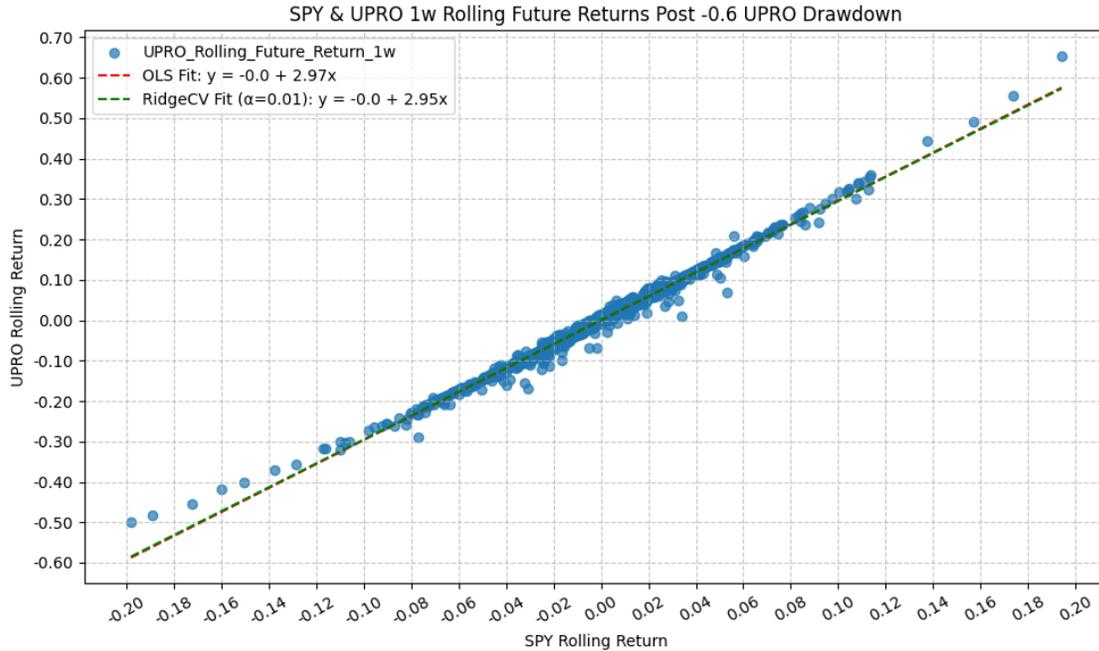
Omnibus:	2273.218	Durbin-Watson:	2.537
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1053036.968
Skew:	2.319	Prob(JB):	0.00
Kurtosis:	93.613	Cond. No.	73.0

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1w    R-squared:
0.992
Model:                  OLS                            Adj. R-squared:
0.992
Method:                 Least Squares                 F-statistic:
3.762e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:08                     Log-Likelihood:
10750.
No. Observations:      3070                          AIC:
-2.150e+04
Df Residuals:          3068                          BIC:
-2.148e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0001    0.000      -1.043    0.297

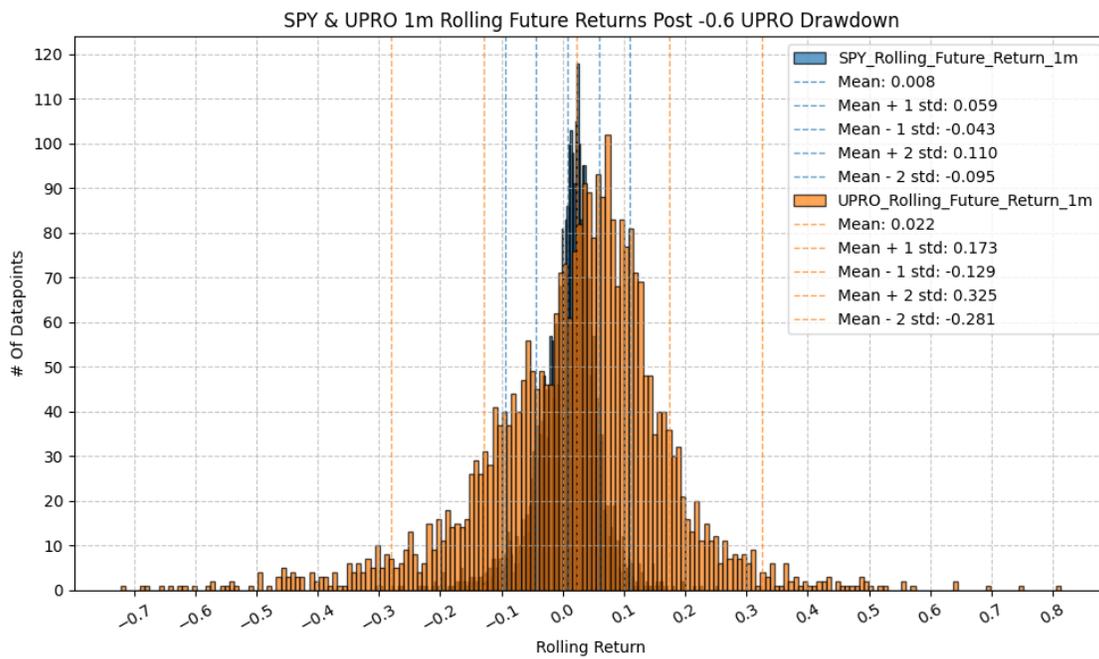
```

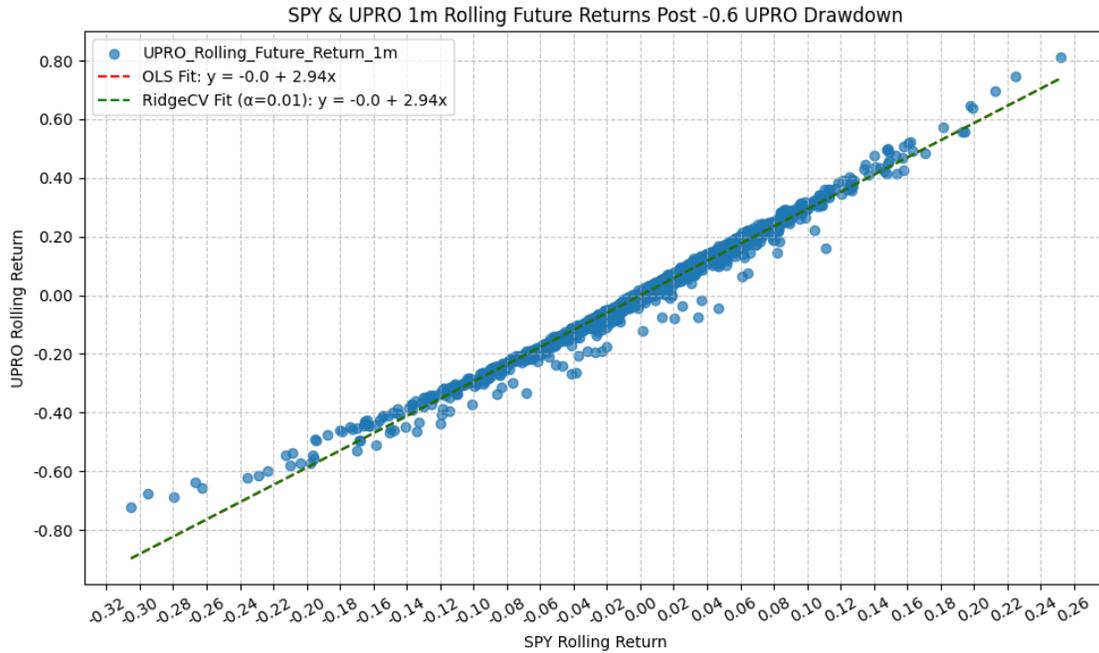
-0.000	0.000				
SPY_Rolling_Future_Return_1w	2.9678	0.005	613.318	0.000	
2.958	2.977				

```
=====
Omnibus:                1399.948    Durbin-Watson:                1.060
Prob(Omnibus):          0.000      Jarque-Bera (JB):            313435.830
Skew:                   -0.997     Prob(JB):                     0.00
Kurtosis:               52.460     Cond. No.                    36.7
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1m    R-squared:
0.986
Model:                  OLS                            Adj. R-squared:
0.986
Method:                 Least Squares                 F-statistic:
2.086e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:09                     Log-Likelihood:
7938.3
No. Observations:      3070                          AIC:
-1.587e+04
Df Residuals:          3068                          BIC:
-1.586e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0006    0.000    -1.711    0.087

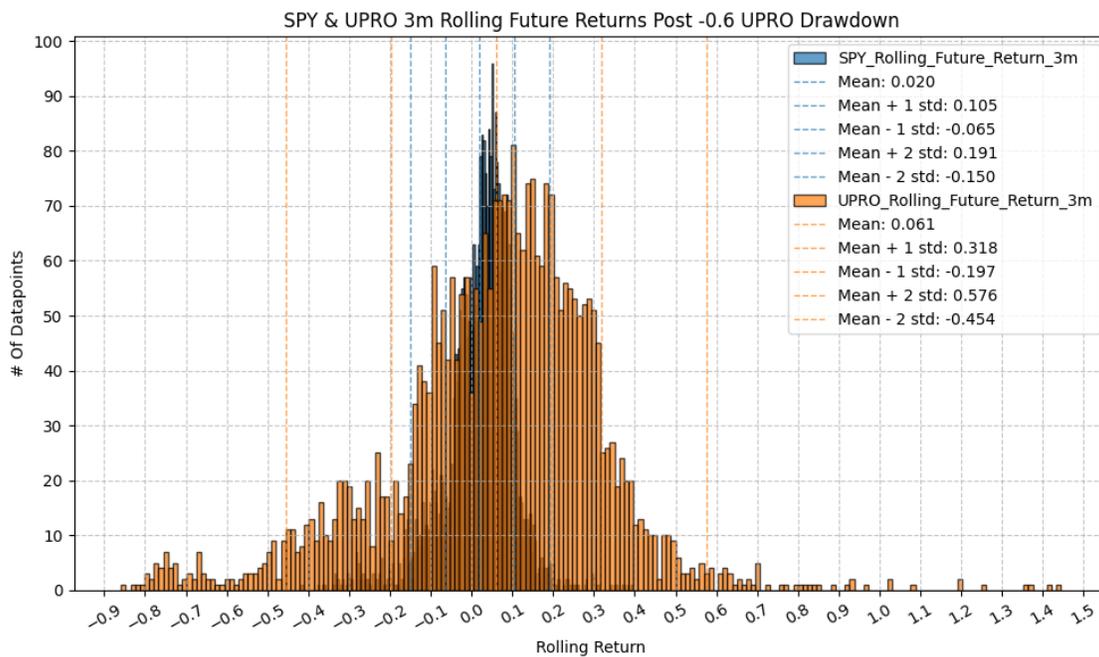
```

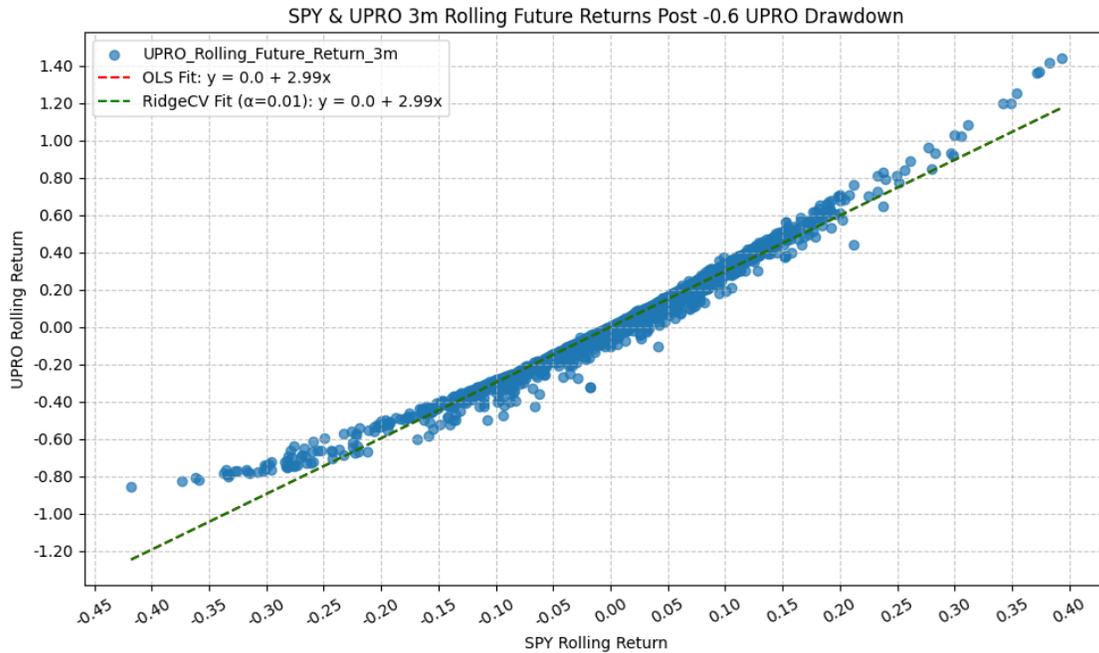
-0.001 8.3e-05
 SPY_Rolling_Future_Return_1m 2.9397 0.006 456.774 0.000
 2.927 2.952

```
=====
Omnibus:                            1387.733      Durbin-Watson:                            0.407
Prob(Omnibus):                        0.000      Jarque-Bera (JB):                        109426.463
Skew:                                 -1.256      Prob(JB):                                 0.00
Kurtosis:                              32.140      Cond. No.                                 19.6
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_3m    R-squared:
0.977
Model:              OLS                            Adj. R-squared:
0.977
Method:             Least Squares                  F-statistic:
1.313e+05
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:               14:29:10                       Log-Likelihood:
5610.5
No. Observations:  3070                            AIC:
-1.122e+04
Df Residuals:      3068                            BIC:
-1.121e+04
Df Model:           1
Covariance Type:   nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                0.0004    0.001    0.589    0.556
=====

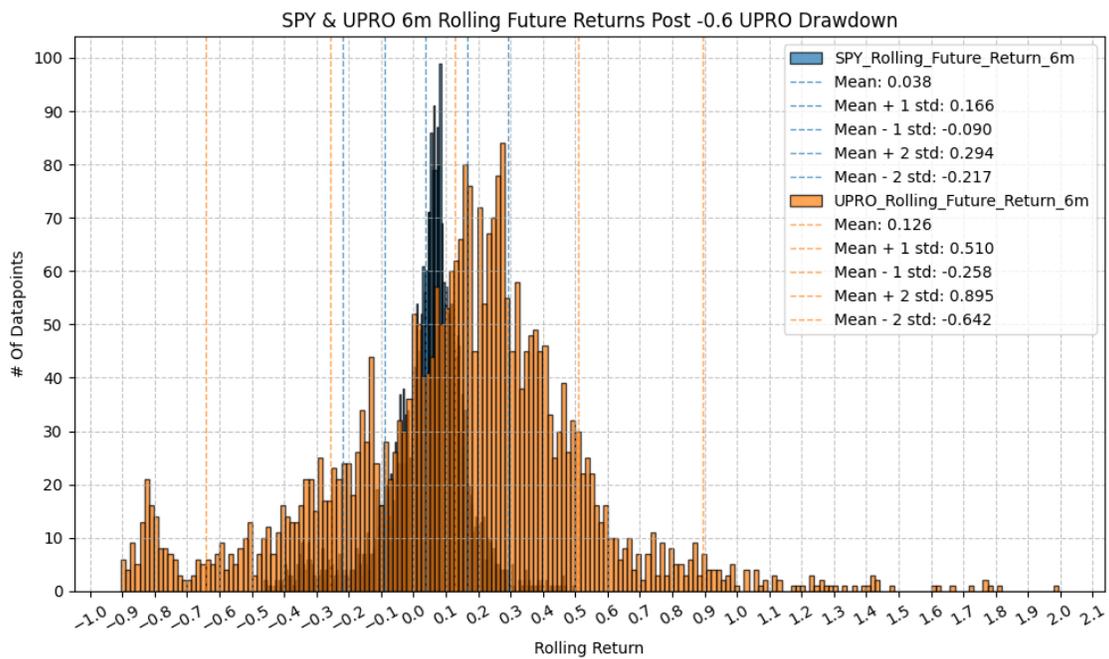
```

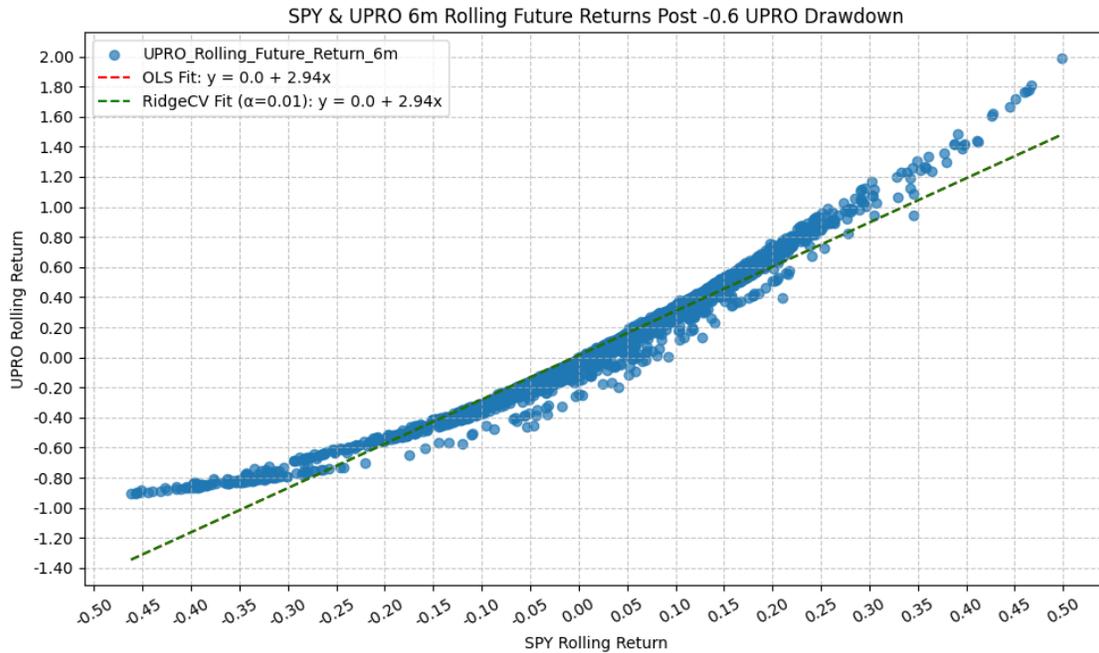
-0.001	0.002				
SPY_Rolling_Future_Return_3m	2.9878	0.008	362.348	0.000	
2.972	3.004				

```
=====
Omnibus:                1129.279   Durbin-Watson:           0.193
Prob(Omnibus):          0.000     Jarque-Bera (JB):       29419.559
Skew:                   1.166     Prob(JB):                0.00
Kurtosis:               17.985    Cond. No.                11.7
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_6m    R-squared:
0.956
Model:                  OLS                            Adj. R-squared:
0.956
Method:                 Least Squares                 F-statistic:
6.658e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:11                     Log-Likelihood:
3373.6
No. Observations:      3070                          AIC:
-6743.
Df Residuals:          3068                          BIC:
-6731.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0138	0.002	9.062	0.000

0.011	0.017				
SPY_Rolling_Future_Return_6m	2.9412	0.011	258.024	0.000	
2.919	2.964				

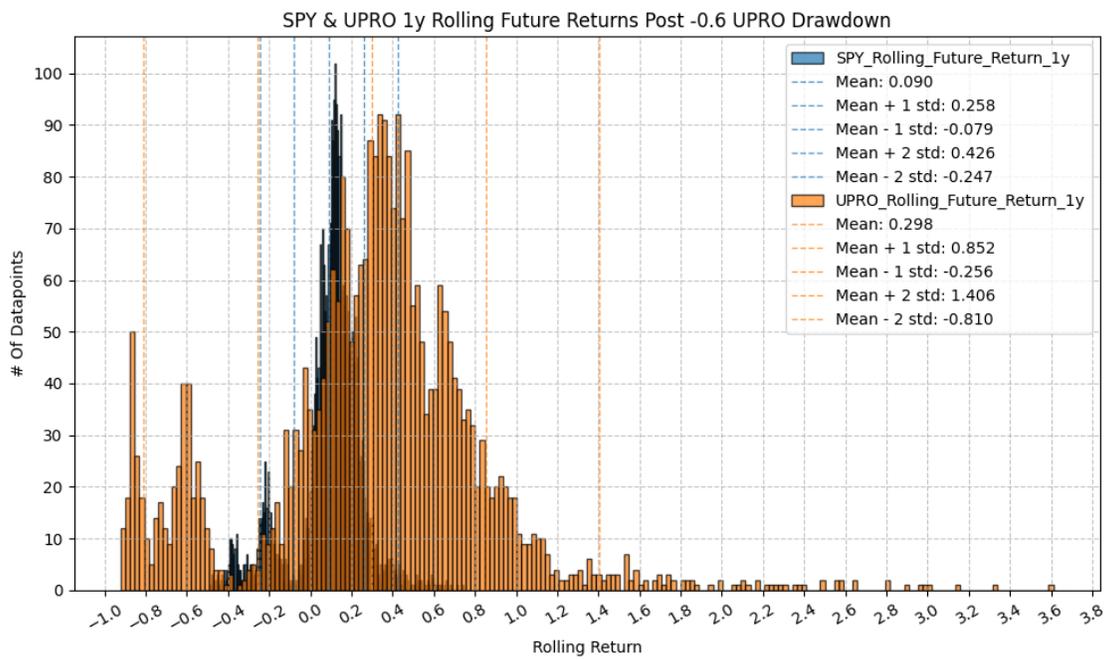
```

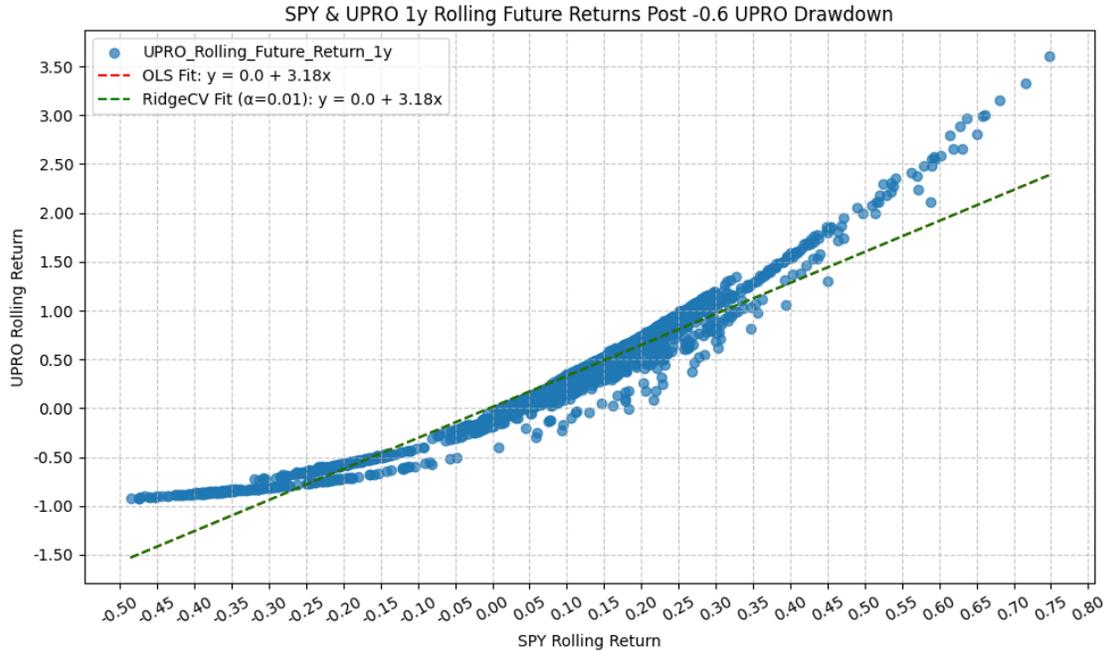
=====
Omnibus:                862.196   Durbin-Watson:           0.075
Prob(Omnibus):          0.000   Jarque-Bera (JB):       5064.599
Skew:                   1.201   Prob(JB):               0.00
Kurtosis:               8.816   Cond. No.               7.84
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1y    R-squared:
0.932
Model:                  OLS                            Adj. R-squared:
0.932
Method:                 Least Squares                  F-statistic:
4.197e+04
Date:                   Mon, 16 Mar 2026               Prob (F-statistic):
0.00
Time:                   14:29:12                       Log-Likelihood:
1581.2
No. Observations:      3070                            AIC:
-3158.
Df Residuals:          3068                            BIC:
-3146.
Df Model:              1
Covariance Type:      nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	0.0132	0.003	4.453	0.000

0.007 0.019
 SPY_Rolling_Future_Return_1y 3.1762 0.016 204.862 0.000
 3.146 3.207

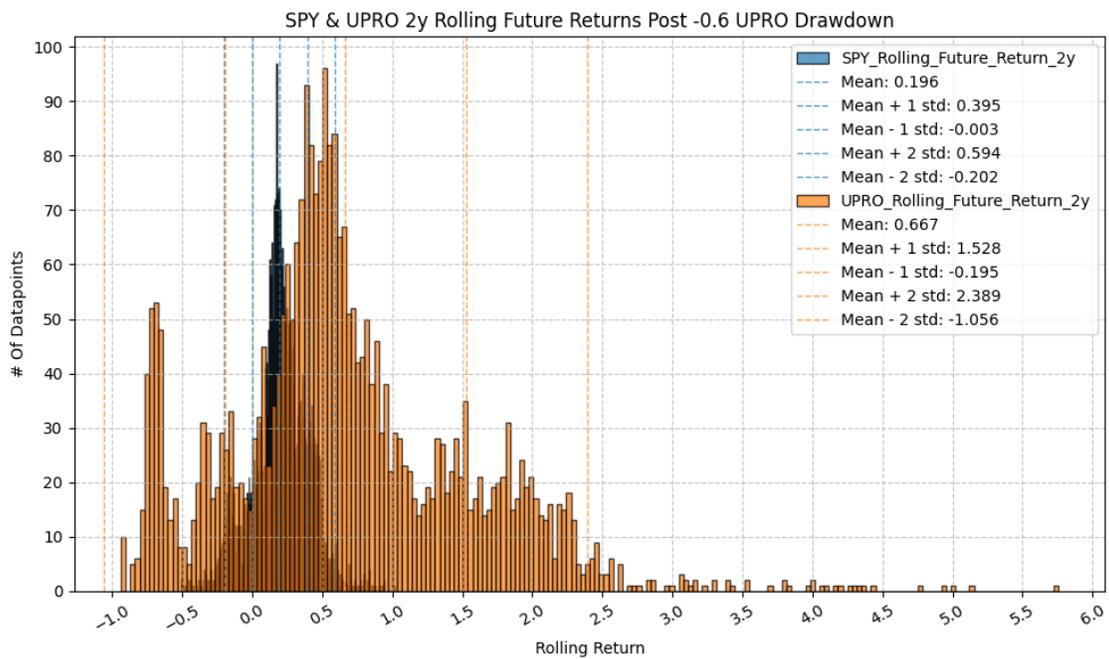
```
=====
```

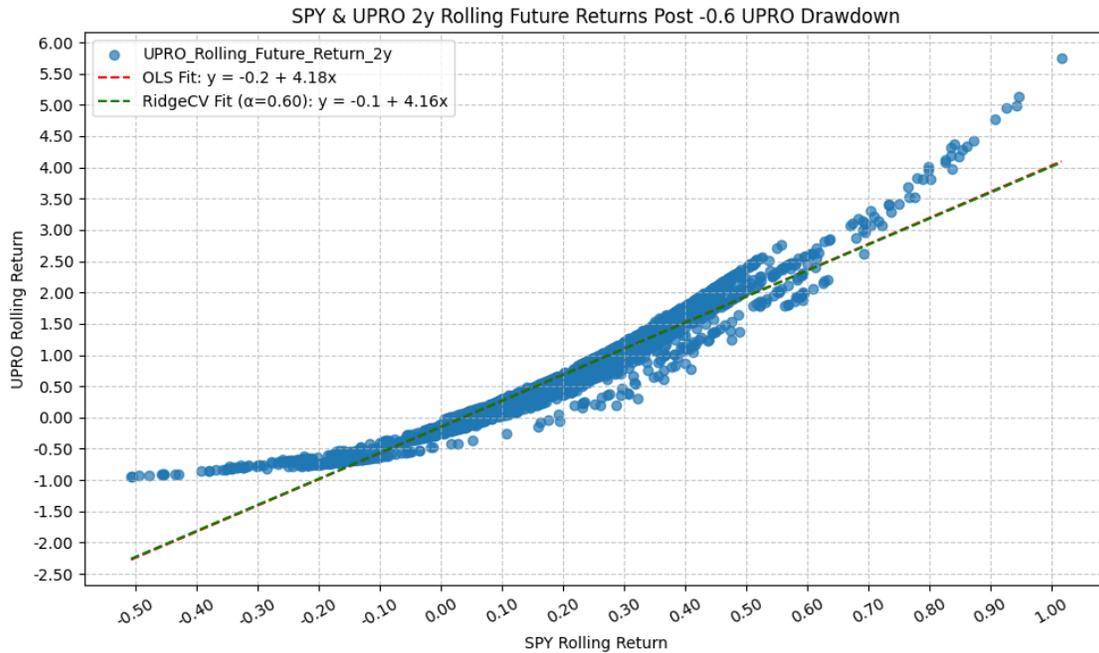
Omnibus:	1210.909	Durbin-Watson:	0.065
Prob(Omnibus):	0.000	Jarque-Bera (JB):	10511.033
Skew:	1.634	Prob(JB):	0.00
Kurtosis:	11.455	Cond. No.	5.99

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_2y    R-squared:
0.932
Model:                  OLS                            Adj. R-squared:
0.932
Method:                 Least Squares                 F-statistic:
4.210e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:14                      Log-Likelihood:
230.85
No. Observations:      3070                          AIC:
-457.7
Df Residuals:          3068                          BIC:
-445.6
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.1524    0.006   -26.793    0.000

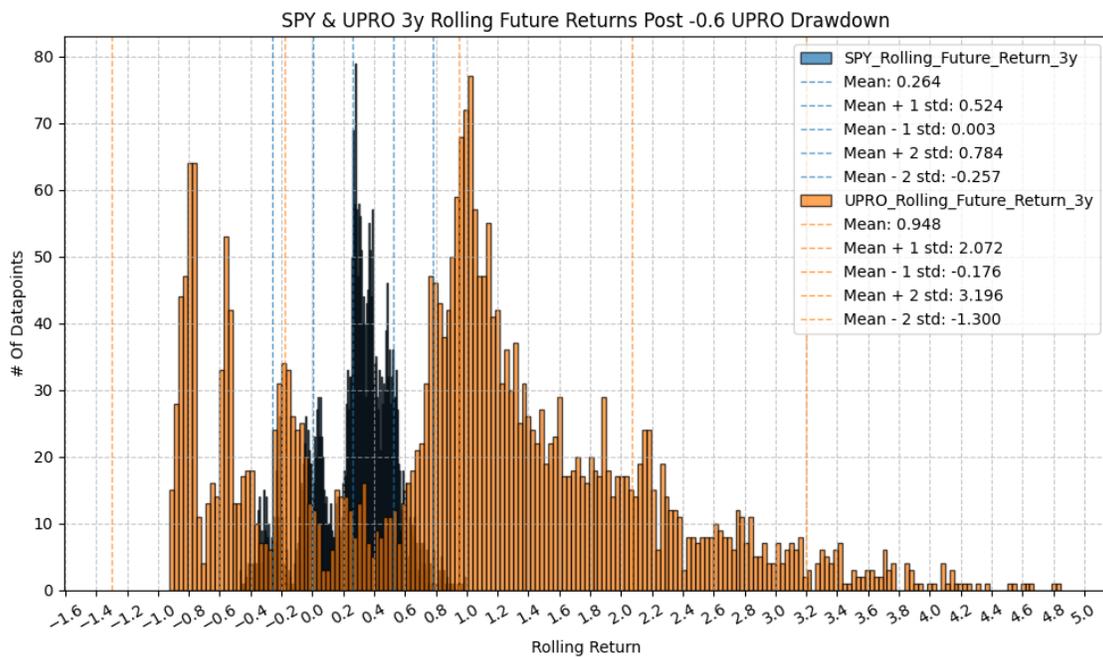
```

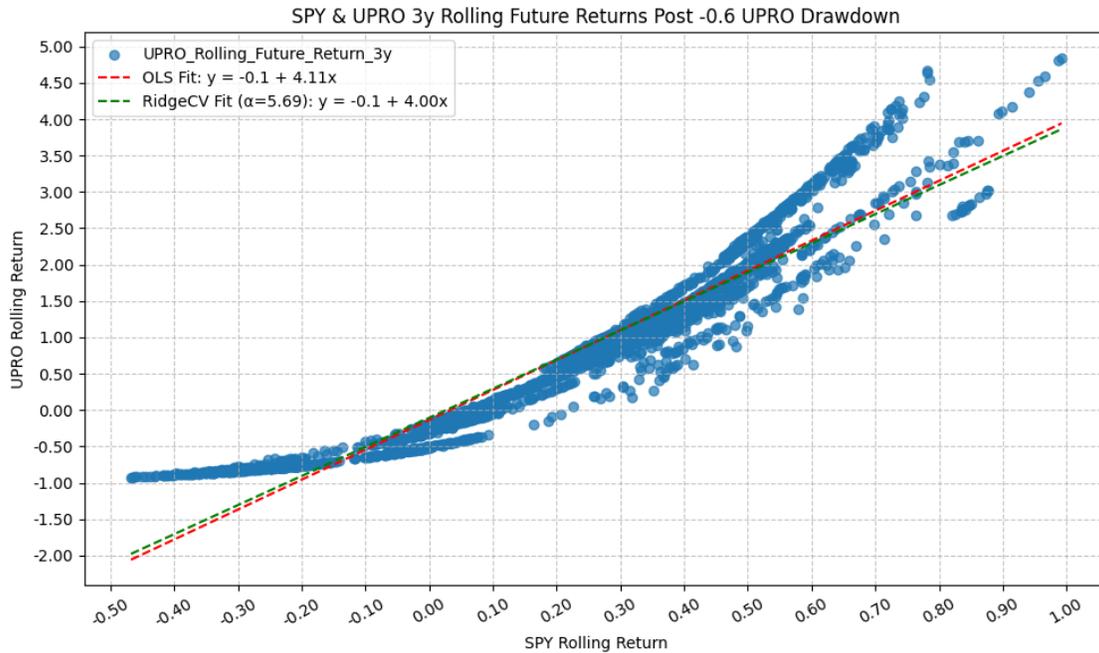
-0.164	-0.141				
SPY_Rolling_Future_Return_2y	4.1802	0.020	205.190	0.000	
4.140	4.220				

Omnibus:	971.652	Durbin-Watson:	0.048
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5574.704
Skew:	1.382	Prob(JB):	0.00
Kurtosis:	8.995	Cond. No.	5.23

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3y    R-squared:
0.906
Model:                  OLS                            Adj. R-squared:
0.906
Method:                 Least Squares                 F-statistic:
2.942e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:15                      Log-Likelihood:
-1092.7
No. Observations:      3070                          AIC:
2189.
Df Residuals:          3068                          BIC:
2201.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.1351    0.009   -15.223    0.000

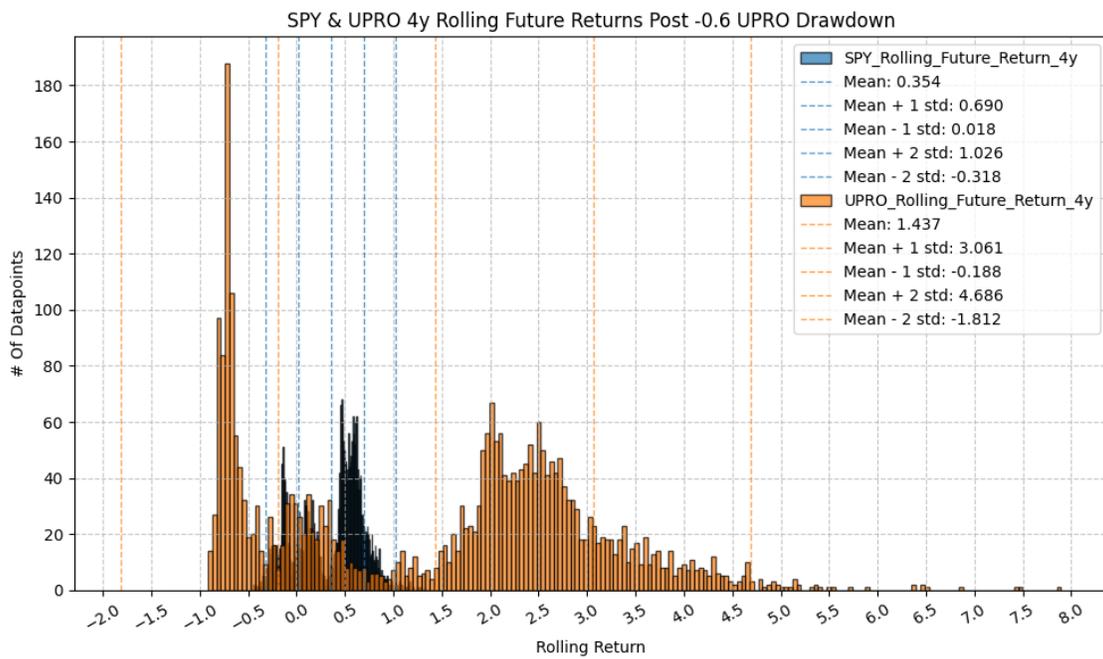
```

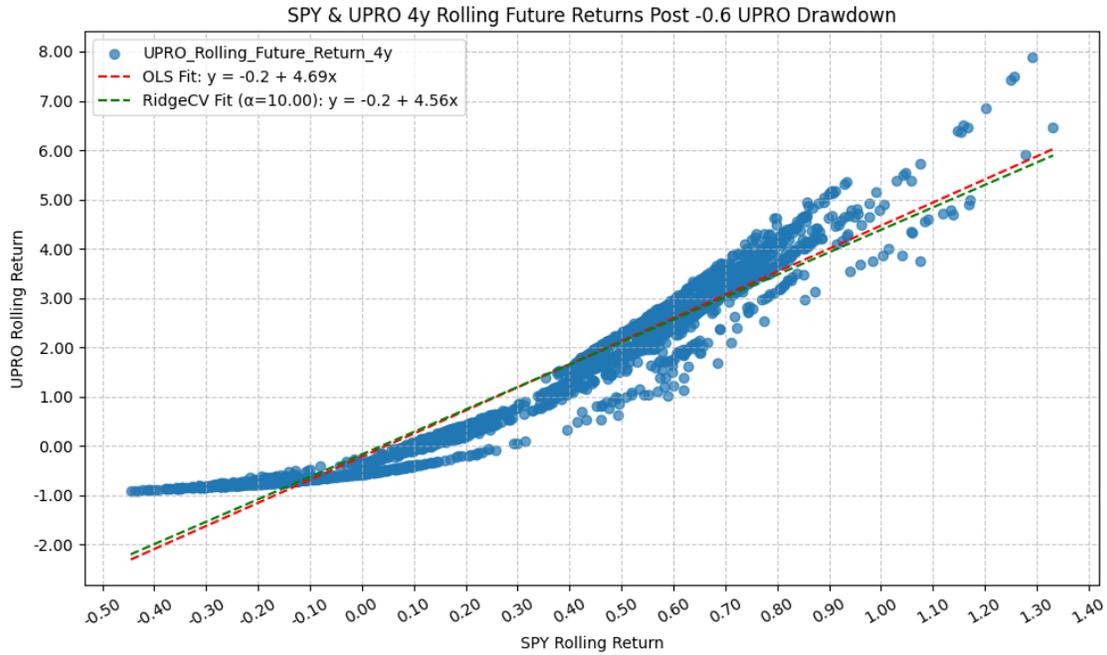
-0.153	-0.118				
SPY_Rolling_Future_Return_3y	4.1099	0.024	171.519	0.000	
4.063	4.157				

```
=====
Omnibus:                    523.372    Durbin-Watson:                0.022
Prob(Omnibus):              0.000    Jarque-Bera (JB):            948.088
Skew:                       1.070    Prob(JB):                    1.33e-206
Kurtosis:                   4.682    Cond. No.                    4.13
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_4y    R-squared:
0.942
Model:                  OLS                            Adj. R-squared:
0.942
Method:                 Least Squares                 F-statistic:
4.920e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:16                     Log-Likelihood:
-1478.5
No. Observations:      3055                          AIC:
2961.
Df Residuals:          3053                          BIC:
2973.
Df Model:               1
Covariance Type:      nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				
const	-0.2228	0.010	-21.595	0.000

-0.243	-0.203				
SPY_Rolling_Future_Return_4y	4.6897	0.021	221.807	0.000	
4.648	4.731				

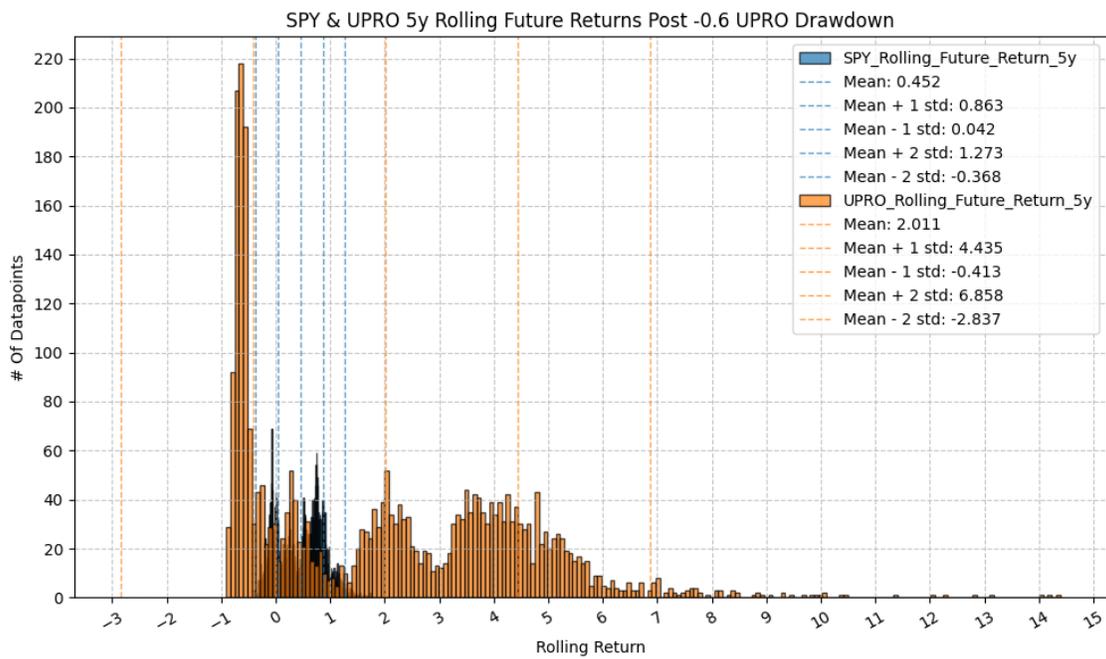
```

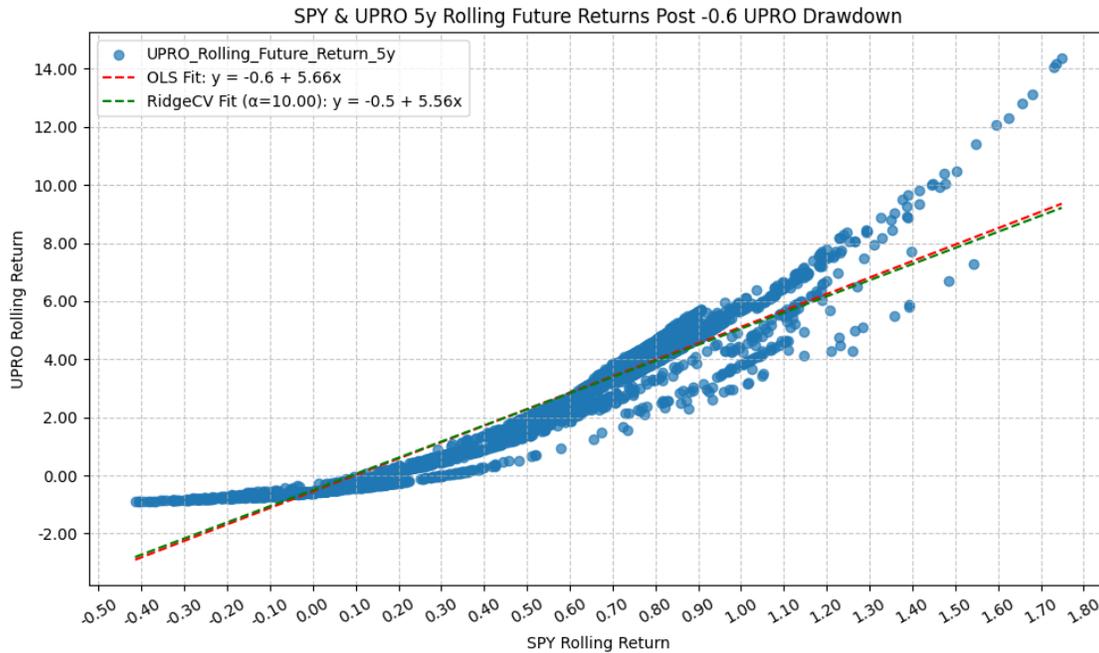
=====
Omnibus:                120.436   Durbin-Watson:           0.033
Prob(Omnibus):          0.000   Jarque-Bera (JB):       311.979
Skew:                   0.172   Prob(JB):                1.80e-68
Kurtosis:               4.527   Cond. No.                3.39
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_5y    R-squared:
0.919
Model:                  OLS                            Adj. R-squared:
0.919
Method:                 Least Squares                 F-statistic:
3.475e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:17                      Log-Likelihood:
-3195.7
No. Observations:      3055                          AIC:
6395.
Df Residuals:          3053                          BIC:
6407.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -0.5517    0.019    -29.728    0.000

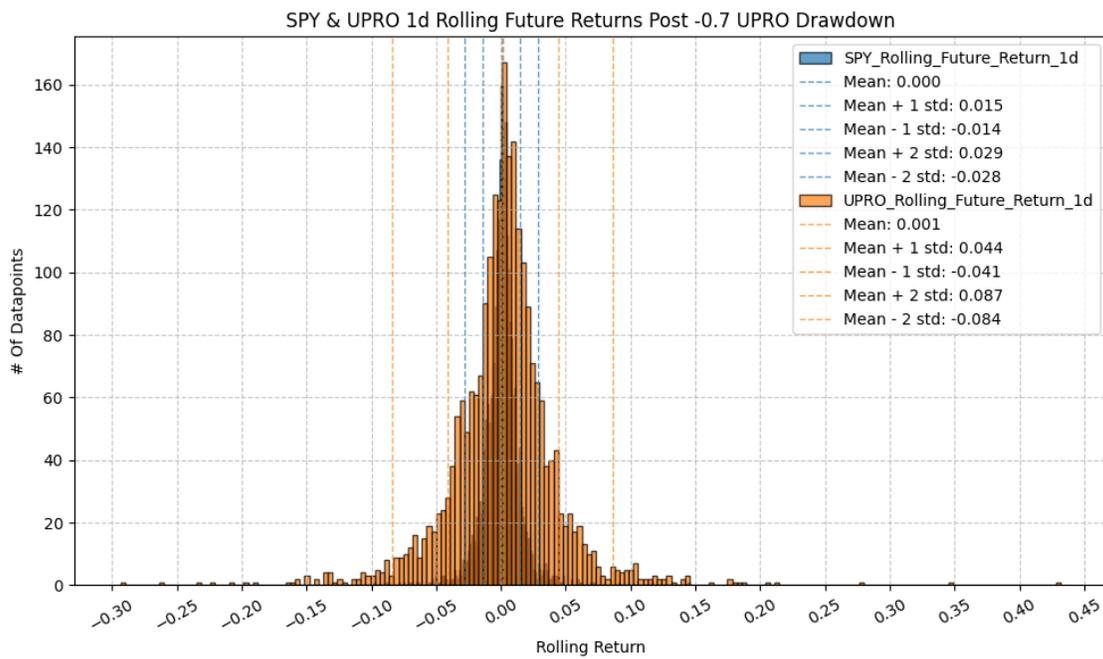
```

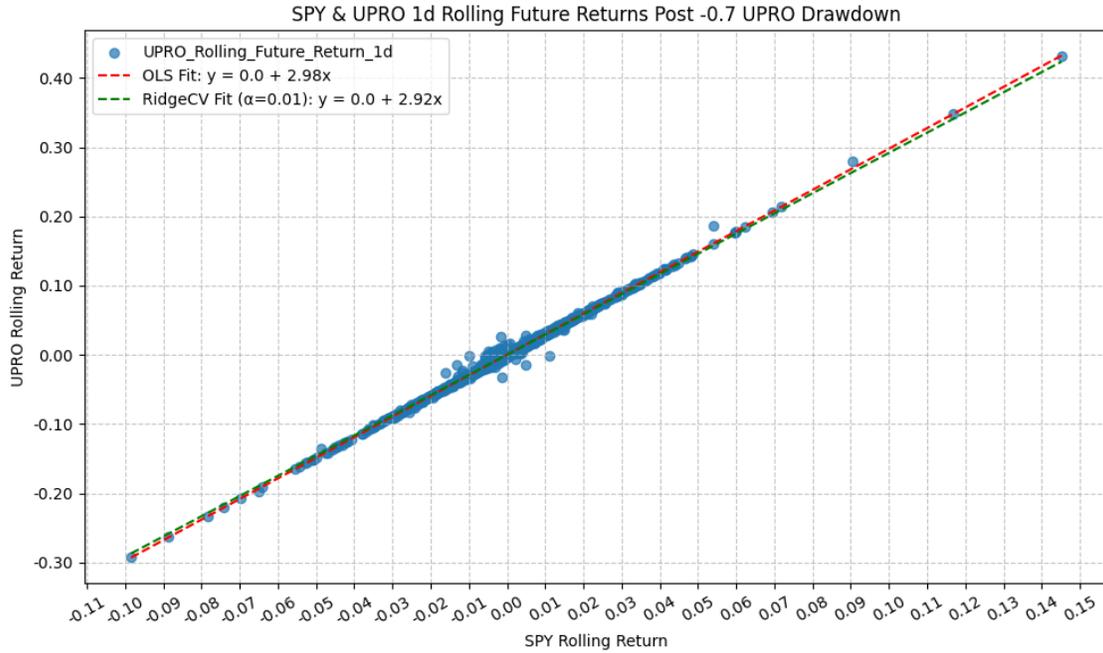
-0.588	-0.515				
SPY_Rolling_Future_Return_5y	5.6649	0.030	186.400	0.000	
5.605	5.724				

```
=====
Omnibus:                454.992    Durbin-Watson:           0.025
Prob(Omnibus):          0.000    Jarque-Bera (JB):       2120.542
Skew:                   0.640    Prob(JB):               0.00
Kurtosis:               6.876    Cond. No.               3.02
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1d    R-squared:
0.997
Model:                  OLS                            Adj. R-squared:
0.997
Method:                 Least Squares                 F-statistic:
7.538e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:18                     Log-Likelihood:
10930.
No. Observations:      2365                          AIC:
-2.186e+04
Df Residuals:          2363                          BIC:
-2.184e+04
Df Model:              1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                8.908e-05    4.9e-05    1.818    0.069
=====

```

-7e-06 0.000
 SPY_Rolling_Future_Return_1d 2.9779 0.003 868.238 0.000
 2.971 2.985

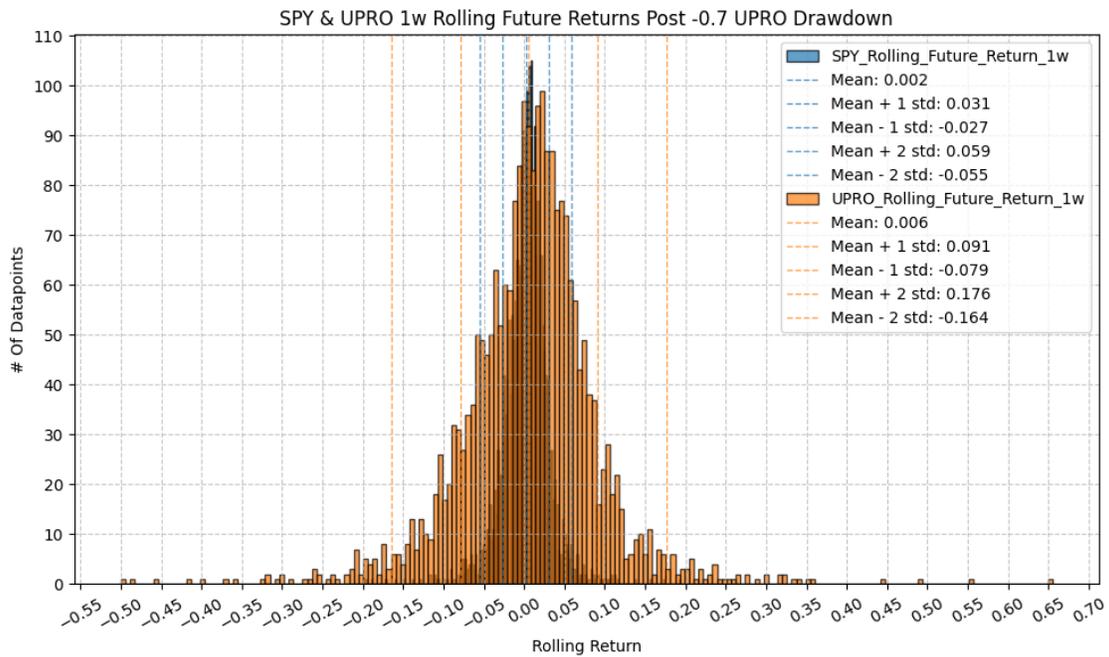
```
=====
```

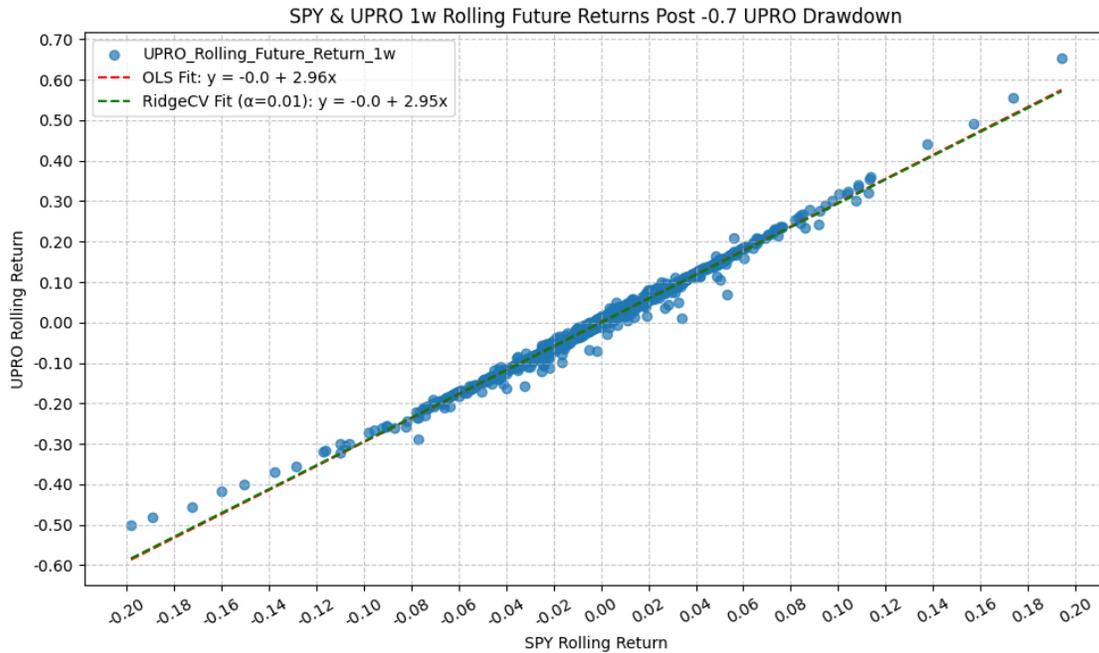
Omnibus:	1557.902	Durbin-Watson:	2.718
Prob(Omnibus):	0.000	Jarque-Bera (JB):	638251.842
Skew:	1.869	Prob(JB):	0.00
Kurtosis:	83.393	Cond. No.	70.0

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1w    R-squared:
0.991
Model:                  OLS                            Adj. R-squared:
0.991
Method:                 Least Squares                  F-statistic:
2.714e+05
Date:                   Mon, 16 Mar 2026               Prob (F-statistic):
0.00
Time:                   14:29:19                       Log-Likelihood:
8089.2
No. Observations:      2365                            AIC:
-1.617e+04
Df Residuals:          2363                            BIC:
-1.616e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -7.288e-05    0.000      -0.447    0.655

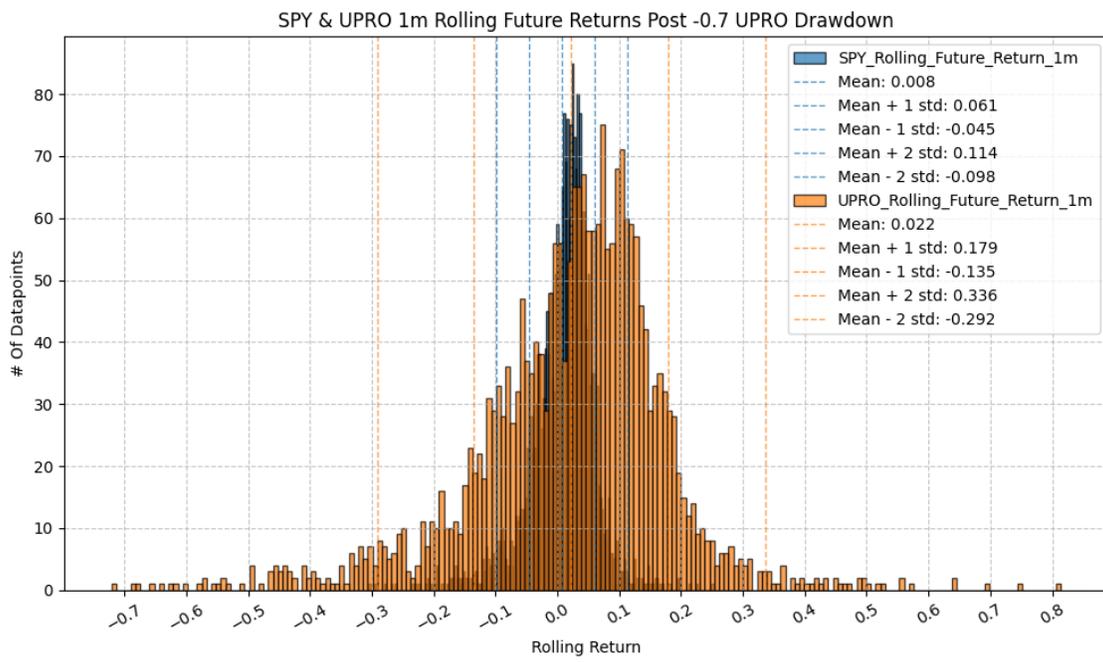
```

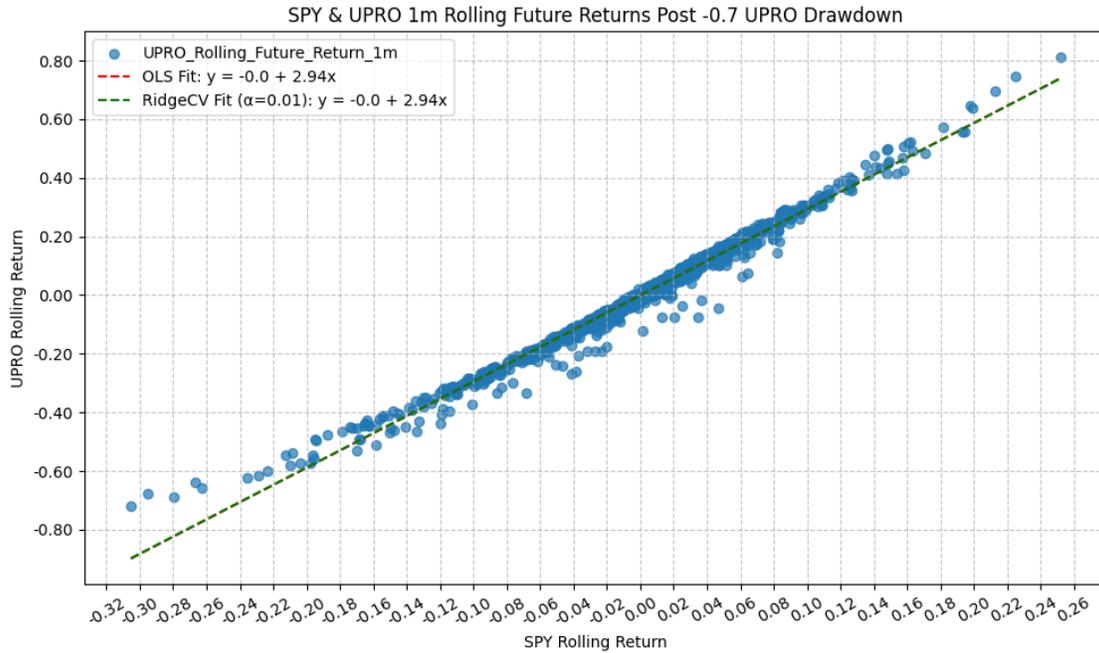
-0.000	0.000				
SPY_Rolling_Future_Return_1w	2.9631	0.006	520.935	0.000	
2.952	2.974				

```
=====
Omnibus:                893.424    Durbin-Watson:                1.046
Prob(Omnibus):          0.000    Jarque-Bera (JB):            167543.096
Skew:                   -0.621    Prob(JB):                     0.00
Kurtosis:                44.215    Cond. No.                     34.9
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1m    R-squared:
0.984
Model:                  OLS                            Adj. R-squared:
0.984
Method:                 Least Squares                 F-statistic:
1.475e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:20                      Log-Likelihood:
5932.1
No. Observations:      2365                          AIC:
-1.186e+04
Df Residuals:          2363                          BIC:
-1.185e+04
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0007    0.000    -1.733    0.083
=====

```

-0.002 9.34e-05
 SPY_Rolling_Future_Return_1m 2.9414 0.008 384.053 0.000
 2.926 2.956

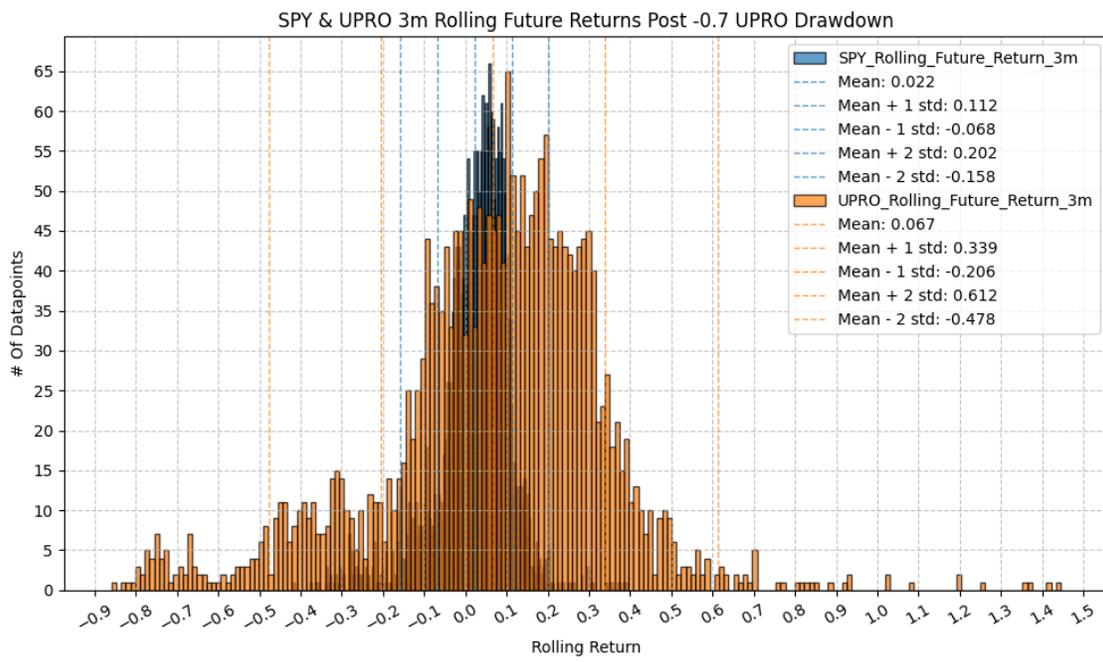
```
=====
```

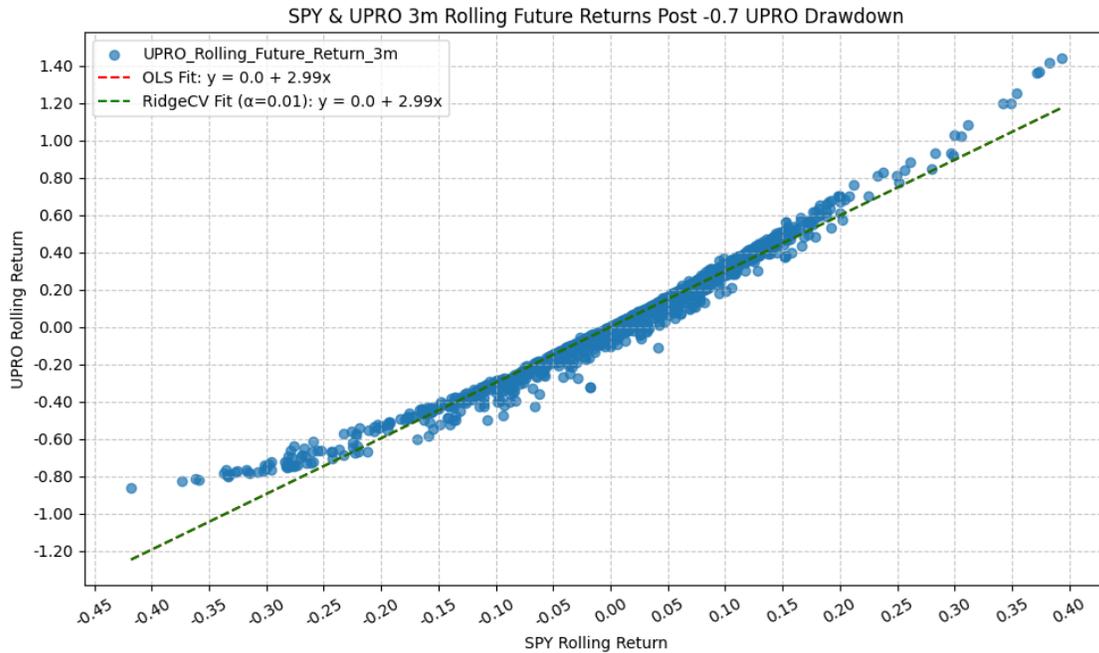
Omnibus:	955.111	Durbin-Watson:	0.364
Prob(Omnibus):	0.000	Jarque-Bera (JB):	63631.709
Skew:	-1.056	Prob(JB):	0.00
Kurtosis:	28.323	Cond. No.	18.9

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_3m    R-squared:
0.976
Model:                  OLS                            Adj. R-squared:
0.976
Method:                 Least Squares                 F-statistic:
9.454e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:21                     Log-Likelihood:
4110.7
No. Observations:      2365                          AIC:
-8217.
Df Residuals:          2363                          BIC:
-8206.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                0.0012    0.001    1.374    0.170

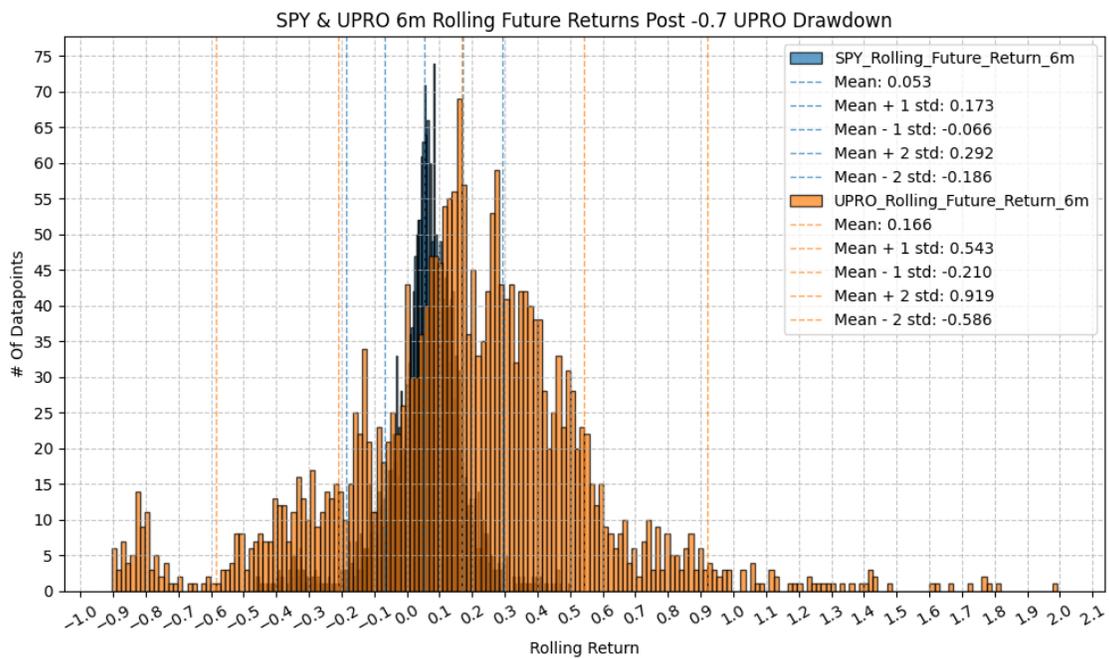
```

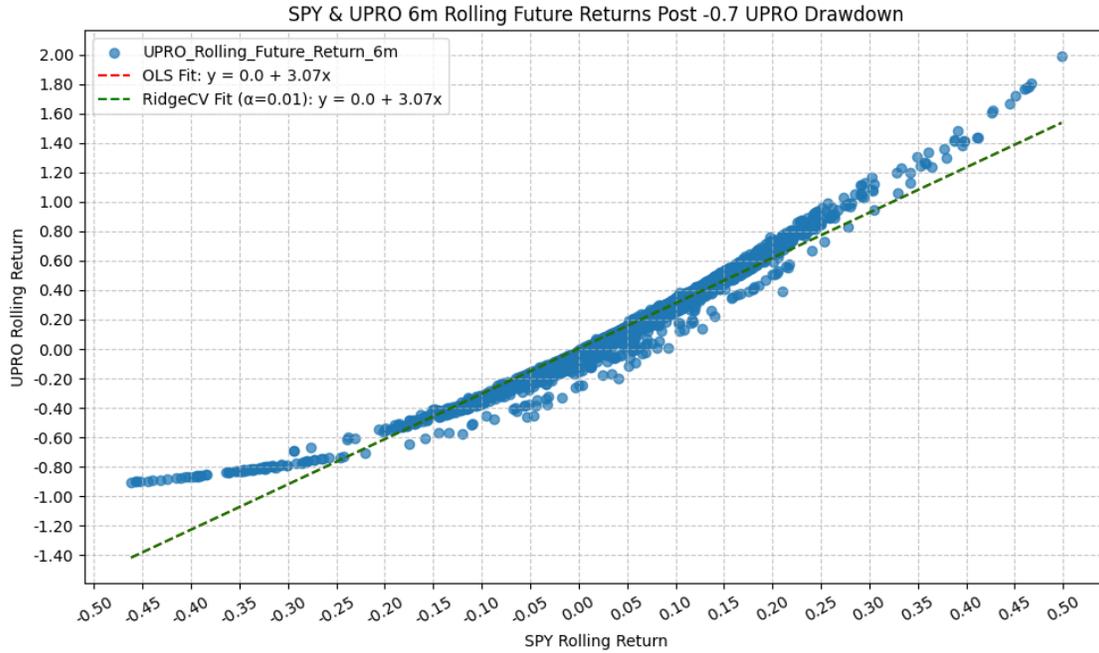
-0.001	0.003				
SPY_Rolling_Future_Return_3m	2.9866	0.010	307.473	0.000	
2.968	3.006				

```
=====
Omnibus:                813.503    Durbin-Watson:          0.169
Prob(Omnibus):          0.000    Jarque-Bera (JB):      16781.750
Skew:                   1.111    Prob(JB):              0.00
Kurtosis:               15.859    Cond. No.              11.1
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_6m    R-squared:
0.954
Model:                  OLS                            Adj. R-squared:
0.954
Method:                 Least Squares                 F-statistic:
4.945e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:23                      Log-Likelihood:
2608.8
No. Observations:      2365                            AIC:
-5214.
Df Residuals:          2363                            BIC:
-5202.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                0.0035    0.002        1.917    0.055

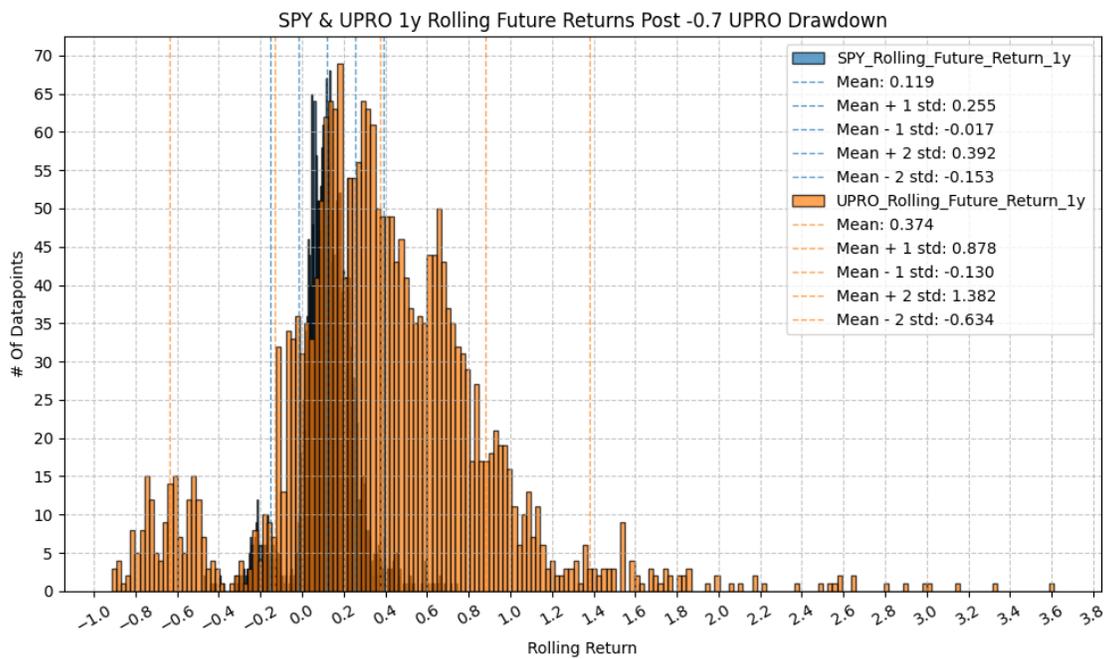
```

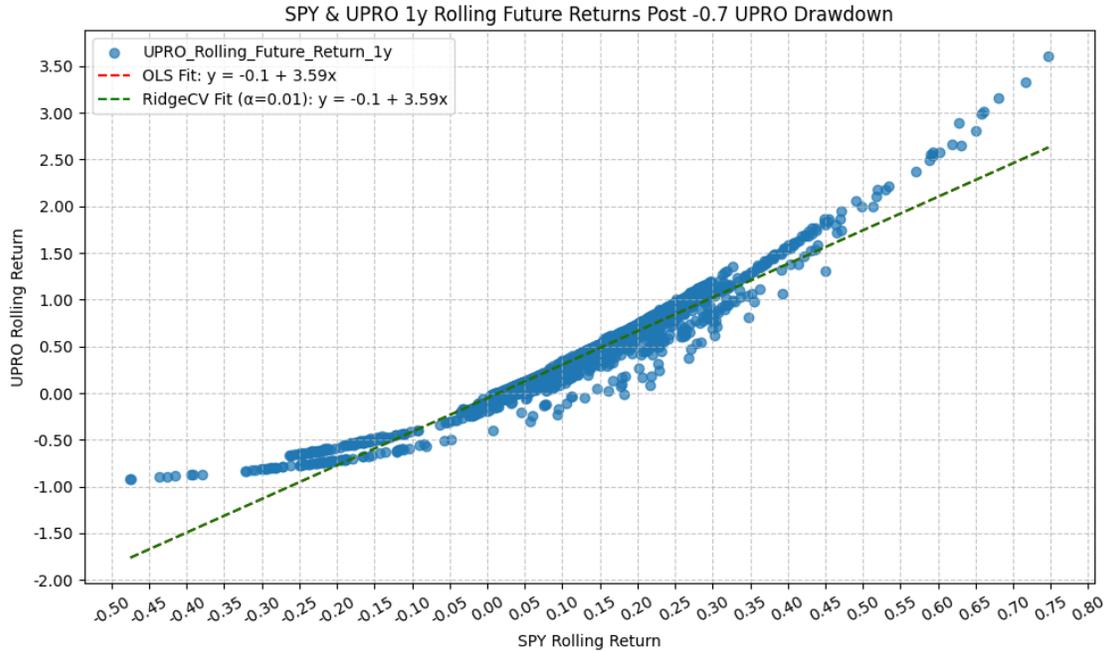
-7.96e-05	0.007				
SPY_Rolling_Future_Return_6m	3.0747	0.014	222.381	0.000	
3.048	3.102				

Omnibus:	829.879	Durbin-Watson:	0.069
Prob(Omnibus):	0.000	Jarque-Bera (JB):	7404.057
Skew:	1.399	Prob(JB):	0.00
Kurtosis:	11.204	Cond. No.	8.39

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1y    R-squared:
0.941
Model:                  OLS                            Adj. R-squared:
0.941
Method:                 Least Squares                 F-statistic:
3.754e+04
Date:                   Mon, 16 Mar 2026               Prob (F-statistic):
0.00
Time:                   14:29:24                       Log-Likelihood:
1607.4
No. Observations:      2365                            AIC:
-3211.
Df Residuals:          2363                            BIC:
-3199.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

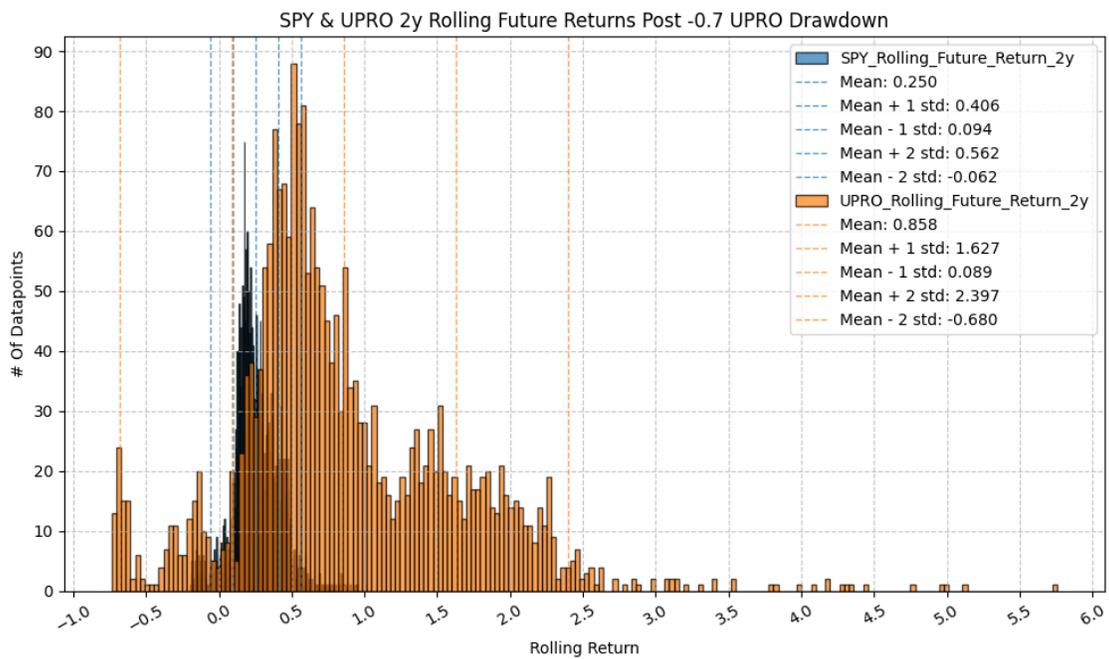
const	-0.0550	0.003	-16.382	0.000

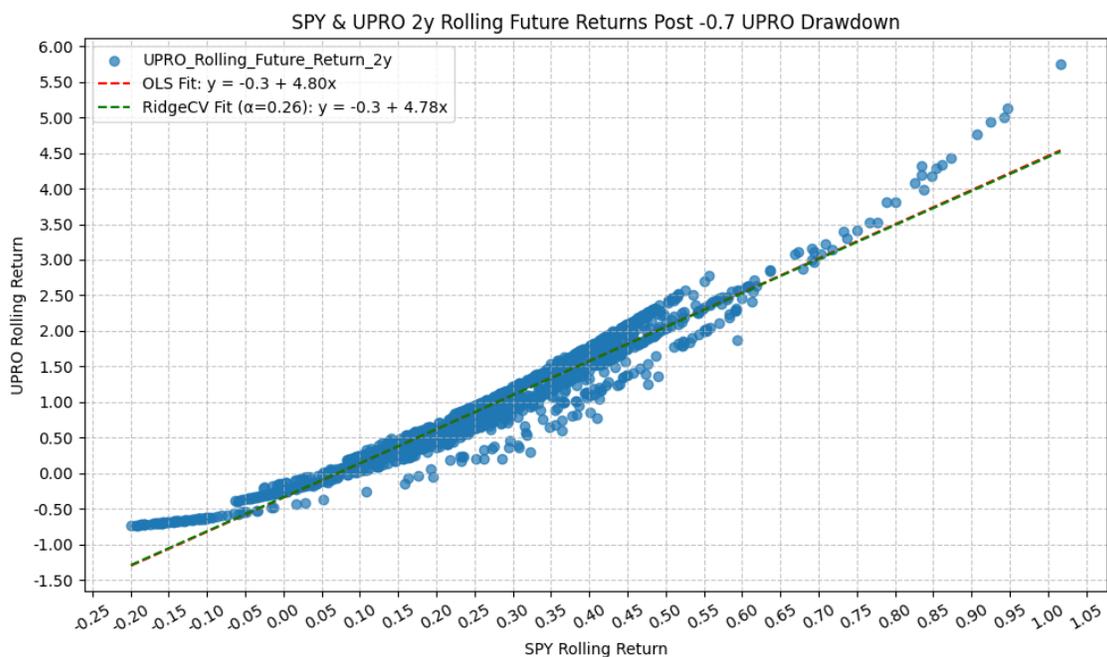
-0.062	-0.048				
SPY_Rolling_Future_Return_1y	3.5929	0.019	193.749	0.000	
3.556	3.629				

Omnibus:	724.737	Durbin-Watson:	0.076
Prob(Omnibus):	0.000	Jarque-Bera (JB):	11317.549
Skew:	1.017	Prob(JB):	0.00
Kurtosis:	13.522	Cond. No.	7.46

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_2y    R-squared:
0.947
Model:                  OLS                            Adj. R-squared:
0.947
Method:                 Least Squares                 F-statistic:
4.184e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:25                     Log-Likelihood:
728.41
No. Observations:      2365                          AIC:
-1453.
Df Residuals:          2363                          BIC:
-1441.
Df Model:              1
Covariance Type:      nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.3422    0.007    -49.482    0.000

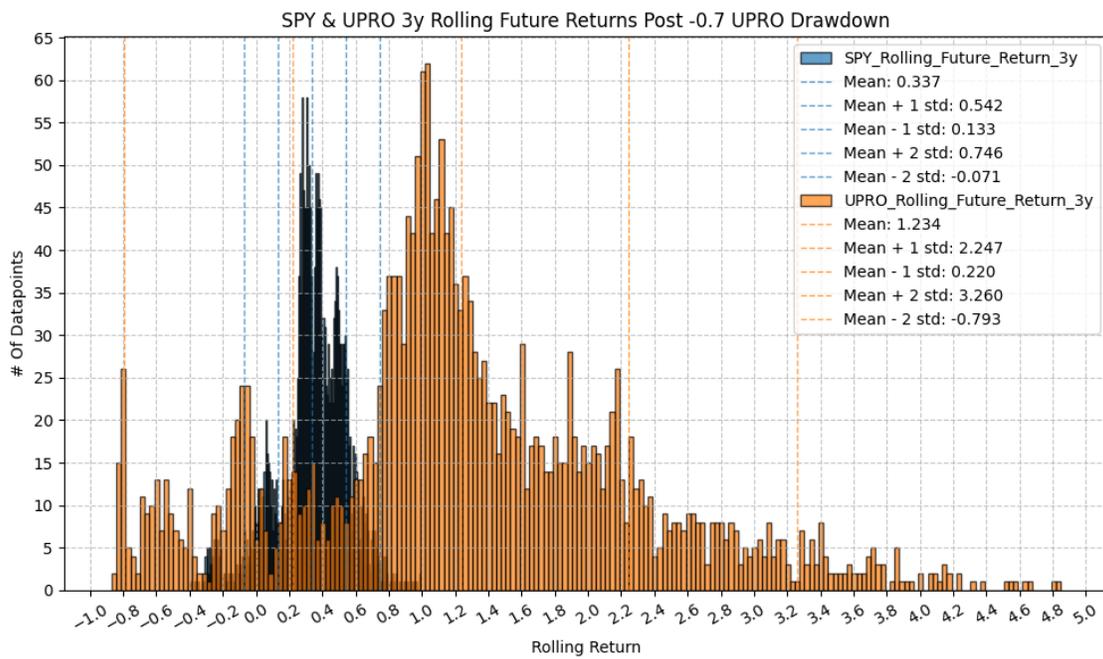
```

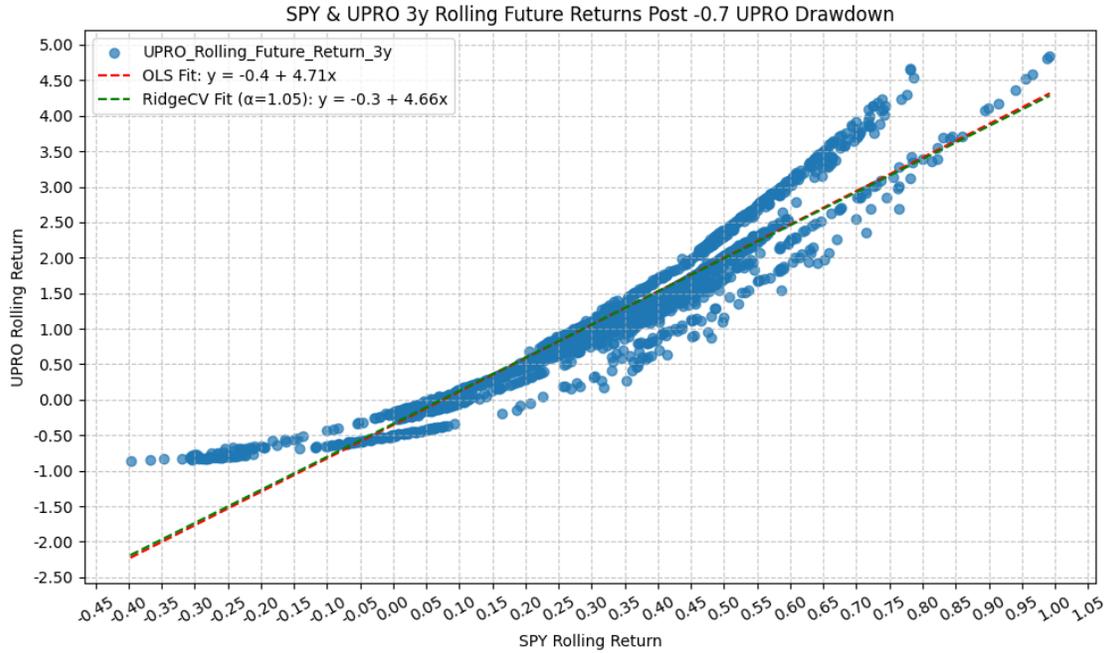
-0.356	-0.329				
SPY_Rolling_Future_Return_2y	4.753	4.7992	0.023	204.538	0.000
	4.845				

Omnibus:	261.292	Durbin-Watson:	0.050
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1788.713
Skew:	-0.271	Prob(JB):	0.00
Kurtosis:	7.226	Cond. No.	6.82

Notes:

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





OLS Regression Results

=====

```

Dep. Variable:          UPRO_Rolling_Future_Return_3y    R-squared:
0.901
Model:                  OLS                            Adj. R-squared:
0.901
Method:                 Least Squares                 F-statistic:
2.158e+04
Date:                  Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                  14:29:26                      Log-Likelihood:
-648.58
No. Observations:      2365                          AIC:
1301.
Df Residuals:          2363                          BIC:
1313.
Df Model:               1
Covariance Type:       nonrobust

```

=====

	coef	std err	t	P> t
[0.025 0.975]				

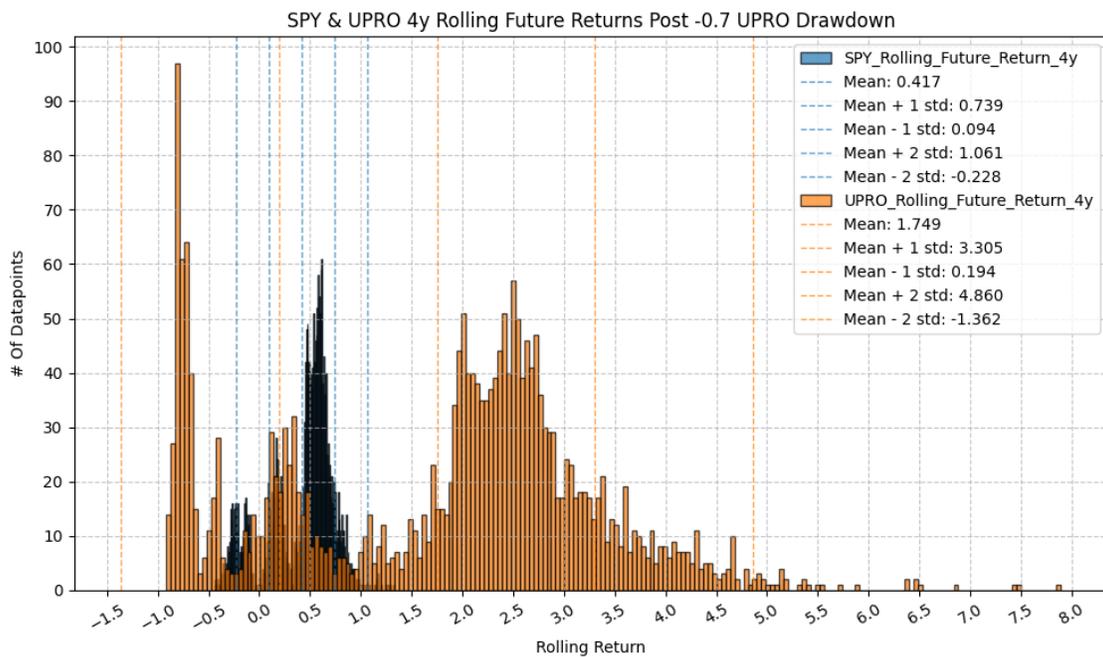
const	-0.3554	0.013	-28.107	0.000

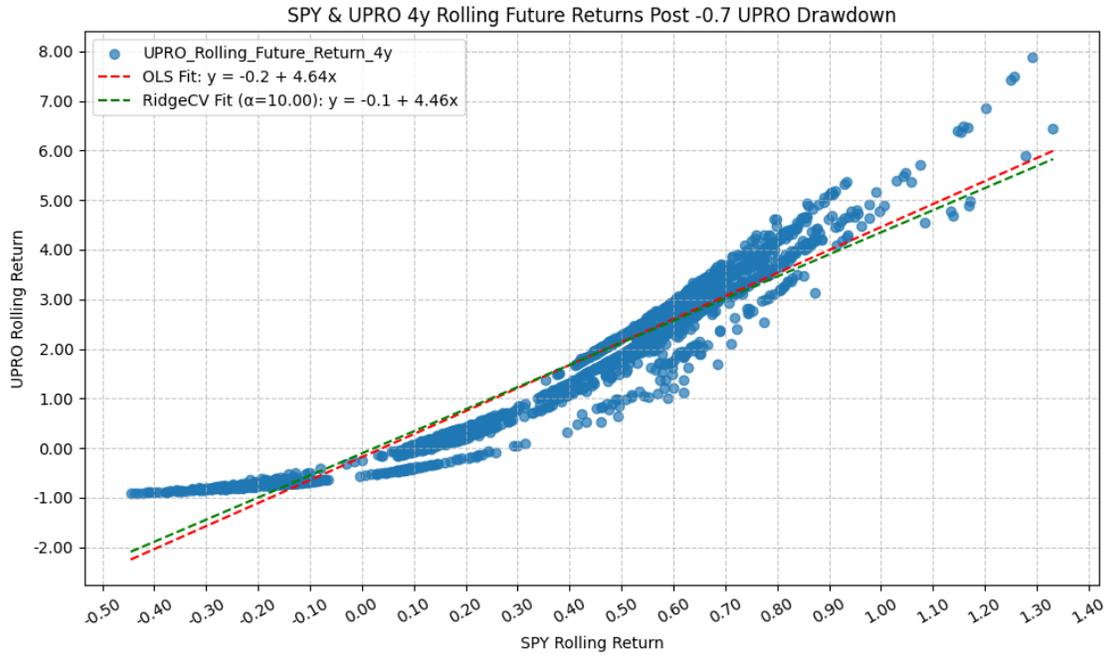
-0.380	-0.331				
SPY_Rolling_Future_Return_3y	4.7081	0.032	146.886	0.000	
4.645	4.771				

Omnibus:	350.033	Durbin-Watson:	0.028
Prob(Omnibus):	0.000	Jarque-Bera (JB):	725.274
Skew:	0.885	Prob(JB):	3.23e-158
Kurtosis:	5.057	Cond. No.	5.47

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_4y    R-squared:
0.925
Model:                  OLS                            Adj. R-squared:
0.925
Method:                 Least Squares                 F-statistic:
2.909e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:27                     Log-Likelihood:
-1339.2
No. Observations:      2365                          AIC:
2682.
Df Residuals:          2363                          BIC:
2694.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -0.1851    0.014   -12.912    0.000

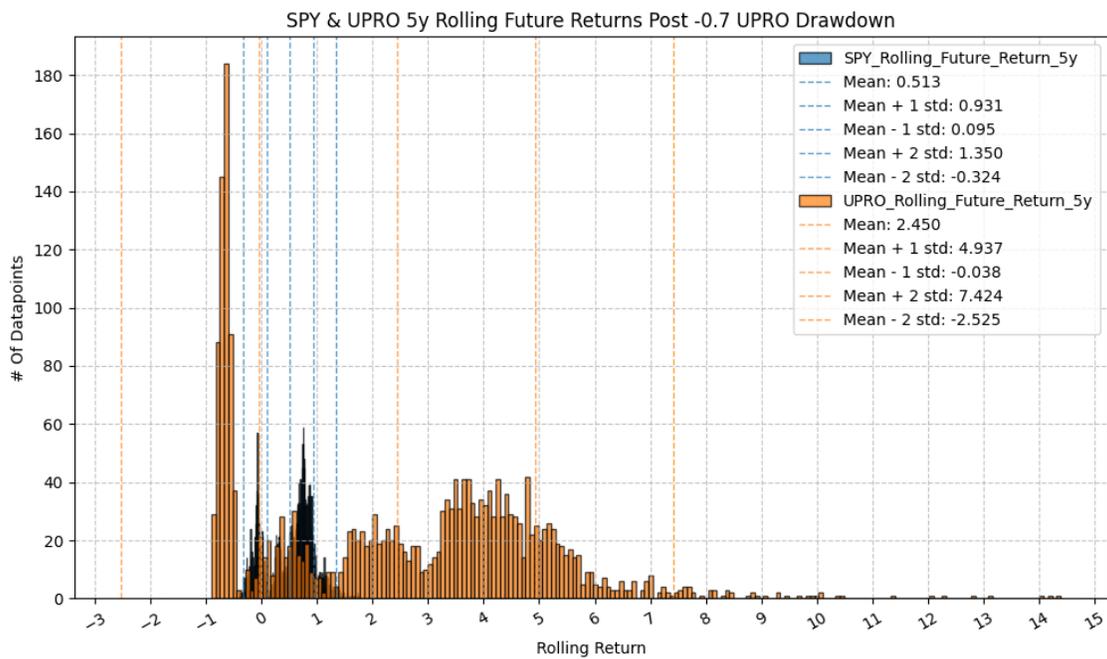
```

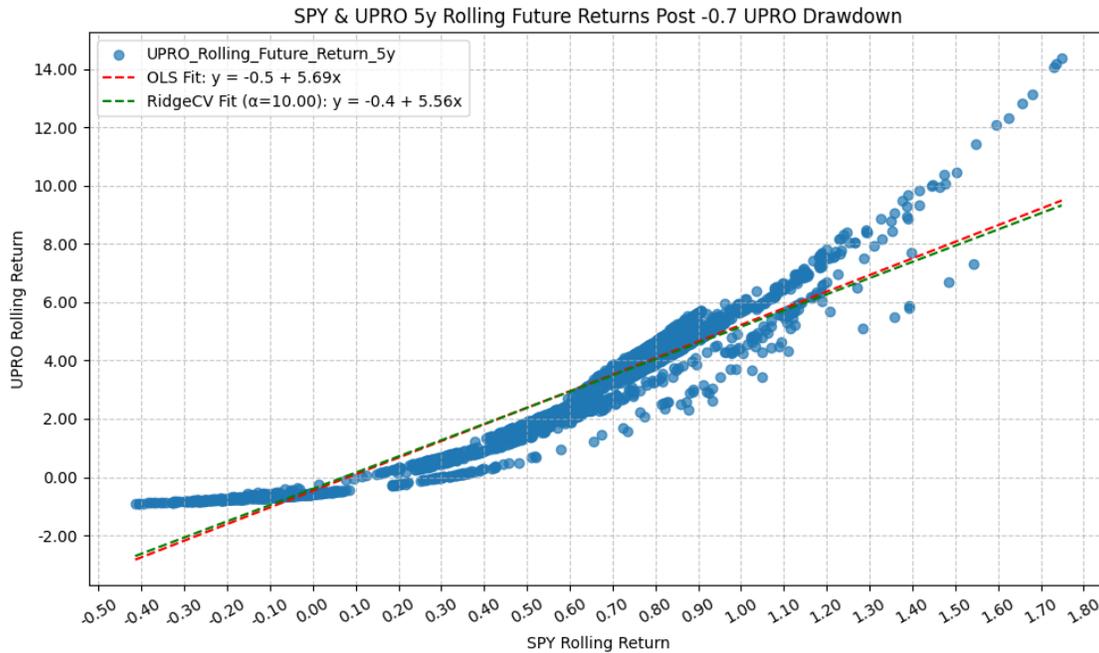
-0.213 -0.157
 SPY_Rolling_Future_Return_4y 4.6425 0.027 170.565 0.000
 4.589 4.696

```
=====
Omnibus:                                    55.496      Durbin-Watson:                                    0.030
Prob(Omnibus):                              0.000      Jarque-Bera (JB):                                    118.356
Skew:                                        0.081      Prob(JB):                                            1.99e-26
Kurtosis:                                    4.084      Cond. No.                                            3.69
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_5y    R-squared:
0.917
Model:                  OLS                            Adj. R-squared:
0.917
Method:                 Least Squares                 F-statistic:
2.615e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:28                      Log-Likelihood:
-2565.1
No. Observations:      2365                          AIC:
5134.
Df Residuals:          2363                          BIC:
5146.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.4704    0.023    -20.191    0.000

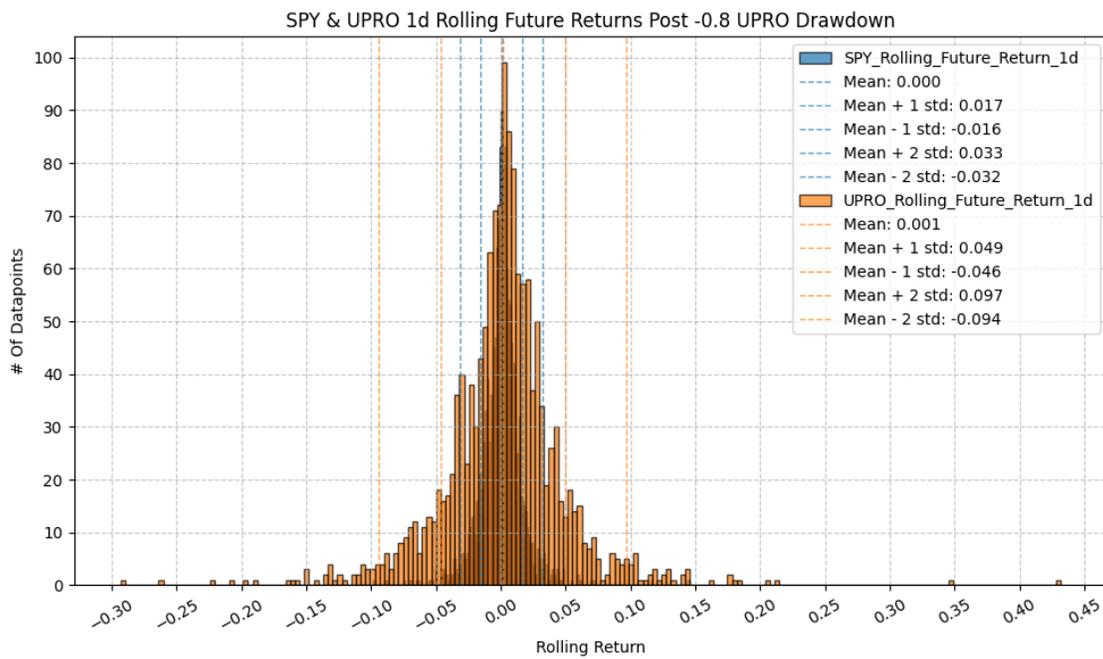
```

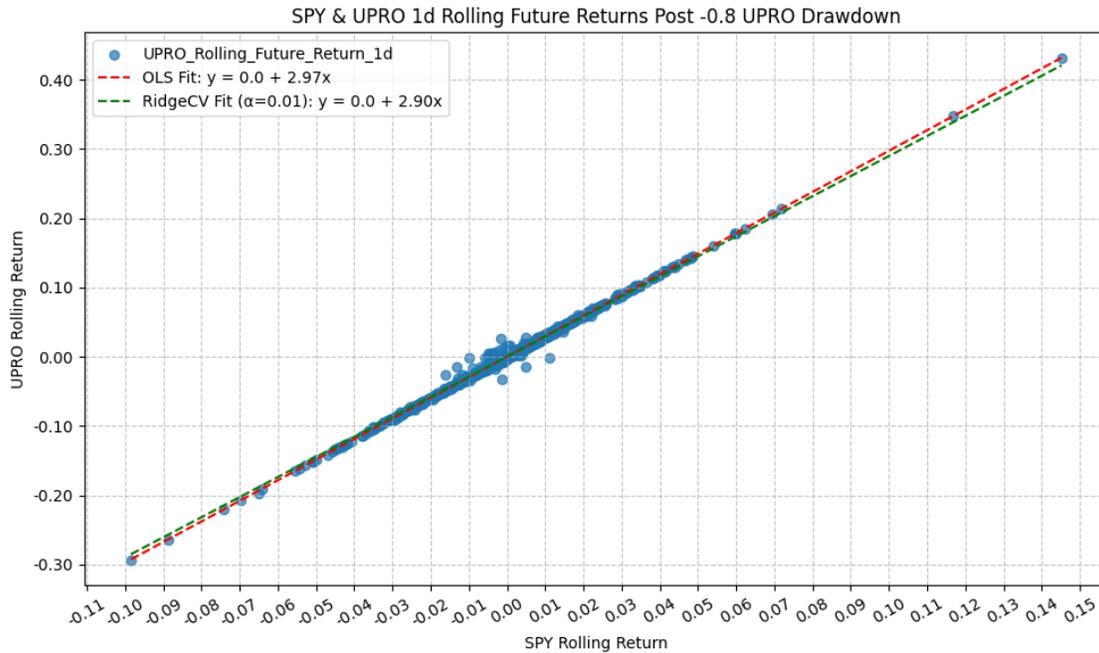
-0.516 -0.425
 SPY_Rolling_Future_Return_5y 5.6929 0.035 161.723 0.000
 5.624 5.762

```
=====
Omnibus:                              311.086      Durbin-Watson:                              0.028
Prob(Omnibus):                        0.000      Jarque-Bera (JB):                        1363.041
Skew:                                    0.566      Prob(JB):                                 1.05e-296
Kurtosis:                               6.543      Cond. No.                                 3.12
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_1d    R-squared:
0.997
Model:              OLS                            Adj. R-squared:
0.997
Method:             Least Squares                  F-statistic:
4.362e+05
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:               14:29:29                       Log-Likelihood:
6607.2
No. Observations:  1479                            AIC:
-1.321e+04
Df Residuals:      1477                            BIC:
-1.320e+04
Df Model:          1
Covariance Type:   nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                0.0001    7.23e-05    1.550    0.121

```

-2.98e-05 0.000
 SPY_Rolling_Future_Return_1d 2.9736 0.005 660.468 0.000
 2.965 2.982

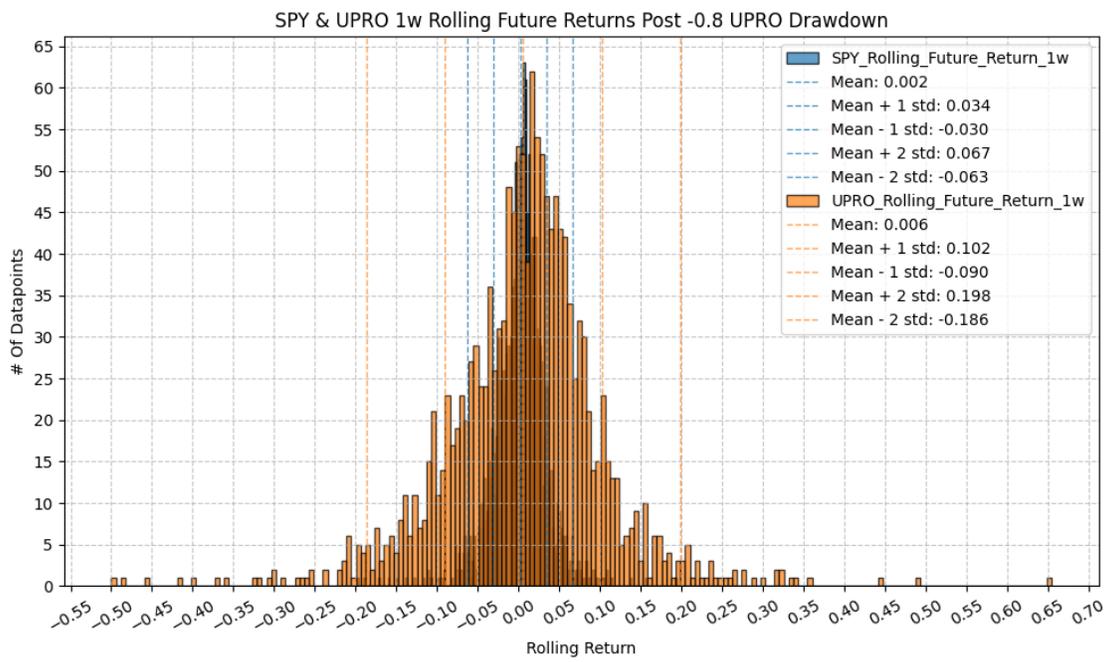
```
=====
```

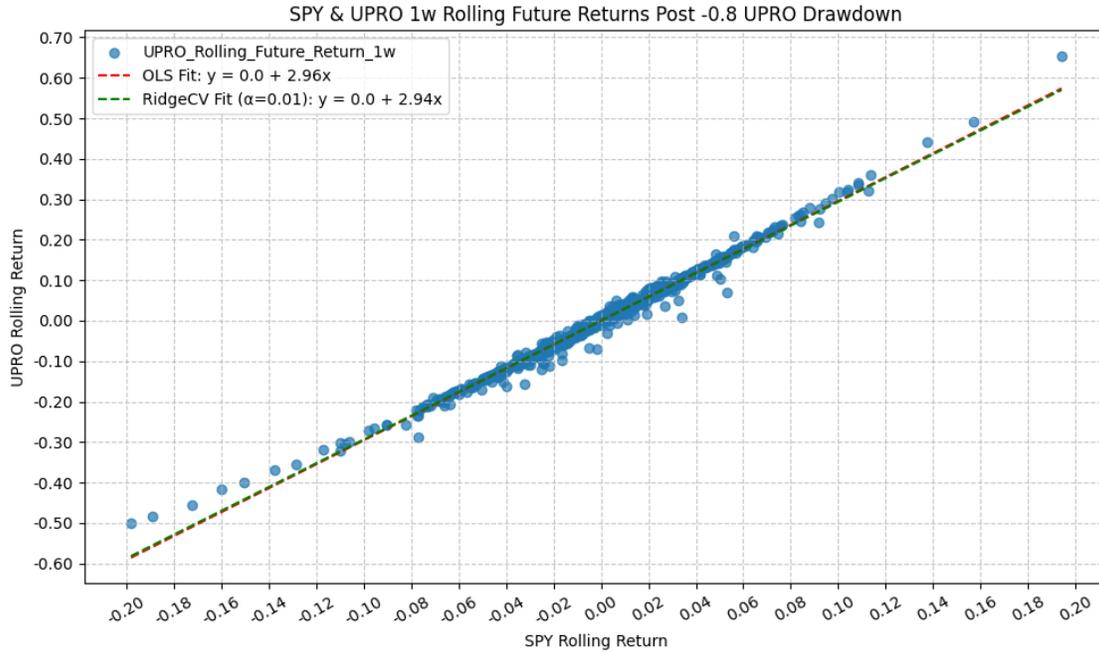
Omnibus:	759.528	Durbin-Watson:	2.689
Prob(Omnibus):	0.000	Jarque-Bera (JB):	237908.791
Skew:	1.142	Prob(JB):	0.00
Kurtosis:	65.092	Cond. No.	62.3

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_1w    R-squared:
0.990
Model:                  OLS                            Adj. R-squared:
0.990
Method:                 Least Squares                 F-statistic:
1.475e+05
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:31                     Log-Likelihood:
4779.3
No. Observations:      1479                          AIC:
-9555.
Df Residuals:          1477                          BIC:
-9544.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	3.196e-06	0.000	0.013	0.990

-0.000	0.000				
SPY_Rolling_Future_Return_1w	2.9572	0.008	384.014	0.000	
2.942	2.972				

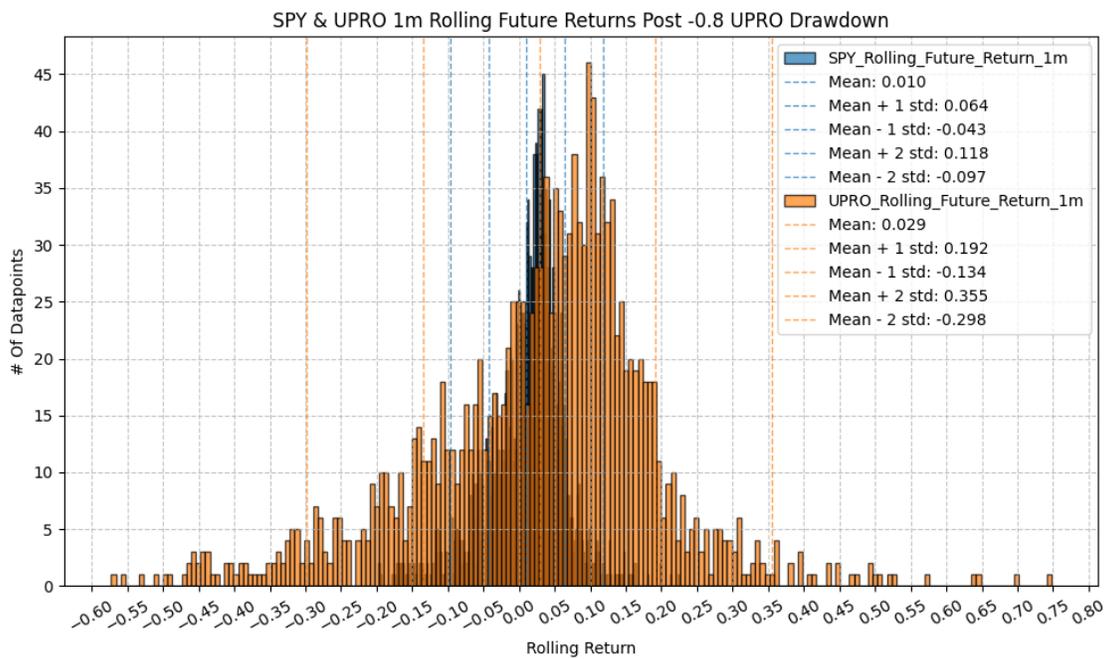
```

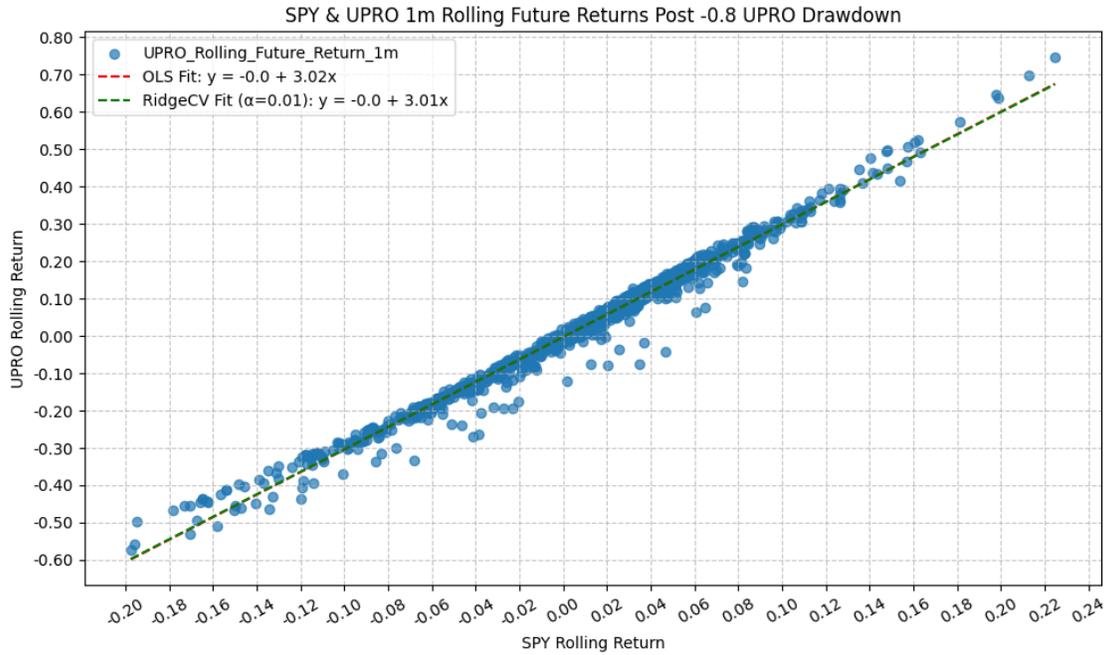
=====
Omnibus:                    517.977   Durbin-Watson:                1.023
Prob(Omnibus):              0.000   Jarque-Bera (JB):            52657.085
Skew:                       -0.625   Prob(JB):                     0.00
Kurtosis:                   32.205   Cond. No.                     31.0
=====

```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_1m    R-squared:
0.983
Model:              OLS                            Adj. R-squared:
0.983
Method:             Least Squares                  F-statistic:
8.452e+04
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:               14:29:32                        Log-Likelihood:
3588.8
No. Observations:  1479                            AIC:
-7174.
Df Residuals:      1477                            BIC:
-7163.
Df Model:          1
Covariance Type:   nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0029    0.001    -5.075    0.000

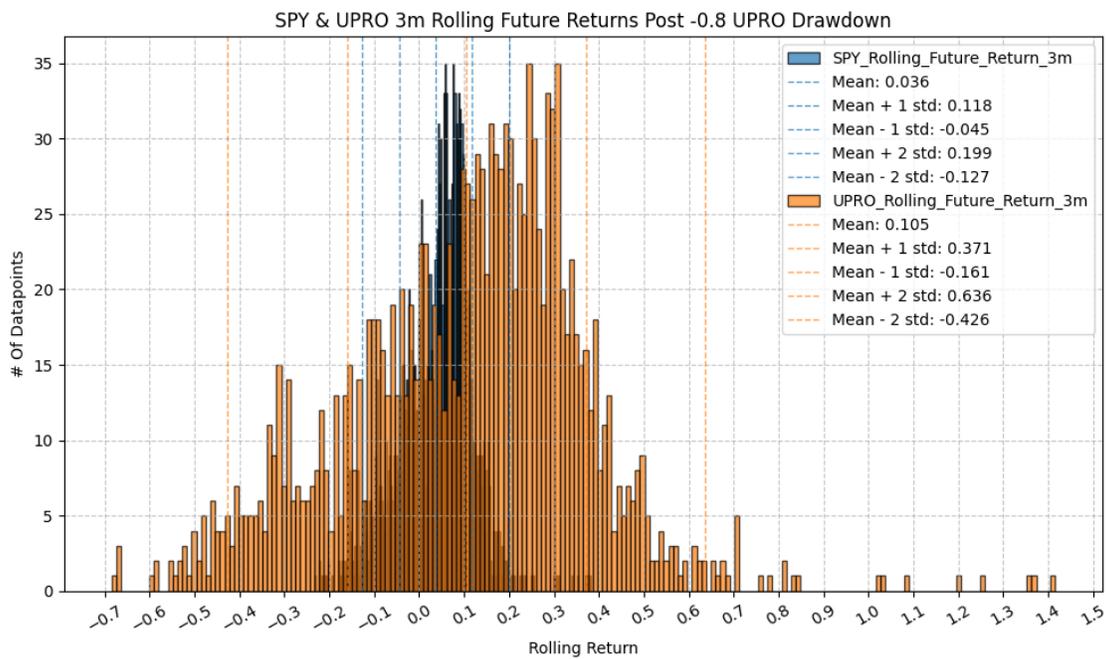
```

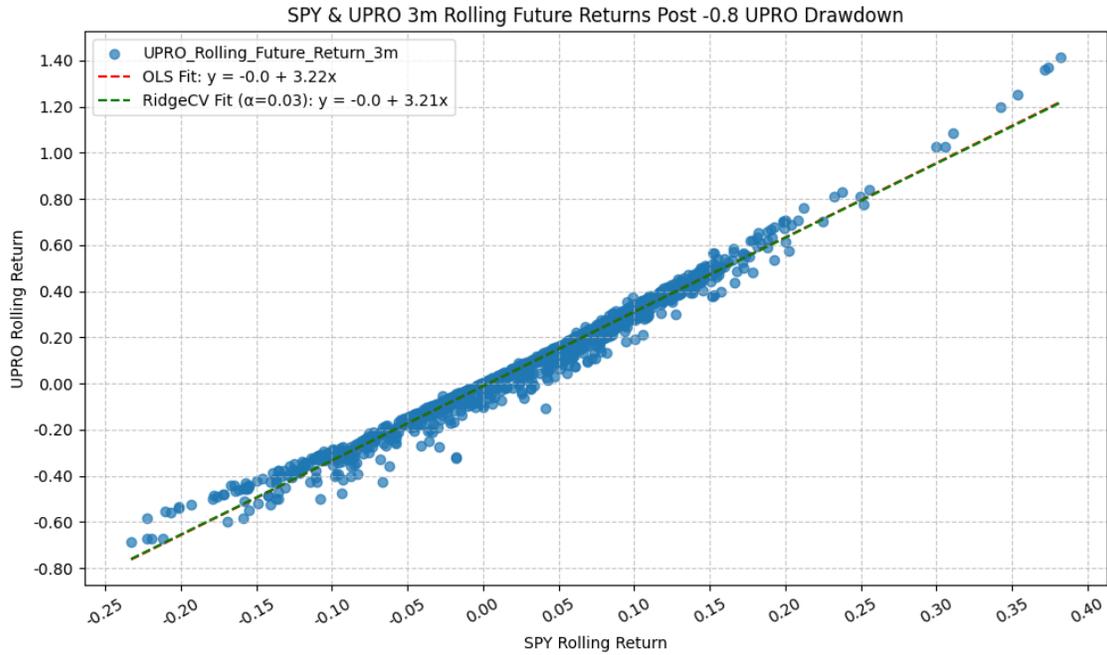
-0.004	-0.002				
SPY_Rolling_Future_Return_1m	3.0167	0.010	290.718	0.000	
2.996	3.037				

```
=====
Omnibus:                951.943    Durbin-Watson:           0.291
Prob(Omnibus):          0.000    Jarque-Bera (JB):       19753.591
Skew:                   -2.649    Prob(JB):                0.00
Kurtosis:               20.102    Cond. No.                18.7
=====
```

Notes:

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





OLS Regression Results

=====

```

Dep. Variable:      UPRO_Rolling_Future_Return_3m    R-squared:
0.980
Model:              OLS                            Adj. R-squared:
0.980
Method:             Least Squares                  F-statistic:
7.182e+04
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:              14:29:33                        Log-Likelihood:
2749.5
No. Observations:  1479                            AIC:
-5495.
Df Residuals:      1477                            BIC:
-5484.
Df Model:           1
Covariance Type:   nonrobust
  
```

=====

	coef	std err	t	P> t
[0.025	0.975]			

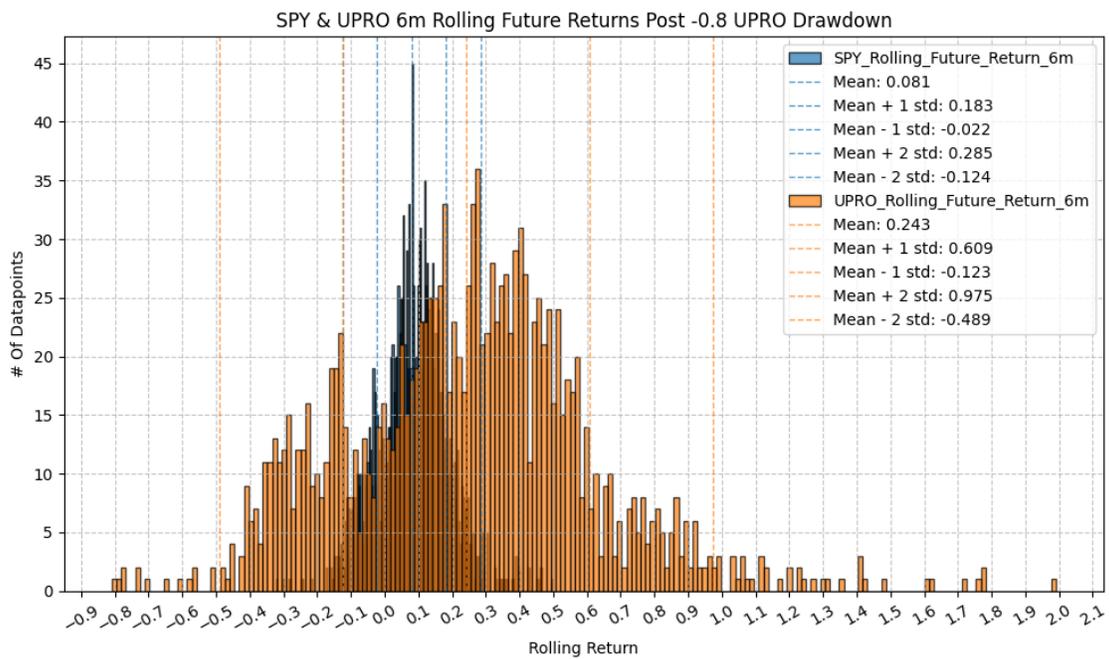
const	-0.0120	0.001	-11.210	0.000

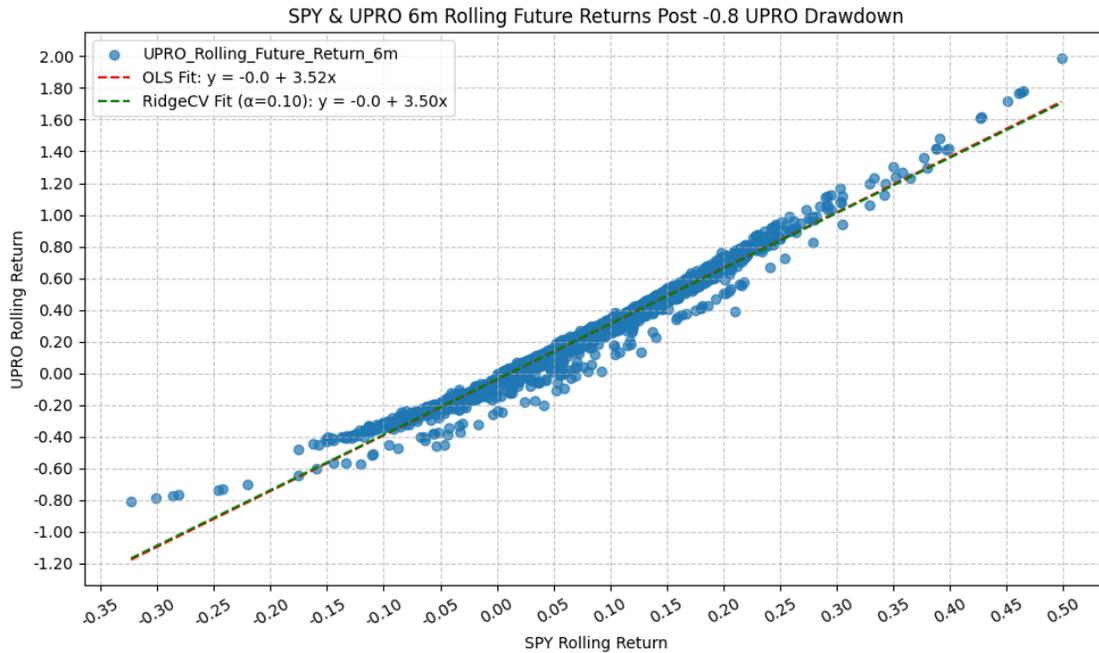
-0.014	-0.010				
SPY_Rolling_Future_Return_3m	3.2239	0.012	267.983	0.000	
3.200	3.248				

```
=====
Omnibus:                396.774   Durbin-Watson:           0.203
Prob(Omnibus):          0.000   Jarque-Bera (JB):       3170.391
Skew:                   -1.021   Prob(JB):                0.00
Kurtosis:               9.876   Cond. No.                12.3
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_6m    R-squared:
0.971
Model:                  OLS                            Adj. R-squared:
0.971
Method:                 Least Squares                 F-statistic:
4.873e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:34                     Log-Likelihood:
1996.2
No. Observations:      1479                          AIC:
-3988.
Df Residuals:          1477                          BIC:
-3978.
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.0410    0.002   -19.752    0.000

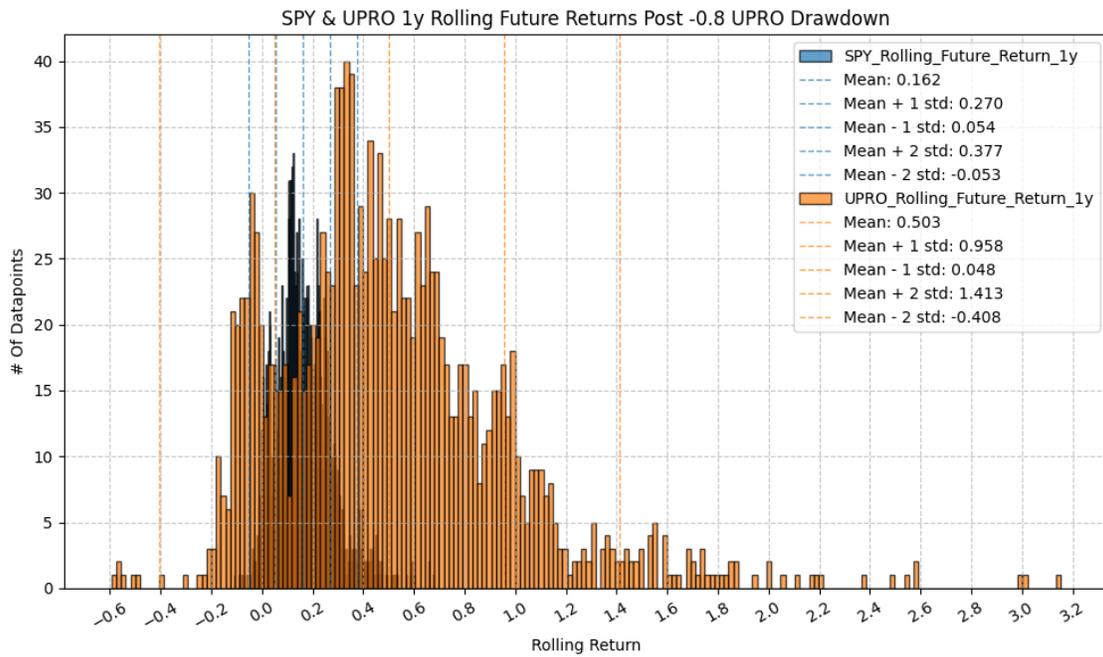
```

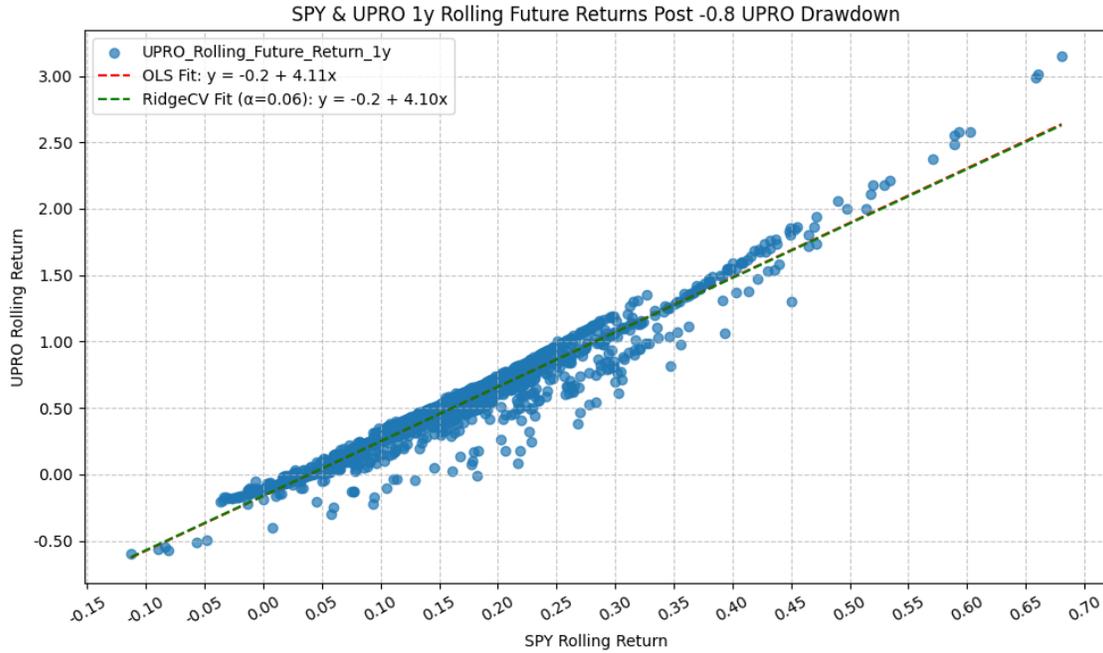
-0.045	-0.037				
SPY_Rolling_Future_Return_6m	3.5211	0.016	220.756	0.000	
3.490	3.552				

```
=====
Omnibus:                303.529   Durbin-Watson:           0.139
Prob(Omnibus):          0.000   Jarque-Bera (JB):       1799.504
Skew:                   -0.818   Prob(JB):                0.00
Kurtosis:               8.150   Cond. No.                9.83
=====
```

Notes:

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





OLS Regression Results

=====

```

Dep. Variable:      UPRO_Rolling_Future_Return_1y    R-squared:
0.945
Model:              OLS                            Adj. R-squared:
0.945
Method:             Least Squares                  F-statistic:
2.531e+04
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:              14:29:35                        Log-Likelihood:
1208.7
No. Observations:  1479                            AIC:
-2413.
Df Residuals:      1477                            BIC:
-2403.
Df Model:           1
Covariance Type:   nonrobust

```

=====

	coef	std err	t	P> t
[0.025 0.975]				

const	-0.1638	0.005	-32.562	0.000

-0.174 -0.154
 SPY_Rolling_Future_Return_1y 4.1149 0.026 159.078 0.000
 4.064 4.166

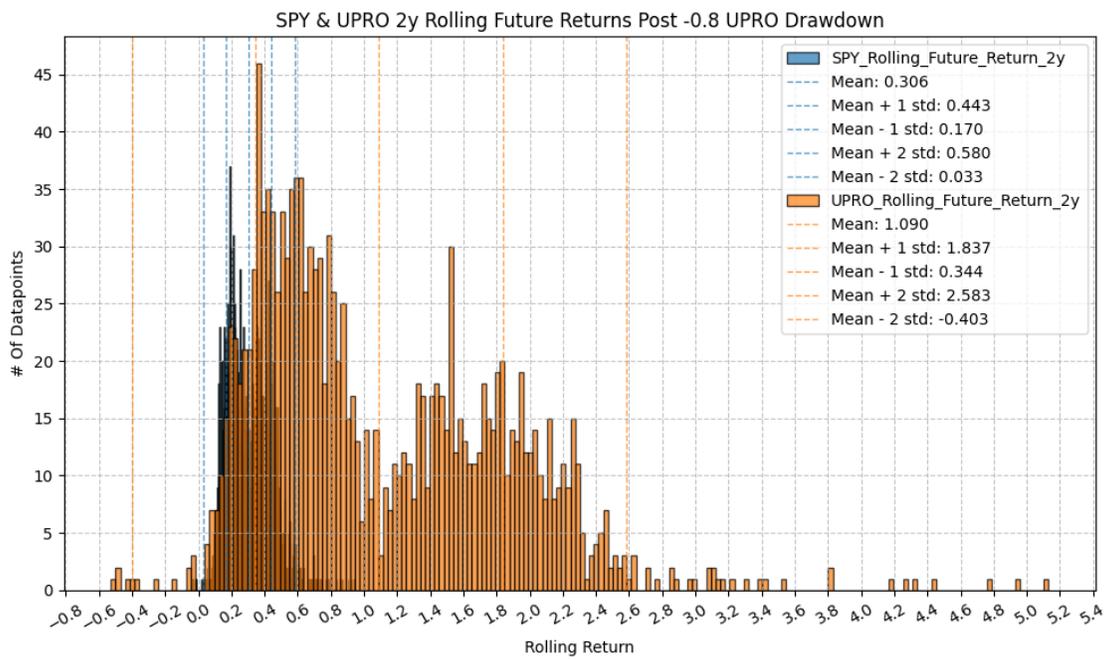
```
=====
```

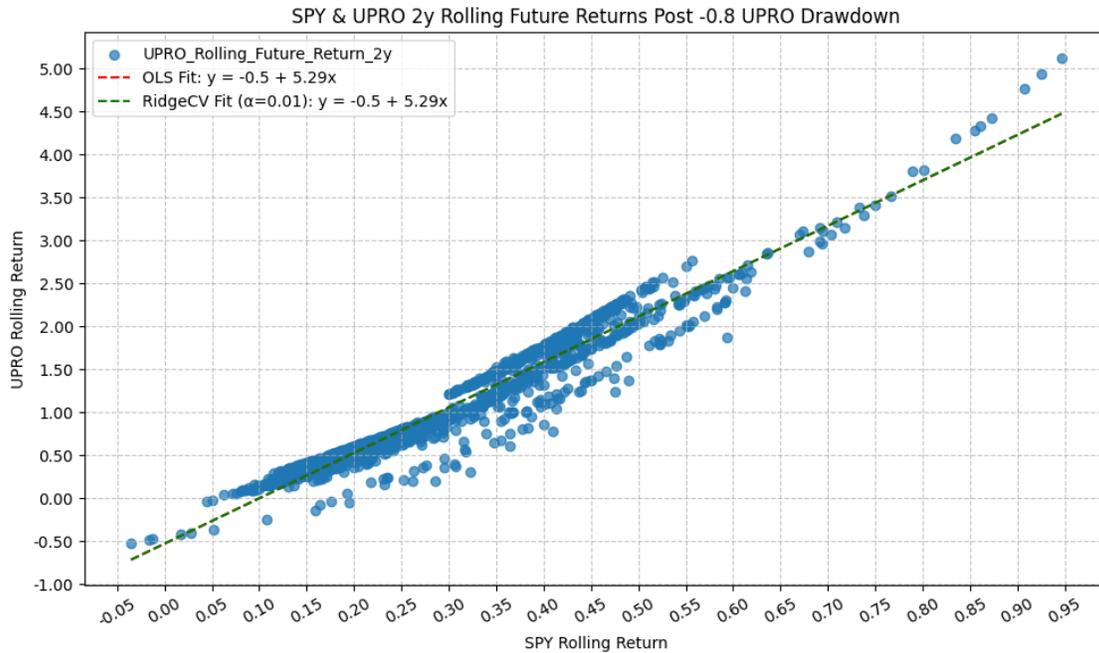
Omnibus:	636.693	Durbin-Watson:	0.055
Prob(Omnibus):	0.000	Jarque-Bera (JB):	4021.716
Skew:	-1.901	Prob(JB):	0.00
Kurtosis:	10.128	Cond. No.	9.55

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_2y    R-squared:
0.940
Model:                  OLS                            Adj. R-squared:
0.940
Method:                 Least Squares                 F-statistic:
2.322e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:36                      Log-Likelihood:
417.22
No. Observations:      1479                          AIC:
-830.4
Df Residuals:          1477                          BIC:
-819.8
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -0.5307    0.012    -45.553    0.000

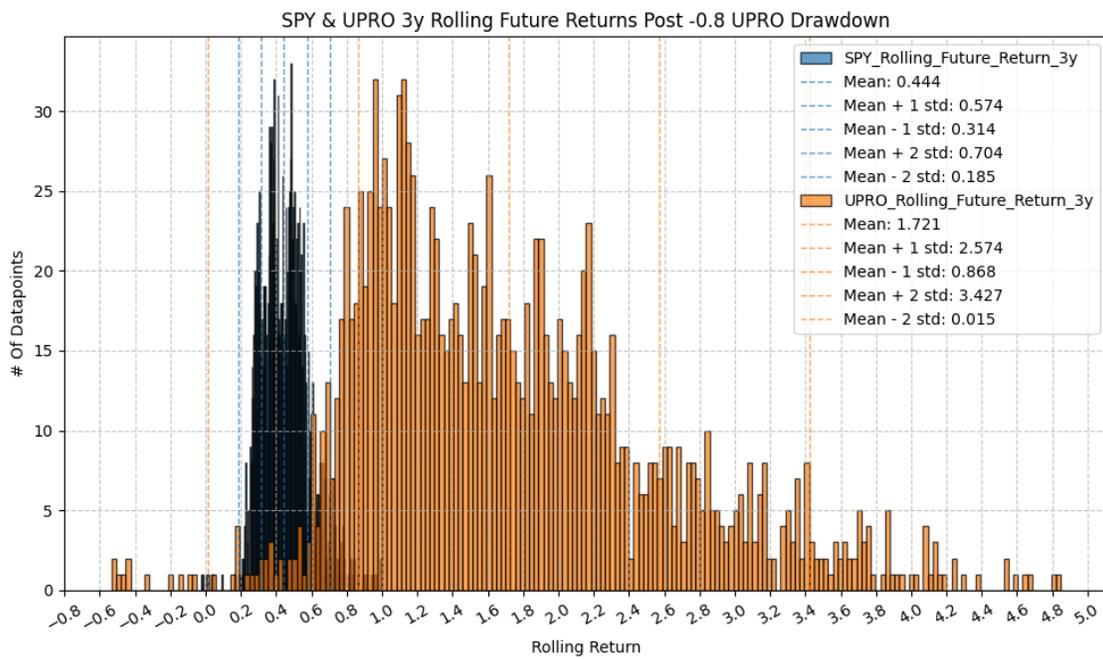
```

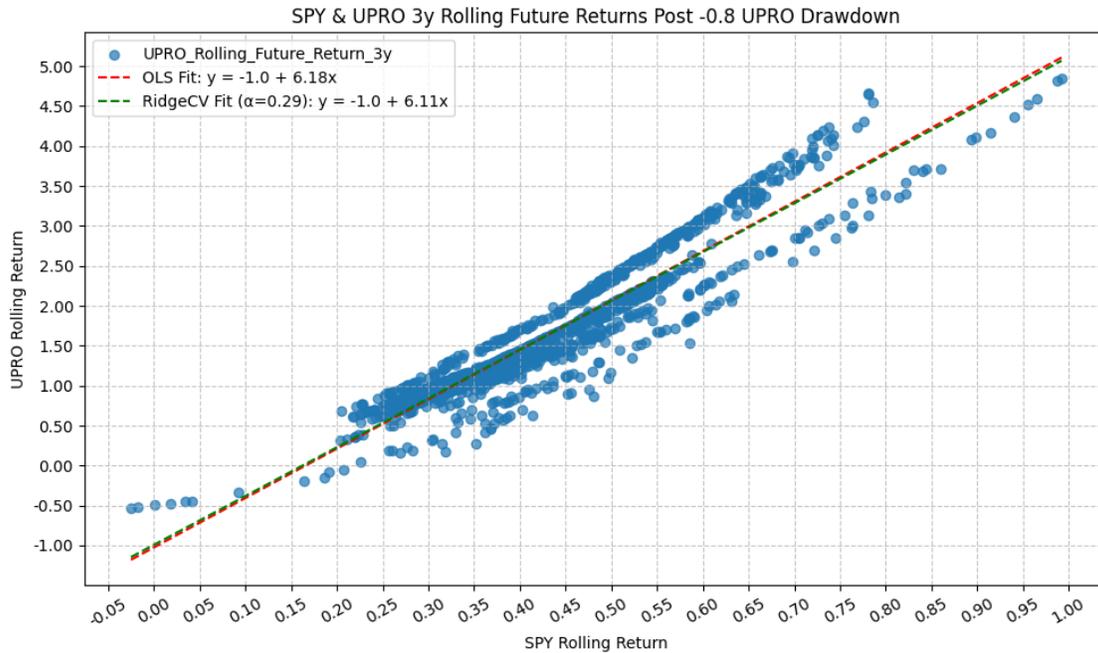
-0.554 -0.508
 SPY_Rolling_Future_Return_2y 5.2906 0.035 152.380 0.000
 5.222 5.359

```
=====
Omnibus:                              350.739      Durbin-Watson:                              0.045
Prob(Omnibus):                        0.000      Jarque-Bera (JB):                        917.233
Skew:                                  -1.244      Prob(JB):                                  6.69e-200
Kurtosis:                              5.949      Cond. No.                                  8.01
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_3y    R-squared:
0.884
Model:              OLS                            Adj. R-squared:
0.884
Method:             Least Squares                  F-statistic:
1.128e+04
Date:               Mon, 16 Mar 2026                Prob (F-statistic):
0.00
Time:               14:29:37                        Log-Likelihood:
-268.54
No. Observations:  1479                            AIC:
541.1
Df Residuals:      1477                            BIC:
551.7
Df Model:           1
Covariance Type:   nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -1.0243    0.027    -38.038    0.000
=====

```

-1.077 -0.972
 SPY_Rolling_Future_Return_3y 6.1791 0.058 106.196 0.000
 6.065 6.293

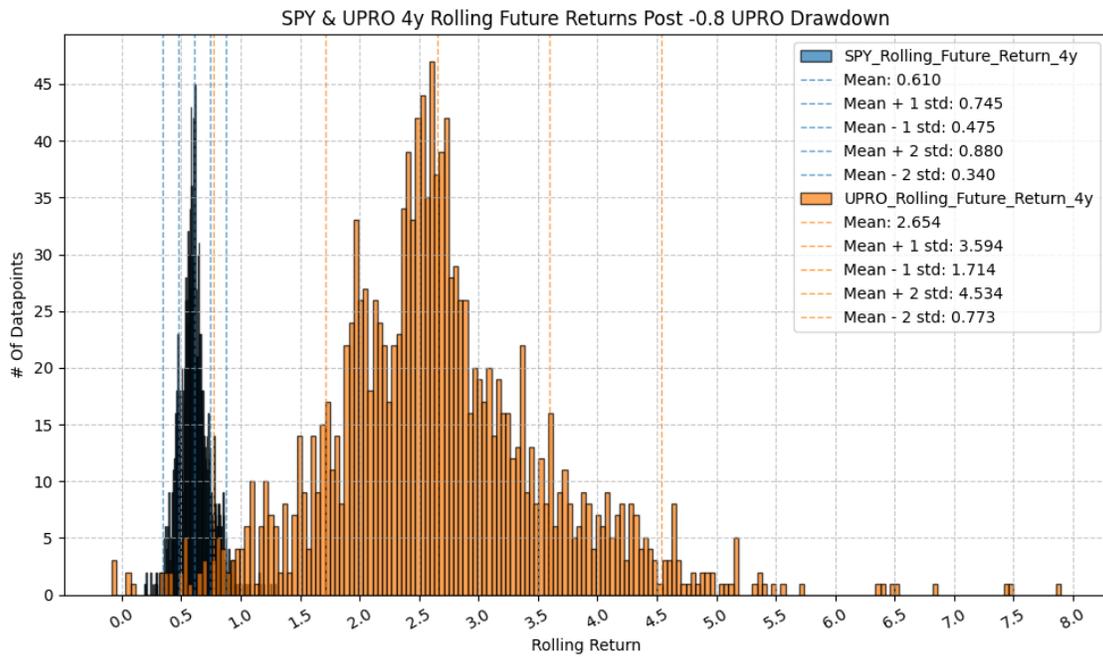
```
=====
```

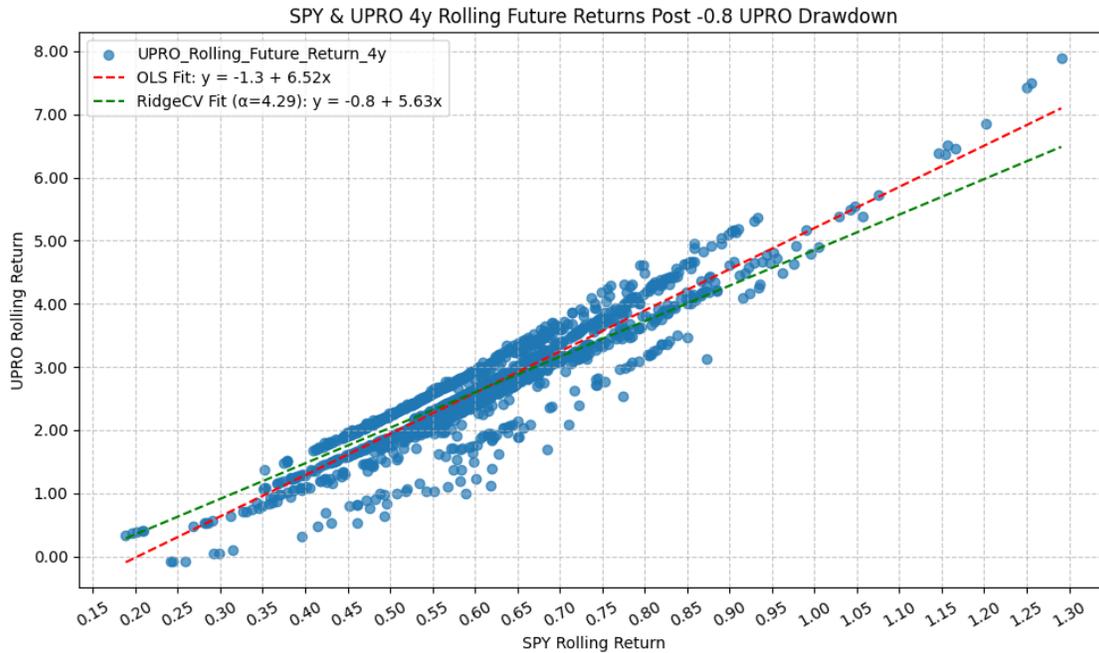
Omnibus:	74.636	Durbin-Watson:	0.032
Prob(Omnibus):	0.000	Jarque-Bera (JB):	91.011
Skew:	-0.512	Prob(JB):	1.73e-20
Kurtosis:	3.655	Cond. No.	9.25

```
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:          UPRO_Rolling_Future_Return_4y    R-squared:
0.877
Model:                  OLS                            Adj. R-squared:
0.876
Method:                 Least Squares                 F-statistic:
1.049e+04
Date:                   Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:                   14:29:38                     Log-Likelihood:
-460.04
No. Observations:      1479                          AIC:
924.1
Df Residuals:          1477                          BIC:
934.7
Df Model:               1
Covariance Type:       nonrobust
=====
=====

```

```

=====
=====
                                coef    std err          t      P>|t|
-----+-----
[0.025    0.975]
-----+-----
const                -1.3231    0.040     -33.268    0.000

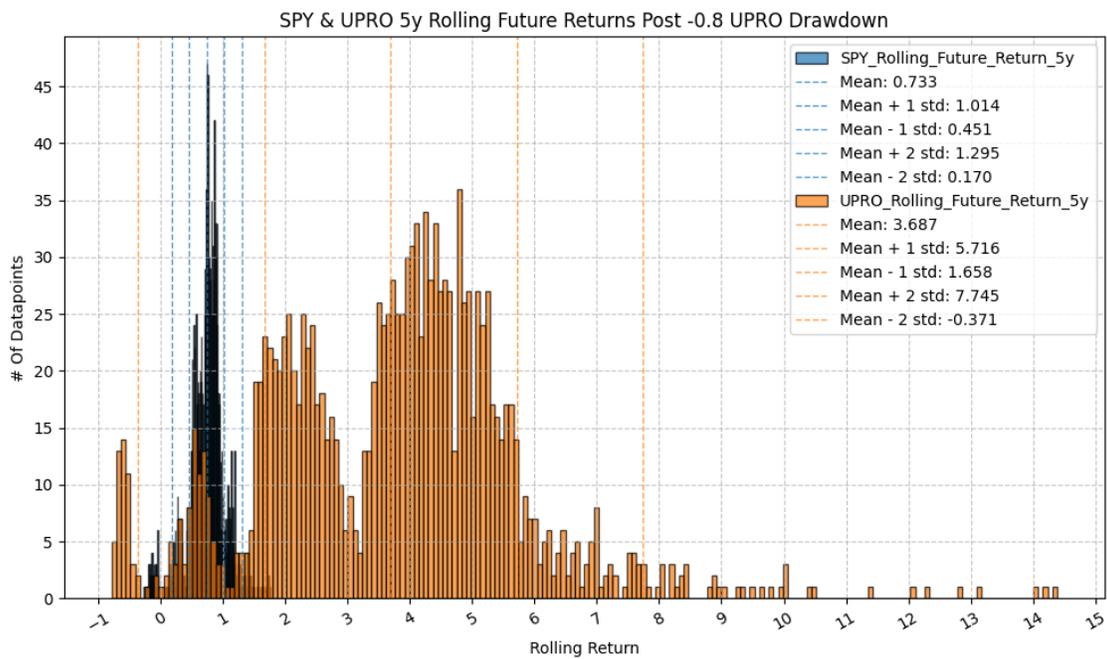
```

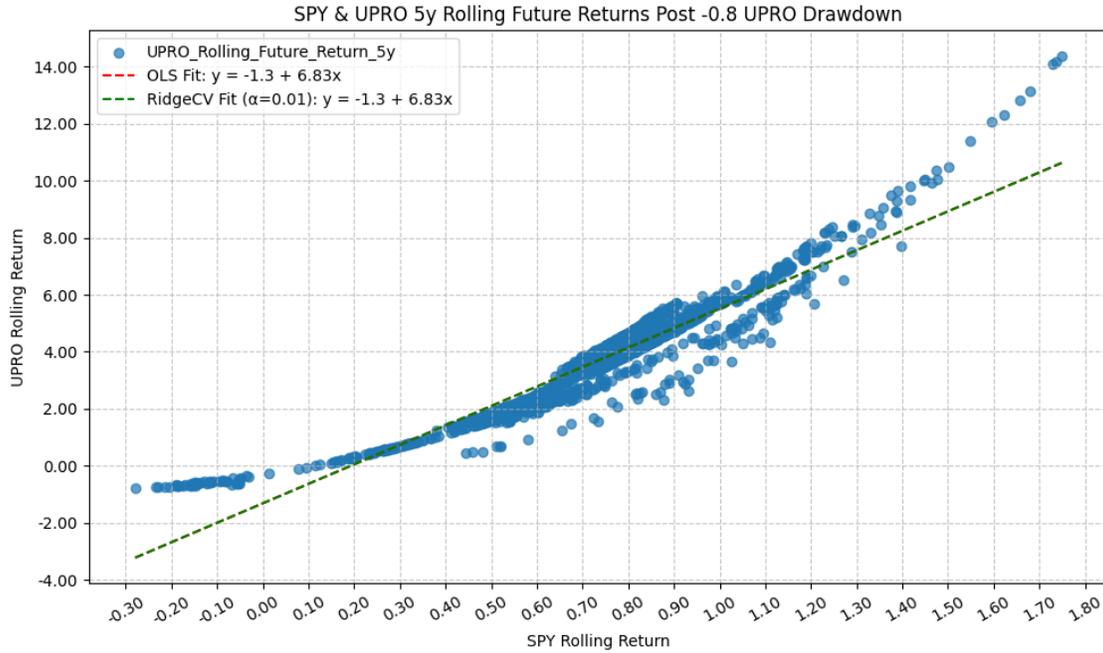
-1.401	-1.245				
SPY_Rolling_Future_Return_4y	6.5218	0.064	102.414	0.000	
6.397	6.647				

```
=====
Omnibus:                317.126   Durbin-Watson:           0.032
Prob(Omnibus):          0.000   Jarque-Bera (JB):       747.178
Skew:                   -1.169   Prob(JB):                5.65e-163
Kurtosis:               5.580   Cond. No.                10.2
=====
```

Notes:

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





OLS Regression Results

```

=====
=====
Dep. Variable:      UPRO_Rolling_Future_Return_5y    R-squared:
0.895
Model:              OLS                            Adj. R-squared:
0.895
Method:             Least Squares                 F-statistic:
1.258e+04
Date:               Mon, 16 Mar 2026              Prob (F-statistic):
0.00
Time:               14:29:39                      Log-Likelihood:
-1478.3
No. Observations:  1479                          AIC:
2961.
Df Residuals:      1477                          BIC:
2971.
Df Model:           1
Covariance Type:   nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

const	-1.3147	0.048	-27.526	0.000

-1.408	-1.221				
SPY_Rolling_Future_Return_5y	6.8270	0.061	112.164	0.000	
6.708	6.946				
=====					
Omnibus:	180.962	Durbin-Watson:		0.042	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		814.106	
Skew:	0.496	Prob(JB):		1.66e-177	
Kurtosis:	6.497	Cond. No.		5.57	
=====					

Notes:

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

0.5.9 Rolling Returns Following Drawdowns Deviation (SPY & UPRO)

```
[72]: rolling_returns_positive_future_returns = pd.DataFrame(index=rolling_windows.
↳keys(), data=rolling_windows.values())
rolling_returns_positive_future_returns.reset_index(inplace=True)
rolling_returns_positive_future_returns.rename(columns={"index": "Period", 0:
↳"Days"}, inplace=True)

for drawdown in drawdown_levels:
    temp = rolling_returns_drawdown_stats.
↳loc[rolling_returns_drawdown_stats["Drawdown"] == drawdown]
    temp = temp[["Period", "Positive_Future_Percentage"]]
    temp.rename(columns={"Positive_Future_Percentage" :↳
↳f"Positive_Future_Percentage_Post_{drawdown}_Drawdown"}, inplace=True)
    rolling_returns_positive_future_returns = pd.
↳merge(rolling_returns_positive_future_returns, temp, left_on="Period",↳
↳right_on="Period", how="outer")
    rolling_returns_positive_future_returns.sort_values(by="Days",↳
↳ascending=True, inplace=True)

rolling_returns_positive_future_returns.drop(columns={"Days"}, inplace=True)
rolling_returns_positive_future_returns.reset_index(drop=True, inplace=True)
display(rolling_returns_positive_future_returns)
```

	Period	Positive_Future_Percentage_Post_{-0.1}_Drawdown	\
0	1d	0.541	
1	1w	0.572	
2	1m	0.625	
3	3m	0.670	
4	6m	0.704	
5	1y	0.733	
6	2y	0.765	
7	3y	0.721	
8	4y	0.688	

9 5y 0.659

Positive_Future_Percentage_Post_-0.2_Drawdown \

0	0.540
1	0.568
2	0.615
3	0.652
4	0.691
5	0.732
6	0.779
7	0.720
8	0.687
9	0.661

Positive_Future_Percentage_Post_-0.3_Drawdown \

0	0.538
1	0.561
2	0.607
3	0.632
4	0.676
5	0.726
6	0.785
7	0.722
8	0.682
9	0.656

Positive_Future_Percentage_Post_-0.4_Drawdown \

0	0.537
1	0.560
2	0.605
3	0.632
4	0.671
5	0.725
6	0.782
7	0.724
8	0.685
9	0.658

Positive_Future_Percentage_Post_-0.5_Drawdown \

0	0.544
1	0.565
2	0.624
3	0.647
4	0.692
5	0.740
6	0.772
7	0.717
8	0.678

9	0.649
Positive_Future_Percentage_Post_-0.6_Drawdown \	
0	0.547
1	0.560
2	0.625
3	0.650
4	0.698
5	0.786
6	0.809
7	0.744
8	0.708
9	0.672

Positive_Future_Percentage_Post_-0.7_Drawdown \	
0	0.547
1	0.566
2	0.625
3	0.656
4	0.735
5	0.836
6	0.916
7	0.870
8	0.813
9	0.740

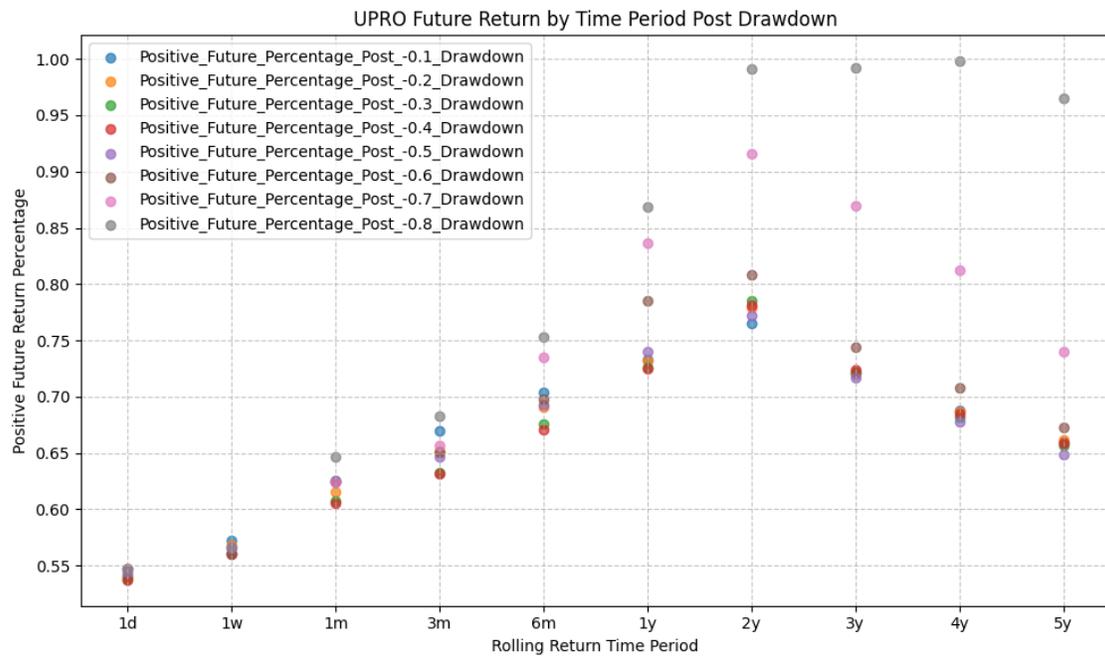
Positive_Future_Percentage_Post_-0.8_Drawdown	
0	0.547
1	0.566
2	0.646
3	0.683
4	0.753
5	0.869
6	0.991
7	0.993
8	0.998
9	0.966

```
[73]: plot_scatter(
    df=rolling_returns_positive_future_returns,
    x_plot_column="Period",
    y_plot_columns=[col for col in rolling_returns_positive_future_returns.
    columns if col != "Period"],
    title="UPRO Future Return by Time Period Post Drawdown",
    x_label="Rolling Return Time Period",
    x_format="String",
    x_format_decimal_places=0,
```

```

x_tick_spacing=1,
x_tick_rotation=0,
y_label="Positive Future Return Percentage",
y_format="Decimal",
y_format_decimal_places=2,
y_tick_spacing="Auto",
y_tick_rotation=0,
plot_OLS_regression_line=False,
OLS_column=None,
plot_Ridge_regression_line=False,
Ridge_column=None,
plot_RidgeCV_regression_line=False,
RidgeCV_column=None,
regression_constant=False,
grid=True,
legend=True,
export_plot=False,
plot_file_name=None,
)

```



This plot summarizes the future rolling returns well. Similar as to QQQ/TQQQ, for rolling returns up to ~3 months *following* all drawdown levels, we see the rolling returns of UPRO are positive ~65% of the time.

As we extend the time horizon, out to the 2y, 3y, 4y, and 5y mark, the percentage of positive rolling returns following an 80% drawdown increases significantly, and is greater than 95%. This suggests

that while the volatility decay effect is present for UPRO, it may not be as severe as that of TQQQ, which could be due to the less extreme return profile of SPY compared to QQQ.

As an investor, this suggests that the optimal time to buy UPRO would be following a drawdown of 50% or more, and holding for at least 2 years. One could dollar cost average into UPRO following a drawdown of 50% or more, and continue to add to the position with a consistent contribution schedule until all capital has been allocated.