01_setup

December 18, 2025

1 Setup and data cleaning

1.1 Notebook setup

[14]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sys
sys.executable
```

[14]:
```
'/Users/fanghema/Desktop/aaSTAT_5200/STAT_5200_final_project/env/bin/python'
```

1.2 Data Preprocessing

I then load in the data from replication dataset.

[2]:
```
data_galvao_et_al = pd.read_csv('../gmo-files/datareturns.txt', sep="\t",␣
↪header=None)
data_galvao_et_al
```

[2]:

	0	1	2	3	4	5	6	7	8	9	…	43	\
0	-0.67	0.00	-0.31	0.01	0.15	0.012	0.33	-0.45	-0.14	-0.20	…	-1.28	
1	0.79	-0.26	0.26	-0.08	-0.19	0.012	0.86	0.65	-0.03	0.29	…	0.34	
2	0.63	-0.17	-0.09	0.19	-0.33	0.012	0.96	0.55	0.83	1.29	…	1.14	
3	0.40	0.08	-0.28	0.07	-0.33	0.012	-0.01	0.09	0.32	0.35	…	1.38	
4	-0.63	0.04	-0.16	-0.31	0.14	0.012	-0.15	-0.28	0.26	-0.37	…	0.18	
…	…	…	…	…	…	…	…	…	…	…	…	…	
12960	0.07	0.32	-0.18	-0.24	-0.08	0.000	-1.30	-0.04	-0.04	-0.10	…	-0.34	
12961	0.39	0.32	-0.24	-0.20	-0.18	0.000	0.23	0.24	-0.06	-0.03	…	0.02	
12962	0.13	0.22	0.61	0.10	0.17	0.000	0.02	-0.22	-0.21	-0.38	…	0.53	
12963	-0.48	0.06	0.23	0.11	0.25	0.000	-0.12	-0.56	-0.39	-0.82	…	-0.30	
12964	-0.93	0.48	-0.45	-0.08	-0.22	0.000	-1.41	-1.51	-1.26	-1.22	…	-1.56	

	44	45	46	47	48	49	50	51	52
0	-0.91	-0.86	-0.33	-0.25	-0.23	-1.35	-0.52	-0.24	-0.07
1	1.15	0.29	0.43	0.72	0.59	0.71	0.37	0.27	-0.26
2	0.60	1.13	0.80	0.96	0.35	0.99	0.41	0.49	0.07

```
3     -0.26  0.61  0.07 -0.16  0.17  1.11  0.03  0.71  0.83
4     -1.27 -0.71 -0.03 -0.42 -0.39 -0.79 -1.08 -0.03 -0.68
…       …    …    …    …    …    …    …    …    …
12960  0.53  0.01 -0.31 -0.02  0.01 -0.03  0.14 -0.08 -0.20
12961  0.21  0.20  0.39  0.67  0.00  0.01  0.46 -0.12 -0.01
12962  0.29  0.21  0.53  0.59  0.44  0.17  0.42  0.11  0.26
12963 -0.10 -0.27 -0.14 -0.68 -0.15  0.16 -0.35 -0.34 -0.23
12964 -0.46 -0.98 -0.32 -0.21 -1.07 -1.26 -1.33 -0.96 -1.09

[12965 rows x 53 columns]
```

Comparing this to the 49-industry dataset from Kenneth French's data library.

[3]:
```
industry_portfolios = pd.read_csv(
    '../data/raw/49_Industry_Portfolios_Daily.csv',
    index_col = 0,
    parse_dates=True
)
ff5_factors = pd.read_csv(
    '../data/raw/F-F_Research_Data_5_Factors_2x3_daily.csv',
    index_col = 0,
    parse_dates=True
)

replication_data = (
    ff5_factors
    .merge(industry_portfolios, left_index=True, right_index=True, how='left')
    .loc["1963-07-01":]
)

replication_data
```

[3]:
```
            Mkt-RF   SMB   HML   RMW   CMA    RF  Agric  Food  Soda  Beer  \
1963-07-01   -0.67  0.00 -0.34 -0.01  0.16  0.01   0.33 -0.45 -0.14 -0.20
1963-07-02    0.79 -0.26  0.26 -0.07 -0.20  0.01   0.86  0.65 -0.03  0.29
1963-07-03    0.63 -0.17 -0.09  0.18 -0.34  0.01   0.96  0.55  0.83  1.29
1963-07-05    0.40  0.08 -0.27  0.09 -0.34  0.01  -0.01  0.09  0.32  0.35
1963-07-08   -0.63  0.04 -0.18 -0.29  0.14  0.01  -0.15 -0.28  0.26 -0.37
…              …    …    …    …    …    …    …    …    …    …
2025-10-27    1.17 -0.81 -1.21 -0.23 -1.19  0.02   0.36  0.59  0.30  1.42
2025-10-28    0.18 -0.34 -0.61  0.63 -1.01  0.02  -0.91 -1.06 -0.01 -1.60
2025-10-29   -0.09 -0.98 -0.81  0.30 -1.37  0.02  -0.46 -3.01 -2.64 -3.19
2025-10-30   -1.10  0.00  0.67 -0.27  0.42  0.02  -2.09 -0.15  0.69  0.82
2025-10-31    0.40 -0.07 -0.24 -1.31  0.18  0.02  -0.29 -0.22 -0.06 -0.69

            …  Boxes  Trans  Whlsl  Rtail  Meals  Banks  Insur  RlEst   Fin  \
1963-07-01  …  -1.28  -0.91  -0.83  -0.33  -0.25  -0.27  -1.35  -0.51 -0.20
1963-07-02  …   0.34   1.15   0.33   0.43   0.69   0.47   0.71   0.33  0.43
```

```
1963-07-03  …   1.14   0.60   1.13   0.80   0.96  -0.01   0.99   0.38  0.80
1963-07-05  …   1.38  -0.26   0.60   0.07  -0.16   0.14   1.11   0.02  0.64
1963-07-08  …   0.18  -1.27  -0.71  -0.03  -0.42  -0.45  -0.79  -1.06 -0.02
…           …   …     …      …      …      …      …      …      …     …
2025-10-27  …   0.11   1.26   0.31   0.56   0.49   0.52   0.33  -0.64  0.91
2025-10-28  …  -0.67  -0.72  -0.93   0.31  -1.57  -0.17  -1.20  -1.14 -0.54
2025-10-29  …  -4.25  -0.13  -0.52  -0.49  -1.19  -1.04  -1.53  -3.46 -1.34
2025-10-30  …  -0.47   0.39   1.36  -1.78  -1.99   0.65  -1.42  -0.67 -0.55
2025-10-31  …   0.22   0.85  -0.06   3.93  -1.09   0.32  -0.38   0.13  0.46

            Other
1963-07-01   0.14
1963-07-02   0.13
1963-07-03   0.09
1963-07-05   1.02
1963-07-08  -0.38
…           …
2025-10-27  -0.72
2025-10-28  -1.40
2025-10-29  -1.51
2025-10-30   0.53
2025-10-31  -0.16

[15690 rows x 55 columns]
```

[4]:
```python
corr_df = pd.DataFrame(
    index = np.arange(data_galvao_et_al.shape[1]),
    columns = replication_data.columns
)

for i in range(data_galvao_et_al.shape[1]):
    for col in replication_data.columns:
        corr = np.corrcoef(
            data_galvao_et_al.iloc[:, i].values,
            replication_data[col][:data_galvao_et_al.shape[0]].values
        )[0, 1]
        corr_df.loc[i, col] = corr
```

[5]:
```python
columns_map = {}
for i in corr_df.index:
    argmax = corr_df.loc[i].argmax()
    max = corr_df.loc[i].max()
    print(f"column number {i}: {replication_data.columns[argmax]} ({max})")
    columns_map[i] = replication_data.columns[argmax]

print(f"Number of keys: {len(set(columns_map.keys()))}")
print(f"Number of values: {len(set(columns_map.values()))}")
```

```
column number 0: Mkt-RF (0.9999631176102544)
column number 1: SMB (0.9983317073995388)
column number 2: HML (0.9707746741309701)
column number 3: RMW (0.9695277483402874)
column number 4: CMA (0.996411334405961)
column number 5: RF (0.9765065560785002)
column number 6: Agric (0.9993517050995383)
column number 7: Food (0.9998997012505297)
column number 8: Soda (0.9999736609358353)
column number 9: Beer (0.9999633984001192)
column number 10: Smoke (0.9996248704879636)
column number 11: Toys (0.9986361761212148)
column number 12: Fun (0.9996860847221328)
column number 13: Books (0.9981487902396878)
column number 14: Hshld (0.9999021300411858)
column number 15: Clths (0.9979290120722208)
column number 16: MedEq (0.9998955127299733)
column number 17: Drugs (0.9998955062570346)
column number 18: Chems (0.9999833203244106)
column number 19: Rubbr (0.9989401195566953)
column number 20: Txtls (0.9978286804583132)
column number 21: BldMt (0.9925498232310794)
column number 22: Cnstr (0.9955760178553862)
column number 23: Steel (0.9990462794382083)
column number 24: FabPr (0.9462112861585128)
column number 25: Mach (0.9897169114843933)
column number 26: ElcEq (0.9981289474892405)
column number 27: Autos (0.9990608501760571)
column number 28: Aero (0.9997757459782651)
column number 29: Ships (0.998256024412168)
column number 30: Guns (0.9997896242645089)
column number 31: Gold (0.9985885553277145)
column number 32: Mines (0.9995911312732187)
column number 33: Coal (0.9986400720334226)
column number 34: Oil (0.9996662148490669)
column number 35: Util (0.9998391848589837)
column number 36: Telcm (0.9989044702521956)
column number 37: PerSv (0.9994444860801095)
column number 38: BusSv (0.9905182743345038)
column number 39: Hardw (0.9961413009522394)
column number 40: Chips (0.9974214473872154)
column number 41: LabEq (0.9971031439150029)
column number 42: Paper (0.9696560686178576)
column number 43: Boxes (0.9978022637534089)
column number 44: Trans (0.9996326924037361)
column number 45: Whlsl (0.9983352779355394)
column number 46: Rtail (0.9999036487527976)
column number 47: Meals (0.9933848285355421)
```

```
column number 48: Banks (0.9989749220253604)
column number 49: Insur (0.9994260713508203)
column number 50: RlEst (0.9459155034739062)
column number 51: Fin (0.9984710426181009)
column number 52: Other (0.984467019976098)
Number of keys: 53
Number of values: 53
```

We check for the two columns that were not matched to any columns in Galvao et al's dataset. This indeed matches their description.

[6]:
```
for col in replication_data.columns:
    if col not in columns_map.values():
        print(col)
```

```
Hlth
Softw
```

We update column names and indices for the original dataframe. We also drop Healthcare and Software from our extended dataframe.

[7]:
```
replication_data = replication_data.drop(columns=['Hlth', 'Softw'])
data_galvao_et_al.rename(columns = columns_map, inplace=True)
data_galvao_et_al.index = replication_data.index[:data_galvao_et_al.shape[0]]
```

Data cleaning and replacing invalid values with 0.

[8]:
```
replication_data = (
    replication_data
    .replace([np.inf, -np.inf], np.nan)
    .fillna(0)
)

data_galvao_et_al = (
    data_galvao_et_al
    .replace([np.inf, -np.inf], np.nan)
    .fillna(0)
)
```

[9]:
```
data_galvao_et_al.to_csv('../data/processed/data_galvao.csv')
replication_data.to_csv("../data/processed/data_extended.csv")
```

1.3 Summary Statistics

[11]:
```
replication_data.describe()
```

[11]:

	Mkt-RF	SMB	HML	RMW	CMA	\
count	15690.000000	15690.000000	15690.000000	15690.000000	15690.000000	
mean	0.028841	0.005815	0.014004	0.012736	0.011643	
std	1.023264	0.551013	0.585571	0.403702	0.382175	

min	-17.440000	-11.150000	-5.030000	-2.970000	-5.310000
25%	-0.420000	-0.280000	-0.240000	-0.180000	-0.180000
50%	0.050000	0.020000	0.010000	0.010000	0.010000
75%	0.510000	0.310000	0.260000	0.190000	0.200000
max	11.360000	6.080000	6.730000	4.570000	2.480000

	RF	Agric	Food	Soda	Beer	\
count	15690.000000	15690.000000	15690.000000	15690.000000	15690.000000	
mean	0.017183	0.049493	0.044612	0.053917	0.049760	
std	0.012740	1.437237	0.905245	1.356966	1.126727	
min	0.000000	-15.270000	-16.080000	-19.220000	-14.730000	
25%	0.010000	-0.630000	-0.410000	-0.610000	-0.530000	
50%	0.020000	0.040000	0.060000	0.050000	0.040000	
75%	0.020000	0.730000	0.510000	0.690000	0.620000	
max	0.060000	20.320000	10.010000	11.680000	11.460000	

	…	Boxes	Trans	Whlsl	Rtail	\
count	…	15690.000000	15690.000000	15690.000000	15690.000000	
mean	…	0.045228	0.045016	0.048480	0.052345	
std	…	1.260816	1.252522	1.088046	1.156068	
min	…	-21.350000	-17.570000	-13.250000	-17.970000	
25%	…	-0.610000	-0.600000	-0.480000	-0.520000	
50%	…	0.050000	0.050000	0.070000	0.070000	
75%	…	0.700000	0.680000	0.610000	0.620000	
max	…	10.910000	12.710000	10.640000	11.750000	

	Meals	Banks	Insur	RlEst	Fin	\
count	15690.000000	15690.000000	15690.000000	15690.000000	15690.000000	
mean	0.054479	0.047213	0.047164	0.035504	0.055850	
std	1.247532	1.417553	1.174384	1.449594	1.427951	
min	-15.260000	-16.960000	-15.200000	-17.640000	-16.360000	
25%	-0.577500	-0.540000	-0.490000	-0.600000	-0.500000	
50%	0.070000	0.040000	0.060000	0.050000	0.070000	
75%	0.690000	0.630000	0.600000	0.680000	0.640000	
max	15.890000	16.940000	17.820000	17.120000	18.180000	

	Other
count	15690.000000
mean	0.030916
std	1.408428
min	-17.230000
25%	-0.590000
50%	0.050000
75%	0.680000
max	16.840000

[8 rows x 53 columns]

[12]:
```
data_galvao_et_al.describe()
```

[12]:

	Mkt-RF	SMB	HML	RMW	CMA	\
count	12965.000000	12965.000000	12965.000000	12965.000000	12965.000000	
mean	0.024251	0.009328	0.017895	0.012640	0.015580	
std	0.992087	0.520785	0.495309	0.348898	0.360934	
min	-17.440000	-11.180000	-5.090000	-2.860000	-5.240000	
25%	-0.420000	-0.260000	-0.210000	-0.160000	-0.170000	
50%	0.050000	0.030000	0.010000	0.010000	0.010000	
75%	0.490000	0.300000	0.240000	0.170000	0.190000	
max	11.350000	6.090000	4.040000	4.100000	2.490000	

	RF	Agric	Food	Soda	Beer	\
count	12965.000000	12965.000000	12965.000000	12965.000000	12965.000000	
mean	0.019350	0.051073	0.050685	0.056383	0.054464	
std	0.012195	1.396318	0.879694	1.406782	1.128794	
min	0.000000	-15.270000	-16.040000	-19.220000	-14.730000	
25%	0.012000	-0.630000	-0.390000	-0.630000	-0.530000	
50%	0.019000	0.040000	0.060000	0.050000	0.040000	
75%	0.025000	0.730000	0.500000	0.720000	0.620000	
max	0.061000	20.320000	9.980000	11.680000	10.120000	

	…	Boxes	Trans	Whlsl	Rtail	\
count	…	12965.000000	12965.000000	12965.000000	12965.000000	
mean	…	0.048595	0.046272	0.048008	0.050200	
std	…	1.243543	1.215566	1.059366	1.133851	
min	…	-21.430000	-17.560000	-13.200000	-18.000000	
25%	…	-0.600000	-0.590000	-0.470000	-0.520000	
50%	…	0.050000	0.050000	0.080000	0.060000	
75%	…	0.680000	0.670000	0.590000	0.600000	
max	…	10.920000	9.330000	9.750000	11.750000	

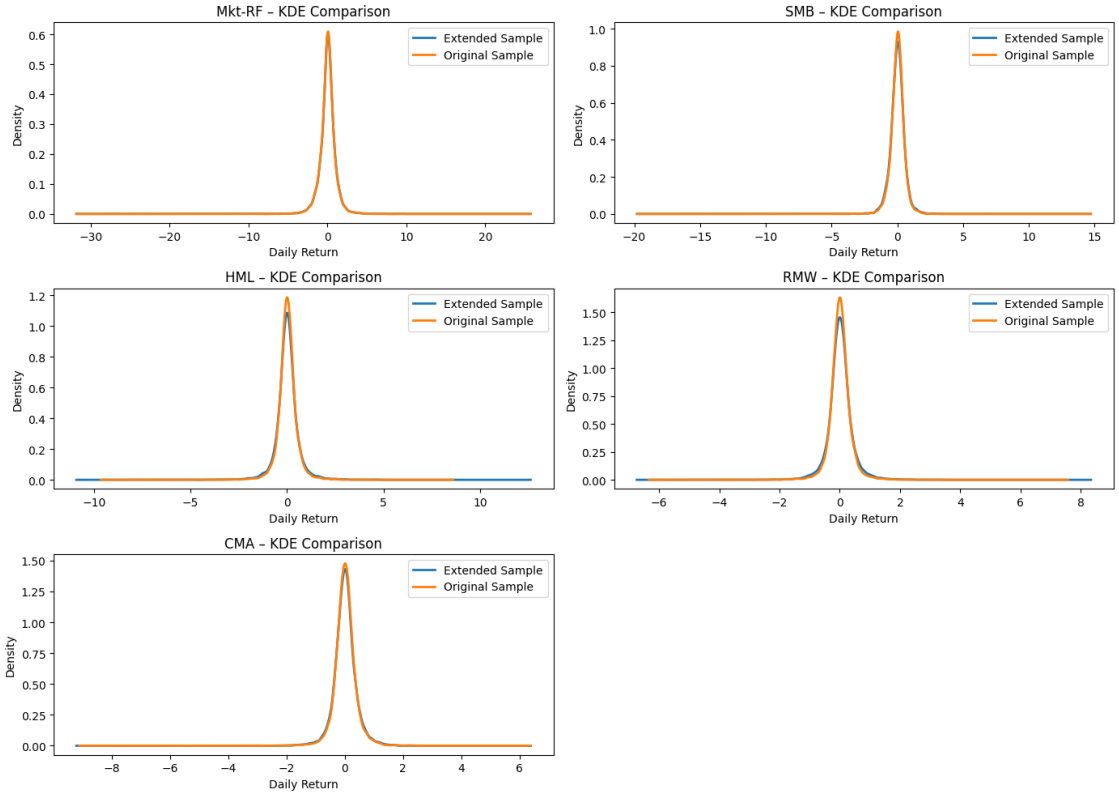
	Meals	Banks	Insur	RlEst	Fin	\
count	12965.000000	12965.000000	12965.000000	12965.000000	12965.000000	
mean	0.055287	0.044963	0.046565	0.029755	0.054201	
std	1.252471	1.382958	1.153460	1.431005	1.414357	
min	-15.480000	-16.980000	-13.980000	-15.500000	-16.280000	
25%	-0.590000	-0.520000	-0.490000	-0.600000	-0.480000	
50%	0.070000	0.040000	0.060000	0.030000	0.060000	
75%	0.720000	0.590000	0.580000	0.680000	0.610000	
max	11.490000	16.960000	17.840000	21.900000	17.940000	

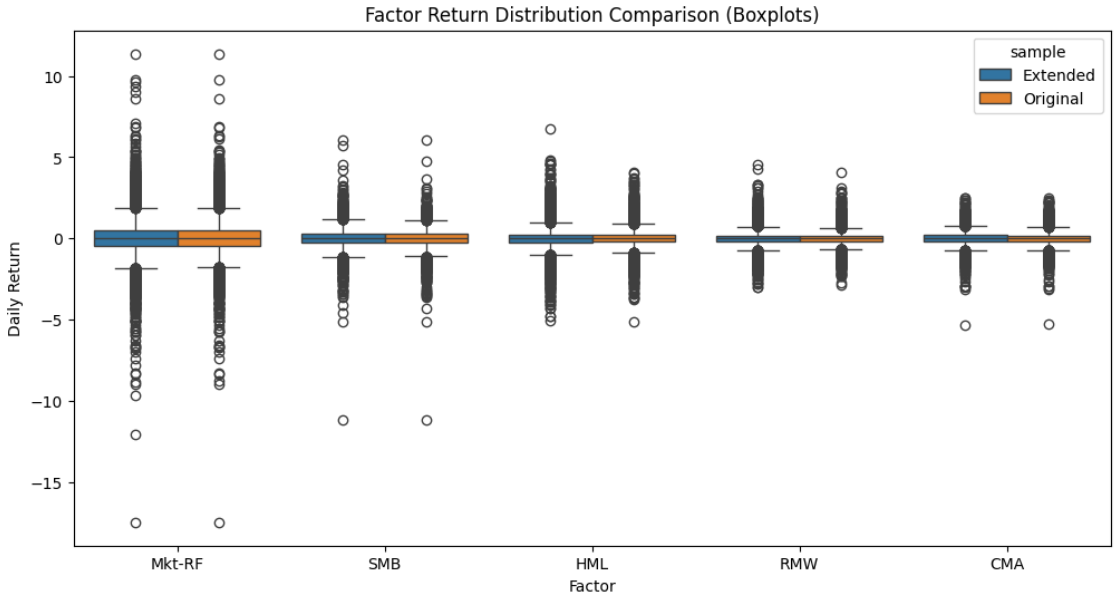
	Other
count	12965.000000
mean	0.029523
std	1.433517
min	-17.260000

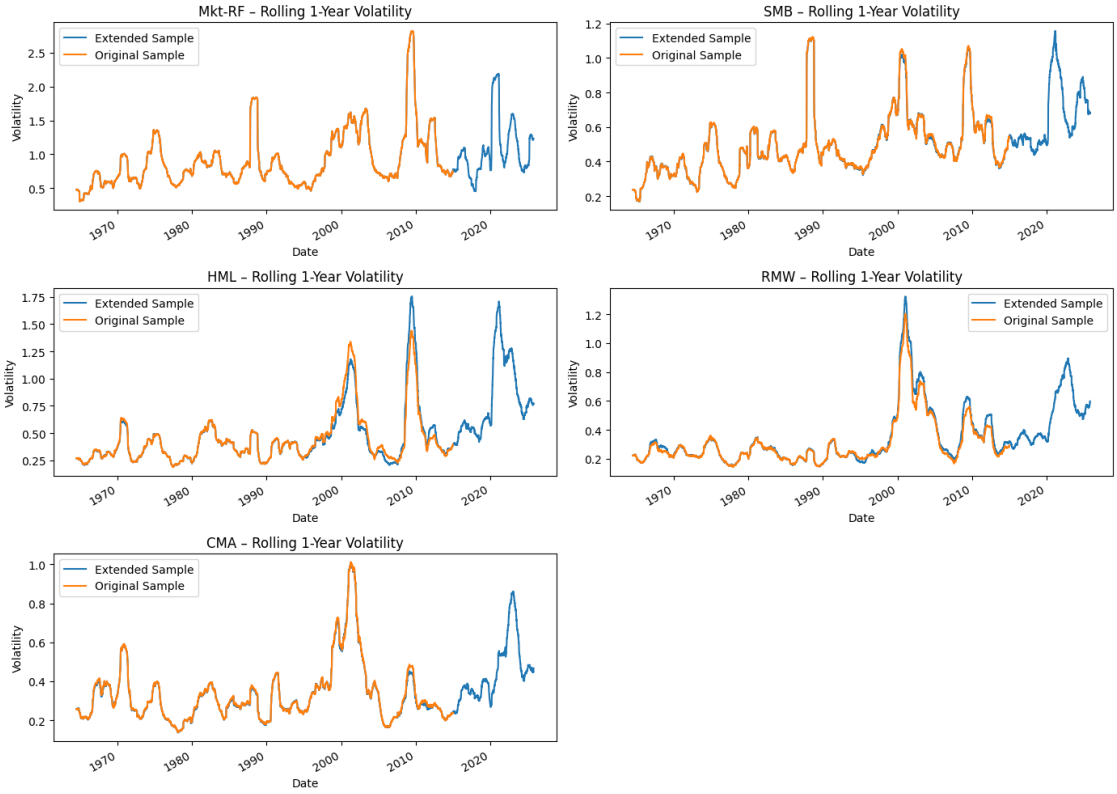
```
25%       -0.610000
50%        0.050000
75%        0.700000
max       16.840000

[8 rows x 53 columns]
```

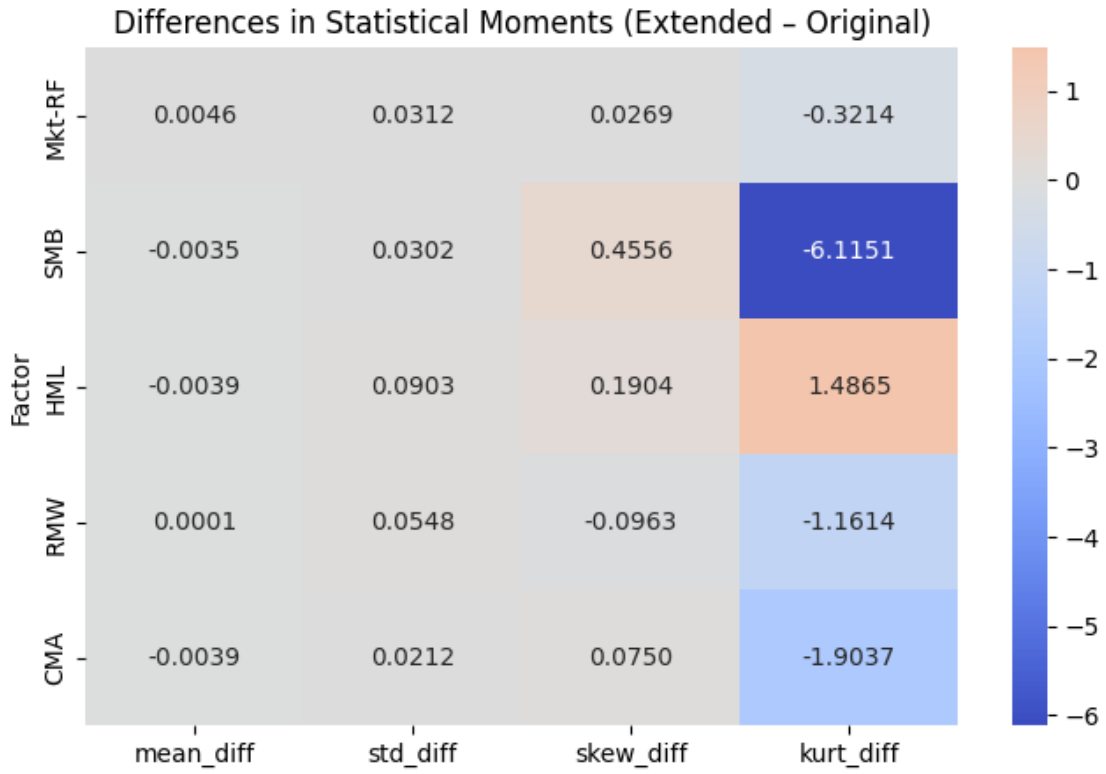
[15]:
```
factors = ["Mkt-RF", "SMB", "HML", "RMW", "CMA"]

plt.figure(figsize=(14, 10))

for i, fac in enumerate(factors, 1):
    plt.subplot(3, 2, i)
    replication_data[fac].plot(kind="kde", label="Extended Sample", linewidth=2)
    data_galvao_et_al[fac].plot(kind="kde", label="Original Sample",␣
 ↪linewidth=2)
    plt.title(f"{fac} - KDE Comparison")
    plt.xlabel("Daily Return")
    plt.legend()

plt.tight_layout()
plt.show()

combined = pd.concat([
    replication_data[factors].assign(sample="Extended"),
    data_galvao_et_al[factors].assign(sample="Original")
])

combined_melted = combined.melt(id_vars="sample")

plt.figure(figsize=(12, 6))
sns.boxplot(data=combined_melted, x="variable", y="value", hue="sample")
plt.title("Factor Return Distribution Comparison (Boxplots)")
plt.xlabel("Factor")
plt.ylabel("Daily Return")
plt.show()

plt.figure(figsize=(14, 10))

for i, fac in enumerate(factors, 1):
    plt.subplot(3, 2, i)
    replication_data[fac].rolling(252).std().plot(label="Extended Sample",␣
 ↪linewidth=1.5)
    data_galvao_et_al[fac].rolling(252).std().plot(label="Original Sample",␣
 ↪linewidth=1.5)
    plt.title(f"{fac} - Rolling 1-Year Volatility")
    plt.xlabel("Date")
```

```
    plt.ylabel("Volatility")
    plt.legend()

plt.tight_layout()
plt.show()


stats = pd.DataFrame({
    "mean_diff": replication_data[factors].mean() - data_galvao_et_al[factors].
 ↪mean(),
    "std_diff": replication_data[factors].std() - data_galvao_et_al[factors].
 ↪std(),
    "skew_diff": replication_data[factors].skew() - data_galvao_et_al[factors].
 ↪skew(),
    "kurt_diff": replication_data[factors].kurt() - data_galvao_et_al[factors].
 ↪kurt()
})

plt.figure(figsize=(8, 5))
sns.heatmap(stats, annot=True, cmap="coolwarm", center=0, fmt=".4f")
plt.title("Differences in Statistical Moments (Extended - Original)")
plt.ylabel("Factor")
plt.show()
```




Factor Return Distribution Comparison (Boxplots)
sample
Extended
Original
Daily Return
10
5
0
−5
−10
−15
Mkt-RF
SMB
HML
RMW
CMA
Factor


Mkt-RF – Rolling 1-Year Volatility
SMB – Rolling 1-Year Volatility
HML – Rolling 1-Year Volatility
RMW – Rolling 1-Year Volatility
CMA – Rolling 1-Year Volatility
Extended Sample
Original Sample
Volatility
Date
1970
1980
1990
2000
2010
2020

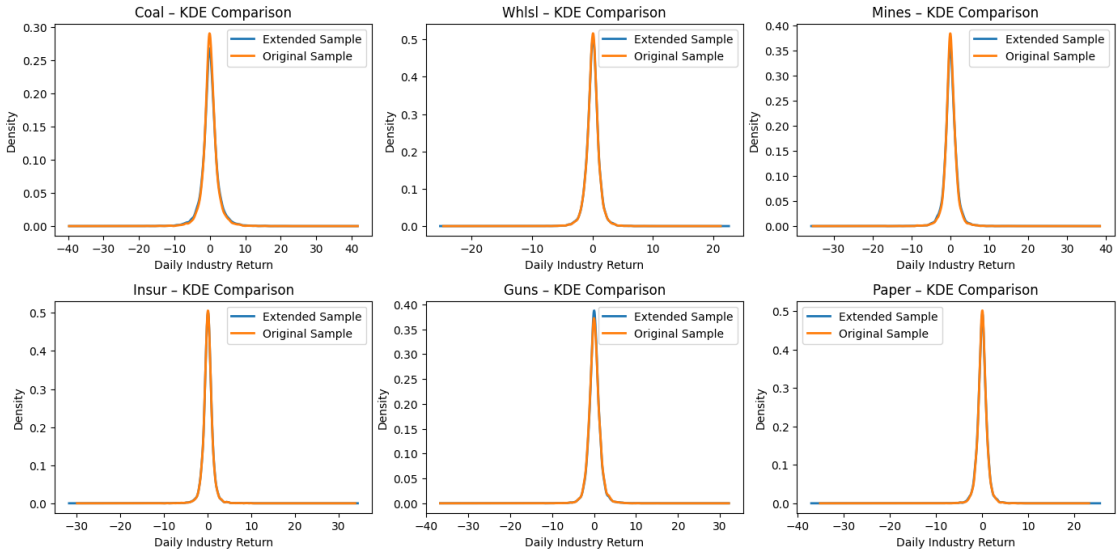


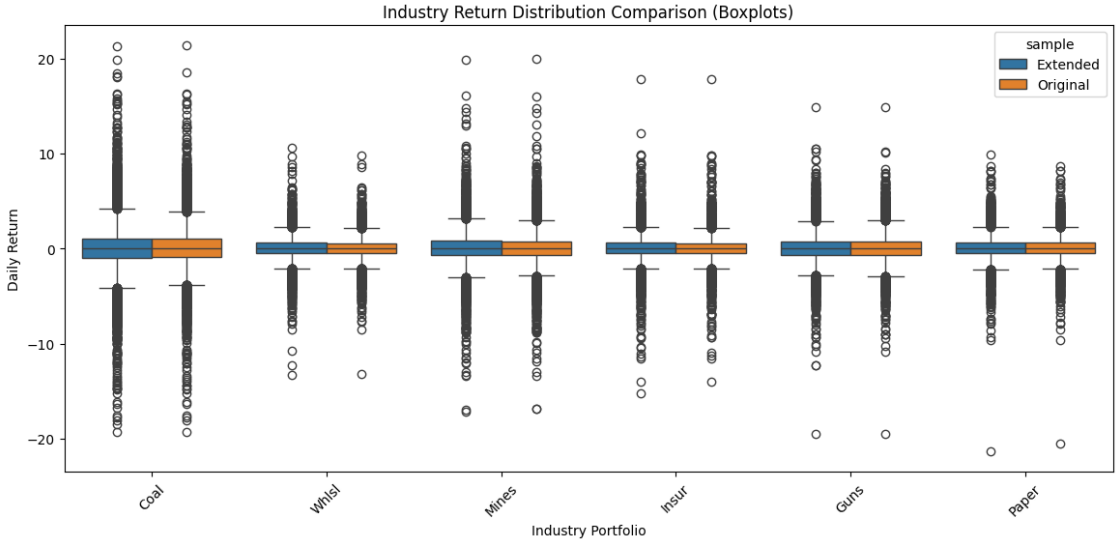
[16]:
```
N_SAMPLE_INDUSTRIES = 6

factor_cols = ["Mkt-RF", "SMB", "HML", "RMW", "CMA", "RF"]
industry_cols = [col for col in replication_data.columns if col not in␣
 ↪factor_cols]

np.random.seed(42)
sampled_industries = np.random.choice(industry_cols, size=N_SAMPLE_INDUSTRIES,␣
 ↪replace=False).tolist()

print("Sampled industries:", sampled_industries)

plt.figure(figsize=(14, 10))

for i, ind in enumerate(sampled_industries, 1):
    plt.subplot(3, 3, i)
    replication_data[ind].plot(kind="kde", label="Extended Sample", linewidth=2)
    data_galvao_et_al[ind].plot(kind="kde", label="Original Sample",␣
 ↪linewidth=2)
    plt.title(f"{ind} - KDE Comparison")
    plt.xlabel("Daily Industry Return")
    plt.legend()
```

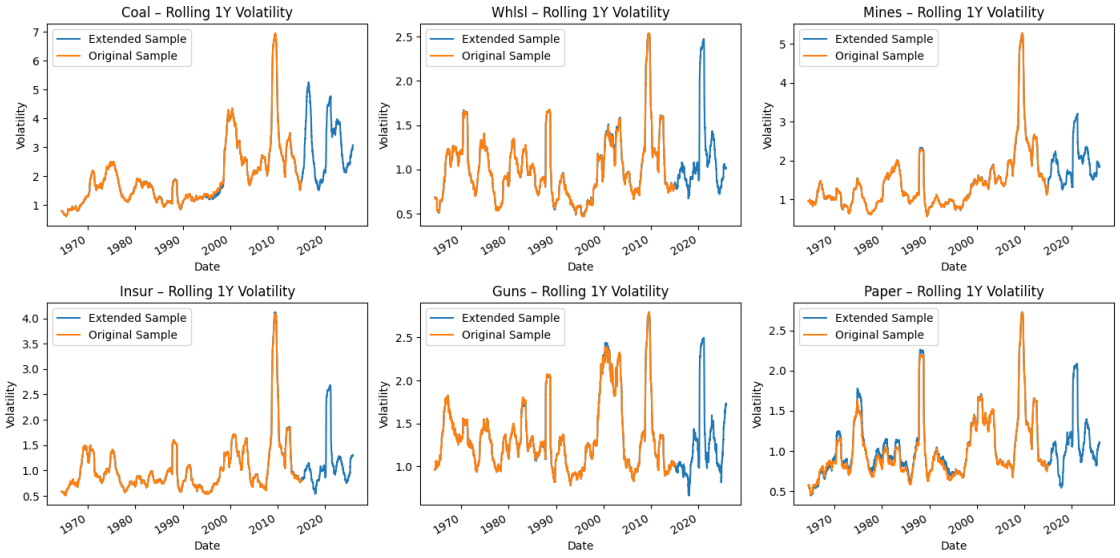
```
plt.tight_layout()
plt.show()


combined_ind = pd.concat([
    replication_data[sampled_industries].assign(sample="Extended"),
    data_galvao_et_al[sampled_industries].assign(sample="Original")
])

combined_ind_melted = combined_ind.melt(id_vars="sample")

plt.figure(figsize=(14, 6))
sns.boxplot(data=combined_ind_melted, x="variable", y="value", hue="sample")
plt.title("Industry Return Distribution Comparison (Boxplots)")
plt.xlabel("Industry Portfolio")
plt.ylabel("Daily Return")
plt.xticks(rotation=45)
plt.show()


plt.figure(figsize=(14, 10))

for i, ind in enumerate(sampled_industries, 1):
    plt.subplot(3, 3, i)
    replication_data[ind].rolling(252).std().plot(label="Extended Sample",␣
 ↪linewidth=1.5)
    data_galvao_et_al[ind].rolling(252).std().plot(label="Original Sample",␣
 ↪linewidth=1.5)
    plt.title(f"{ind} - Rolling 1Y Volatility")
    plt.xlabel("Date")
    plt.ylabel("Volatility")
    plt.legend()

plt.tight_layout()
plt.show()


stats_ind = pd.DataFrame({
    "mean_diff": replication_data[sampled_industries].mean() -␣
 ↪data_galvao_et_al[sampled_industries].mean(),
    "std_diff": replication_data[sampled_industries].std() -␣
 ↪data_galvao_et_al[sampled_industries].std(),
    "skew_diff": replication_data[sampled_industries].skew() -␣
 ↪data_galvao_et_al[sampled_industries].skew(),
    "kurt_diff": replication_data[sampled_industries].kurt() -␣
 ↪data_galvao_et_al[sampled_industries].kurt()
```

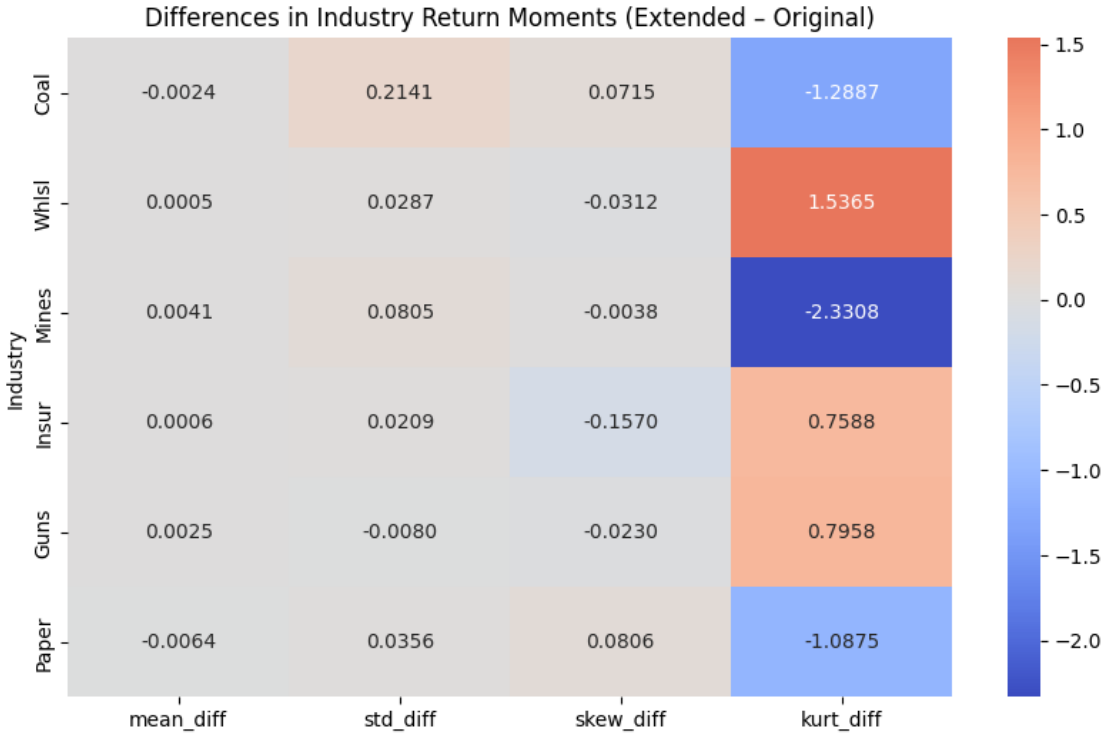
```
})

plt.figure(figsize=(10, 6))
sns.heatmap(stats_ind, annot=True, cmap="coolwarm", center=0, fmt=".4f")
plt.title("Differences in Industry Return Moments (Extended - Original)")
plt.ylabel("Industry")
plt.show()
```

```
Sampled industries: ['Coal', 'Whlsl', 'Mines', 'Insur', 'Guns', 'Paper']
```






Coal – Rolling 1Y Volatility
Whlsl – Rolling 1Y Volatility
Mines – Rolling 1Y Volatility
Insur – Rolling 1Y Volatility
Guns – Rolling 1Y Volatility
Paper – Rolling 1Y Volatility
Extended Sample
Original Sample
Volatility
Date


Differences in Industry Return Moments (Extended – Original)
Industry
Coal
Whlsl
Mines
Insur
Guns
Paper
-0.0024
0.2141
0.0715
-1.2887
0.0005
0.0287
-0.0312
1.5365
0.0041
0.0805
-0.0038
-2.3308
0.0006
0.0209
-0.1570
0.7588
0.0025
-0.0080
-0.0230
0.7958
-0.0064
0.0356
0.0806
-1.0875
mean_diff
std_diff
skew_diff
kurt_diff
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0