tactical-data-analysis

October 2, 2025

1 Settings

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from scipy.stats import jarque_bera, normaltest
import gc
from IPython.display import display
import math

import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

# Visualisation settings
plt.style.use('seaborn-v0_8-whitegrid')
sns.set_palette('viridis')
pd.options.display.float_format = '{:,.4f}'.format
plt.rcParams['figure.figsize'] = (18, 8)
plt.rcParams['axes.titlesize'] = 16
plt.rcParams['axes.labelsize'] = 14

# --- Function to reduce memory consumption ---
def reduce_mem_usage(df, verbose=True):
    numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    start_mem = df.memory_usage().sum() / 1024**2
    for col in df.columns:
        col_type = df[col].dtypes
        if col_type in numerics:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8).
↪max:
                    df[col] = df[col].astype(np.int8)
```

```
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.
↪int16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.
↪int32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.
↪int64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float32).min and c_max < np.finfo(np.
↪float32).max:
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)
    end_mem = df.memory_usage().sum() / 1024**2
    if verbose: print(f'Mem. usage decreased to {end_mem:5.2f} Mb ({100 *␣
↪(start_mem - end_mem) / start_mem:.1f}% reduction)')
    return df

print("OK.")
```

```
OK.
```

2 Loading and Initial Inspection of Data

[2]:
```
TRAIN_PATH = '/kaggle/input/hull-tactical-market-prediction/train.csv'

df = pd.read_csv(TRAIN_PATH).set_index('date_id')
df = reduce_mem_usage(df)

print(f"Dataset shape: {df.shape}")
print(f"Time range of data: from {df.index.min()} to {df.index.max()}")

display(df.head())
display(df.tail())
```

```
Mem. usage decreased to  3.16 Mb (52.9% reduction)
Dataset shape: (8990, 97)
Time range of data: from 0 to 8989
```

```
          D1  D2  D3  D4  D5  D6  D7  D8  D9  E1  ...  V3  V4  V5  V6  V7  V8  \
date_id                                           ...
0          0   0   0   1   1   0   0   0   1 NaN  ... NaN NaN NaN NaN NaN NaN
1          0   0   0   1   1   0   0   0   1 NaN  ... NaN NaN NaN NaN NaN NaN
2          0   0   0   1   0   0   0   0   1 NaN  ... NaN NaN NaN NaN NaN NaN
3          0   0   0   1   0   0   0   0   0 NaN  ... NaN NaN NaN NaN NaN NaN
```

```
4          0   0   0   1   0   0   0   0   0 NaN  ... NaN NaN NaN NaN NaN NaN

         V9  forward_returns  risk_free_rate  market_forward_excess_returns
date_id
0       NaN          -0.0024          0.0003                        -0.0030
1       NaN          -0.0085          0.0003                        -0.0091
2       NaN          -0.0096          0.0003                        -0.0102
3       NaN           0.0047          0.0003                         0.0040
4       NaN          -0.0117          0.0003                        -0.0123

[5 rows x 97 columns]
         D1  D2  D3  D4  D5  D6  D7  D8  D9     E1  ...     V3     V4     V5  \
date_id                                             ...
8985      0   0   0   0   0   0   0   0   0 1.5654  ... 0.4696 0.8380 1.2268
8986      0   0   0   0   0   0   0   0   0 1.5629  ... 0.6720 0.8380 0.7859
8987      0   0   1   0   0   0   0   0   0 1.5605  ... 0.4815 0.7877 0.8349
8988      0   0   0   0   0   0   0   0   0 1.5581  ... 0.6554 0.7837 0.9940
8989      0   0   0   0   0   0   0   0   0 1.5557  ... 0.0668 0.7837 1.0680

            V6      V7     V8      V9  forward_returns  risk_free_rate  \
date_id
8985    0.8228 -0.7074 0.1429 -0.6496           0.0025          0.0002
8986    0.8056 -0.7157 0.1961 -0.6683           0.0023          0.0002
8987    0.8234 -0.7239 0.1339 -0.6709           0.0029          0.0002
8988    0.8519 -0.6849 0.1019 -0.6463           0.0083          0.0002
8989    0.8796 -0.7648 0.0790 -0.7057           0.0001          0.0002

         market_forward_excess_returns
date_id
8985                            0.0020
8986                            0.0018
8987                            0.0024
8988                            0.0078
8989                           -0.0004

[5 rows x 97 columns]
```

[3]:
```
df.describe()
```

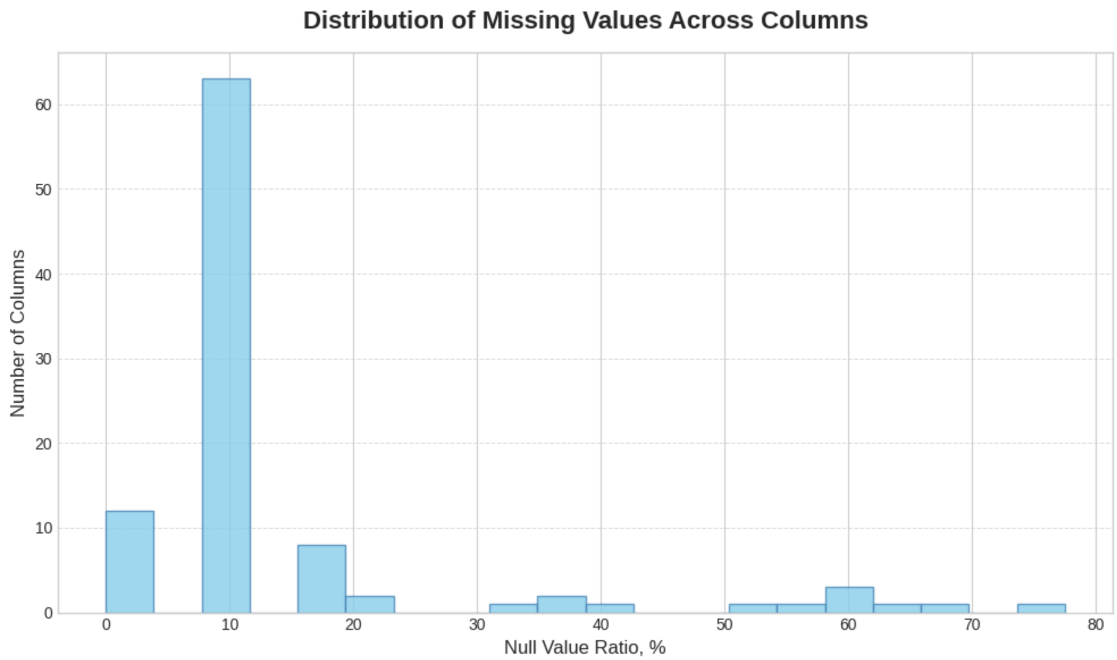
[3]:
```
             D1         D2         D3         D4         D5         D6  \
count 8,990.0000 8,990.0000 8,990.0000 8,990.0000 8,990.0000 8,990.0000
mean      0.0316     0.0316     0.0478     0.5752     0.1907    -0.2380
std       0.1749     0.1749     0.2134     0.4943     0.3928     0.4259
min       0.0000     0.0000     0.0000     0.0000     0.0000    -1.0000
25%       0.0000     0.0000     0.0000     0.0000     0.0000     0.0000
50%       0.0000     0.0000     0.0000     1.0000     0.0000     0.0000
75%       0.0000     0.0000     0.0000     1.0000     0.0000     0.0000
```

```
max        1.0000      1.0000      1.0000      1.0000      1.0000      0.0000

                D7          D8          D9          E1  ...          V3          V4  \
count 8,990.0000 8,990.0000 8,990.0000 7,206.0000  ... 7,984.0000 7,984.0000
mean      0.0457      0.1428      0.1432      1.5646  ...      0.4896      0.5069
std       0.2089      0.3499      0.3503      0.6339  ...      0.3062      0.3066
min       0.0000      0.0000      0.0000      0.3251  ...      0.0007      0.0007
25%       0.0000      0.0000      0.0000      1.1146  ...      0.2070      0.2361
50%       0.0000      0.0000      0.0000      1.5167  ...      0.4924      0.5192
75%       0.0000      0.0000      0.0000      1.8770  ...      0.7606      0.7725
max       1.0000      1.0000      1.0000      4.8439  ...      1.0000      1.0000

                V5          V6          V7          V8          V9  forward_returns  \
count 7,478.0000 7,984.0000 7,479.0000 7,984.0000 4,451.0000       8,990.0000
mean      0.3725      0.2872      0.1483      0.3039      0.1292           0.0005
std       1.1533      0.3122      1.3269      0.3511      1.2773           0.0106
min      -2.7235      0.0007     -2.0276      0.0007     -1.4974          -0.0398
25%      -0.4729      0.0007     -0.7972      0.0007     -0.7382          -0.0043
50%       0.2752      0.1802     -0.0977      0.1010     -0.1708           0.0007
75%       1.1251      0.5159      0.7958      0.5900      0.6859           0.0059
max       6.8099      1.0000     12.6783      1.0000     12.9975           0.0407

       risk_free_rate  market_forward_excess_returns
count      8,990.0000                     8,990.0000
mean           0.0001                         0.0001
std            0.0001                         0.0106
min           -0.0000                        -0.0406
25%            0.0000                        -0.0048
50%            0.0001                         0.0003
75%            0.0002                         0.0055
max            0.0003                         0.0406

[8 rows x 97 columns]
```

3 Analysis of Missing Values

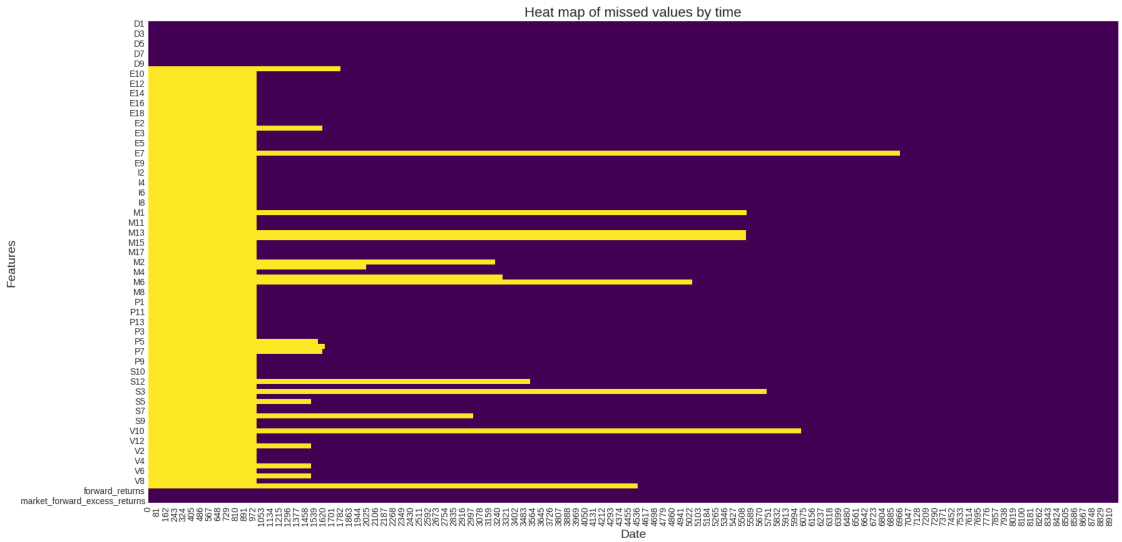
[4]:
```
missing_ratio = df.isnull().sum() * 100 / df.shape[0]

plt.figure(figsize=(10, 6))
plt.hist(missing_ratio, bins=20, color='skyblue', edgecolor='steelblue', alpha=0.
 ↪8)

plt.title('Distribution of Missing Values Across Columns', fontsize=16,␣
 ↪fontweight='bold', pad=15)
plt.xlabel('Null Value Ratio, %', fontsize=12)
plt.ylabel('Number of Columns', fontsize=12)
```

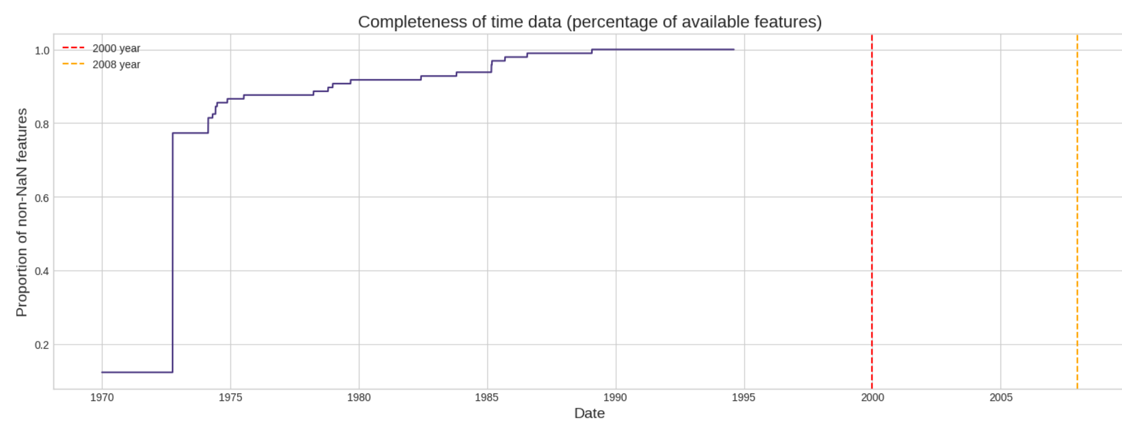
```
plt.grid(axis='y', linestyle='--', alpha=0.7, linewidth=0.7)
plt.tight_layout()
plt.show()
```



[5]:
```
plt.figure(figsize=(20, 10))
# Visualize gaps (yellow - there is data, purple - not)
# Transpose so that the signs are on the Y axis and the time is on the X axis
sns.heatmap(df.isnull().T, cmap='viridis', cbar=False)
plt.title('Heat map of missed values by time')
plt.xlabel('Date')
plt.ylabel('Features')
plt.show()

completeness_by_date = df.notnull().mean(axis=1)

plt.figure(figsize=(18, 6))
completeness_by_date.plot()
plt.title('Completeness of time data (percentage of available features)')
plt.ylabel('Proportion of non-NaN features')
plt.xlabel('Date')
plt.axvline(pd.to_datetime('2000-01-01'), color='red', linestyle='--',␣
 ↪label='2000 year')
plt.axvline(pd.to_datetime('2008-01-01'), color='orange', linestyle='--',␣
 ↪label='2008 year')
plt.legend()
```

```python
plt.show()
```





4 Target Variable Analysis

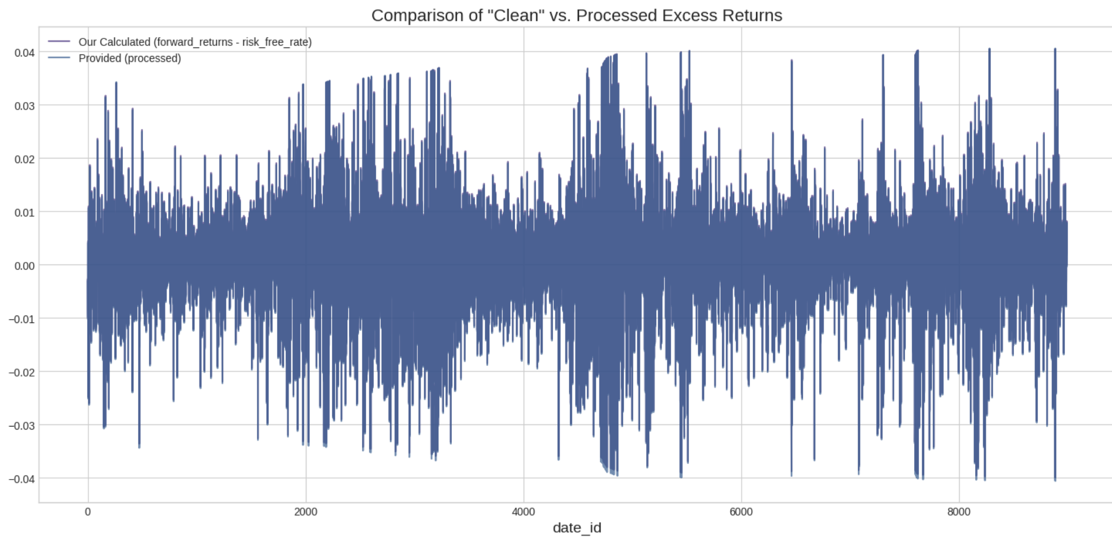
Our goal is to predict excess returns. Let's create this variable and examine it.

[6]:
```python
df['excess_return'] = df['forward_returns'] - df['risk_free_rate']

TARGET_NAME = 'excess_return'

plt.figure(figsize=(18, 6))
df[[TARGET_NAME, 'market_forward_excess_returns']].plot(alpha=0.7)
plt.title('Comparison of "Clean" vs. Processed Excess Returns')
```

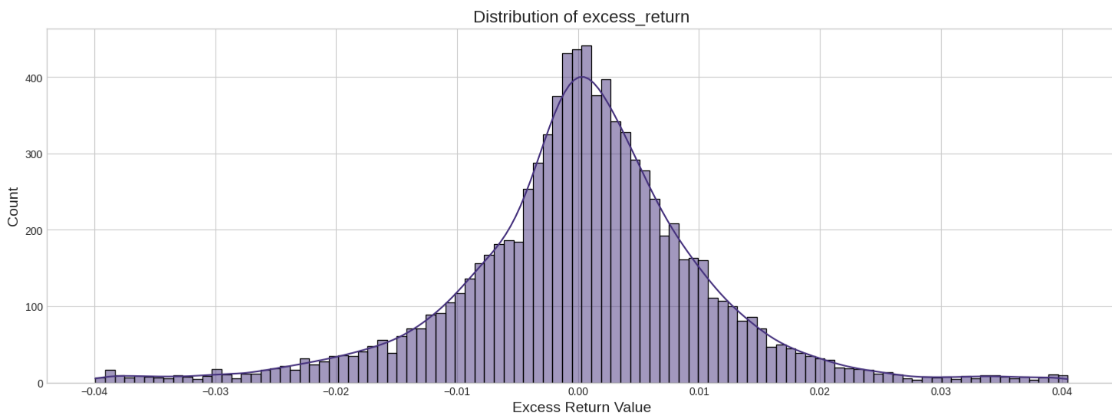
```
plt.legend(['Our Calculated (forward_returns - risk_free_rate)', 'Provided␣
↪(processed)'])
plt.show()
print("The plots are very similar. The provided variable is likely a winsorized␣
↪version of our calculated one.")
print("For our analysis, we'll use our 'clean' version as it's more fundamental.
↪")

# 1. Target Distribution
plt.figure(figsize=(18, 6))
sns.histplot(df[TARGET_NAME].dropna(), kde=True, bins=100)
plt.title(f'Distribution of {TARGET_NAME}')
plt.xlabel('Excess Return Value')

# Normality Test
stat, p_value = jarque_bera(df[TARGET_NAME].dropna())
print(f"Jarque-Bera Test: Statistic={stat:.2f}, p-value={p_value:.3f}")
if p_value < 0.05:
    print("The null hypothesis of normality is rejected. The distribution has␣
↪'heavy tails', which is typical for financial markets.")
plt.show()

# 2. Behavior Over Time
plt.figure(figsize=(18, 6))
df[TARGET_NAME].plot(alpha=0.8, style='-', lw=0.5)
plt.title(f'Daily {TARGET_NAME}')
plt.ylabel('Return')
plt.show()
print("Volatility clustering is evident: periods of high and low variance (e.g.,␣
↪crises of 2000, 2008, 2020).")

# 3. Cumulative Return (Buy-and-Hold Strategy)
plt.figure(figsize=(18, 6))
df[TARGET_NAME].cumsum().plot()
plt.title('Cumulative Excess Return (Buy-and-Hold S&P500)')
plt.ylabel('Total Return')
plt.show()

# 4. Autocorrelation
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(18, 6))
plot_acf(df[TARGET_NAME].dropna(), lags=40, ax=ax1, title='Autocorrelation␣
↪(ACF)')
plot_pacf(df[TARGET_NAME].dropna(), lags=40, ax=ax2, title='Partial␣
↪Autocorrelation (PACF)')
plt.show()
```

```
print("Autocorrelation is very weak and close to zero. This supports the efficient-market hypothesis at short lags.")
print("This means that simply using yesterday's return to predict today's is a poor strategy.")
```

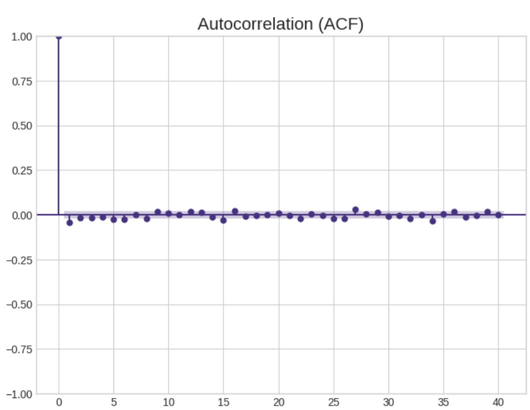
```
<Figure size 1800x600 with 0 Axes>
```

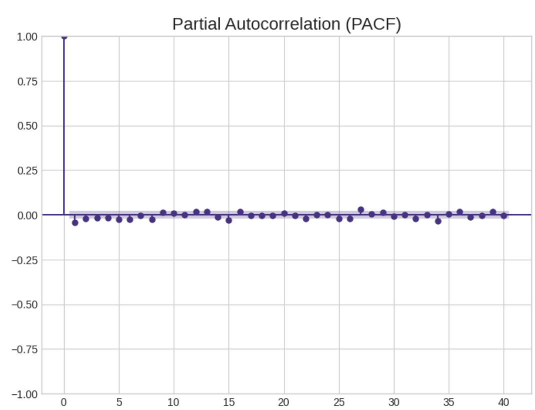



```
The plots are very similar. The provided variable is likely a winsorized version
of our calculated one.
For our analysis, we'll use our 'clean' version as it's more fundamental.
Jarque-Bera Test: Statistic=1838.26, p-value=0.000
The null hypothesis of normality is rejected. The distribution has 'heavy
tails', which is typical for financial markets.
```



Volatility clustering is evident: periods of high and low variance (e.g., crises of 2000, 2008, 2020).





Autocorrelation is very weak and close to zero. This supports the efficient-

```
market hypothesis at short lags.
This means that simply using yesterday's return to predict today's is a poor
strategy.
```

5 Feature Analysis by Group

5.1 Time Series

[7]:
```python
completeness_by_date = df.notnull().mean(axis=1)
try:
    start_id = (completeness_by_date >= 0.95).idxmax()
    print(f"Dynamically determined start_id: {start_id} (the first day with >=␣
↪95% data completeness)")
except ValueError:
    start_id = df.index[int(len(df) * 0.5)]
    print(f"Warning: Could not find a 95% completeness point. Falling back to a␣
↪default start_id: {start_id}")

df_filtered = df.loc[df.index >= start_id].copy()
print(f"Filtered dataset shape: {df_filtered.shape}")

feature_cols = [col for col in df.columns if '*' not in col and col not in␣
↪['forward_returns', 'risk_free_rate', 'market_forward_excess_returns',␣
↪'excess_return']]

groups = {
    'M': [f for f in feature_cols if f.startswith('M')],
    'E': [f for f in feature_cols if f.startswith('E')],
    'I': [f for f in feature_cols if f.startswith('I')],
    'P': [f for f in feature_cols if f.startswith('P')],
    'V': [f for f in feature_cols if f.startswith('V')],
    'S': [f for f in feature_cols if f.startswith('S')],
    'MOM': [f for f in feature_cols if f.startswith('MOM')],
    'D': [f for f in feature_cols if f.startswith('D')]
}

groups_filtered = {key: [col for col in item if col in df.columns] for key, item␣
↪in groups.items()}

n_groups = len(groups_filtered)
cols = 3
rows = math.ceil(n_groups / cols)

fig, axes = plt.subplots(rows, cols, figsize=(16, 5 * rows), sharex=True)
axes = axes.flatten() if n_groups > 1 else [axes]

for idx, (key, columns) in enumerate(groups_filtered.items()):
```

```
    ax = axes[idx]
    colors = sns.color_palette("husl", len(columns))

    for i, col in enumerate(columns):
        ax.plot(df.index, df[col], label=col, color=colors[i], linewidth=1.2)

    ax.set_title(f'Group "{key}"', fontsize=14, fontweight='bold', pad=15)
    ax.legend(loc='upper left', fontsize=9, frameon=True, fancybox=True,␣
↪shadow=False)
    ax.grid(True, alpha=0.5)
    ax.set_ylabel("Values", fontsize=10)

for idx in range(n_groups, len(axes)):
    fig.delaxes(axes[idx])

plt.suptitle("Time series by feature groups", fontsize=18, fontweight='bold',␣
↪y=0.98)
plt.xlabel("Time", fontsize=12)
plt.tight_layout(rect=[0, 0, 1, 0.97])

plt.show()
```

```
Dynamically determined start_id: 5540 (the first day with >= 95% data
completeness)
Filtered dataset shape: (3450, 98)
```

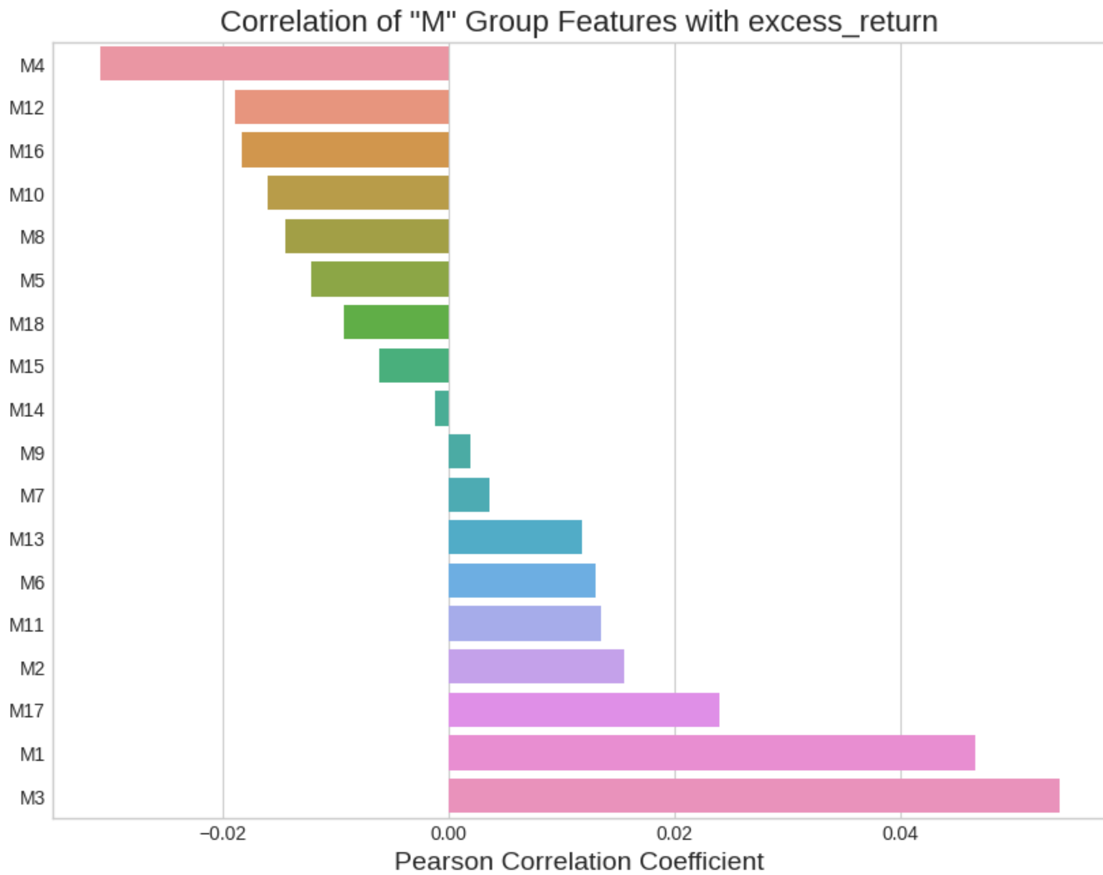
5.2 Correlation

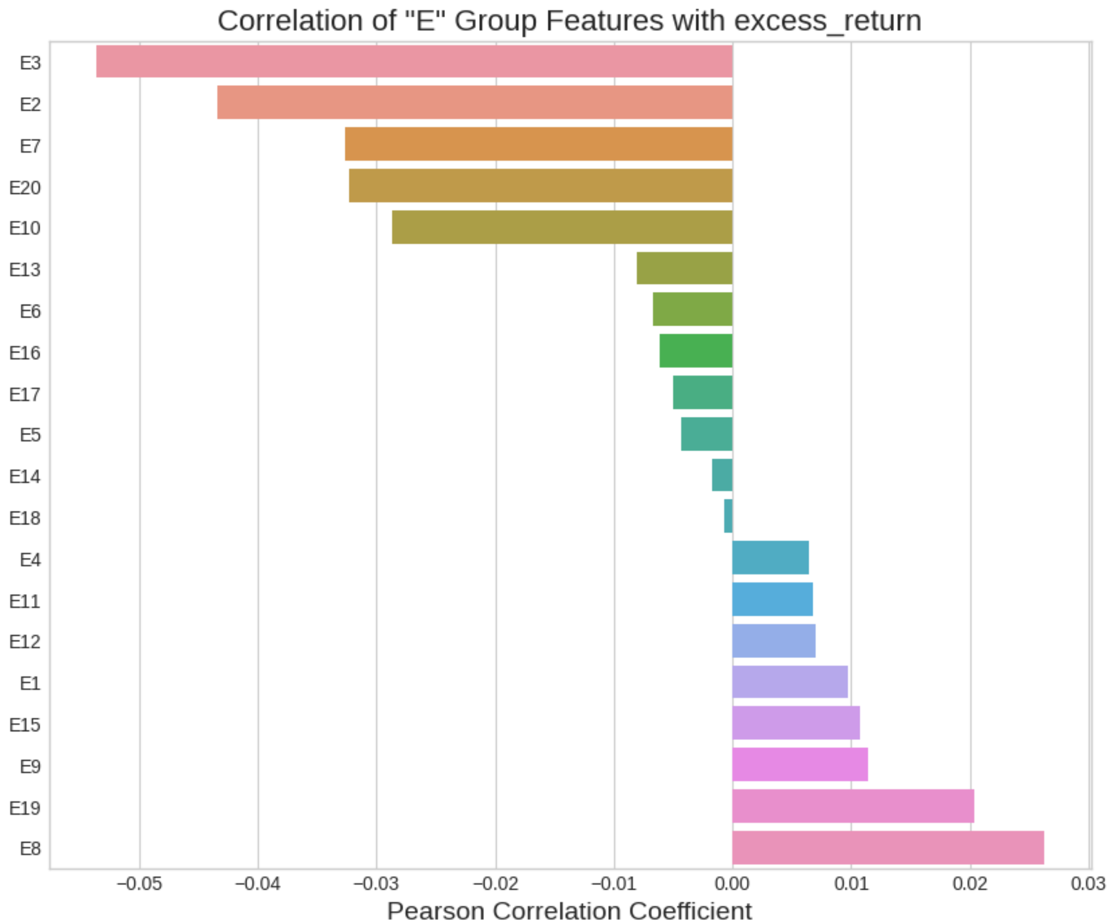
[8]:
```python
completeness_by_date = df.notnull().mean(axis=1)
try:
    start_id = (completeness_by_date >= 0.95).idxmax()
    print(f"Dynamically determined start_id: {start_id} (the first day with >=95% data completeness)")
except ValueError:
    start_id = df.index[int(len(df) * 0.5)]
    print(f"Warning: Could not find a 95% completeness point. Falling back to a default start_id: {start_id}")

df_filtered = df.loc[df.index >= start_id].copy()
print(f"Filtered dataset shape: {df_filtered.shape}")
```

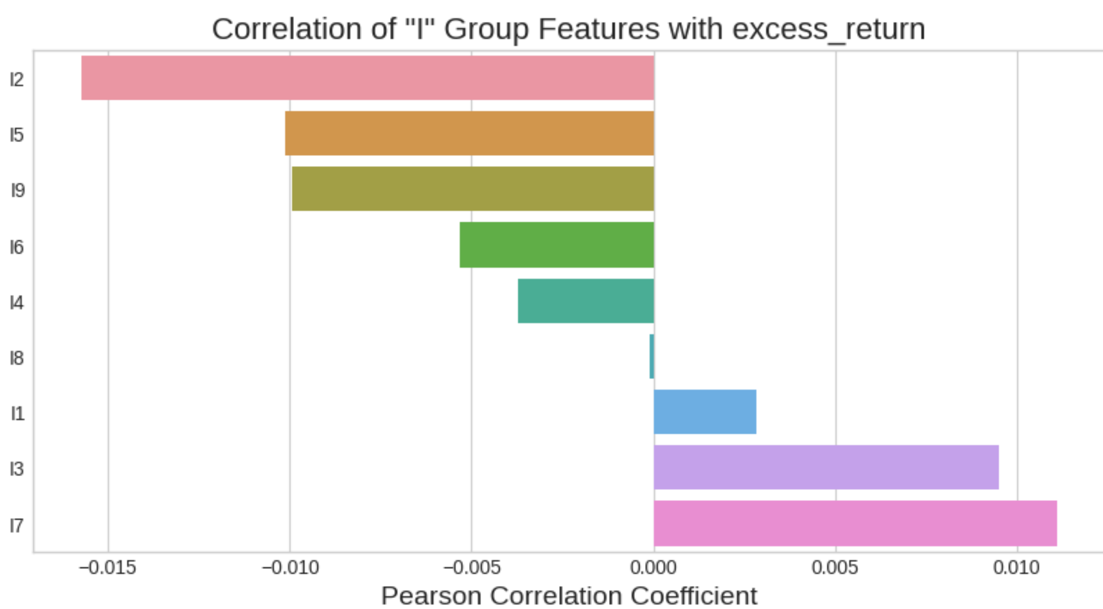
```
feature_cols = [col for col in df.columns if '*' not in col and col not in␣
↪['forward_returns', 'risk_free_rate', 'market_forward_excess_returns',␣
↪'excess_return']]

groups = {
    'M': [f for f in feature_cols if f.startswith('M')],
    'E': [f for f in feature_cols if f.startswith('E')],
    'I': [f for f in feature_cols if f.startswith('I')],
    'P': [f for f in feature_cols if f.startswith('P')],
    'V': [f for f in feature_cols if f.startswith('V')],
    'S': [f for f in feature_cols if f.startswith('S')],
    'MOM': [f for f in feature_cols if f.startswith('MOM')],
    'D': [f for f in feature_cols if f.startswith('D')]
}

if TARGET_NAME in df_filtered.columns:
    correlations = df_filtered[feature_cols + [TARGET_NAME]].
↪corr(method='pearson')[TARGET_NAME].drop(TARGET_NAME)

    print("\nAnalyzing feature correlations with the target variable␣
↪(excess_return):")

    for prefix, features in groups.items():
        if not features: continue

        group_corr_series = correlations.reindex(features).dropna()

        if group_corr_series.empty:
            print(f"No correlations to plot for group '{prefix}'.")
            continue

        plt.figure(figsize=(10, len(group_corr_series) * 0.3 + 2))
        group_corr_series = group_corr_series.sort_values()

        sns.barplot(x=group_corr_series.values, y=group_corr_series.index,␣
↪orient='h')
        plt.title(f'Correlation of "{prefix}" Group Features with {TARGET_NAME}')
        plt.xlabel('Pearson Correlation Coefficient')
        plt.show()
else:
    print(f"Target '{TARGET_NAME}' not found in df_filtered. Skipping␣
↪correlation plots.")
```

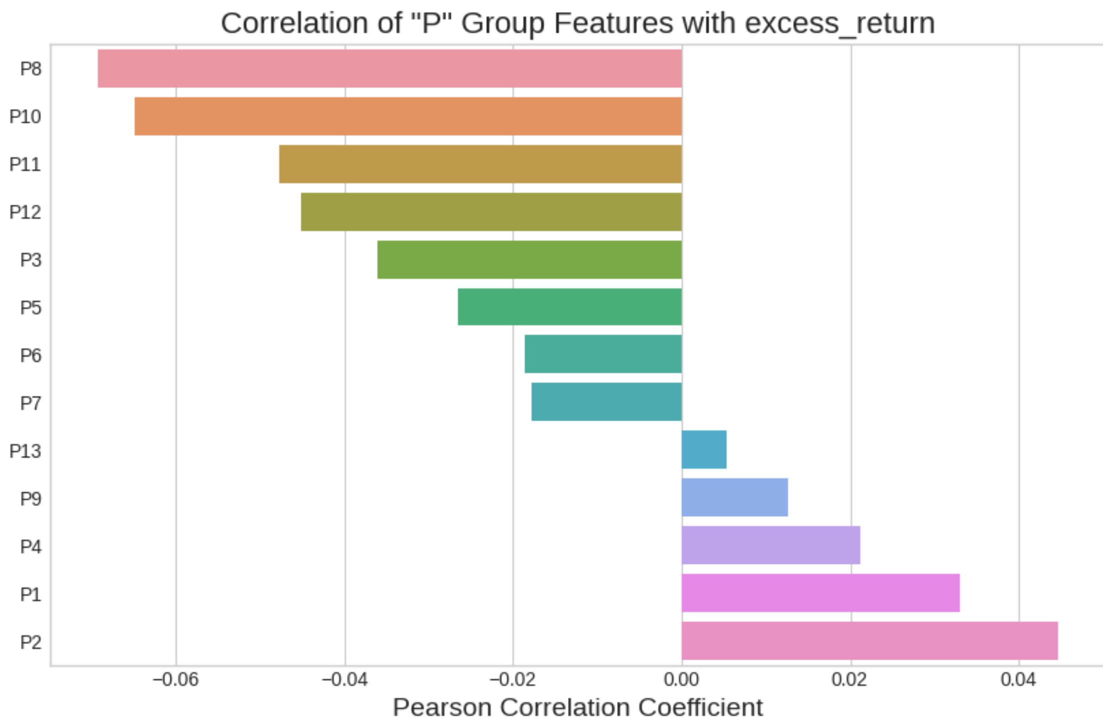
```
Dynamically determined start_id: 5540 (the first day with >= 95% data
completeness)
Filtered dataset shape: (3450, 98)
```

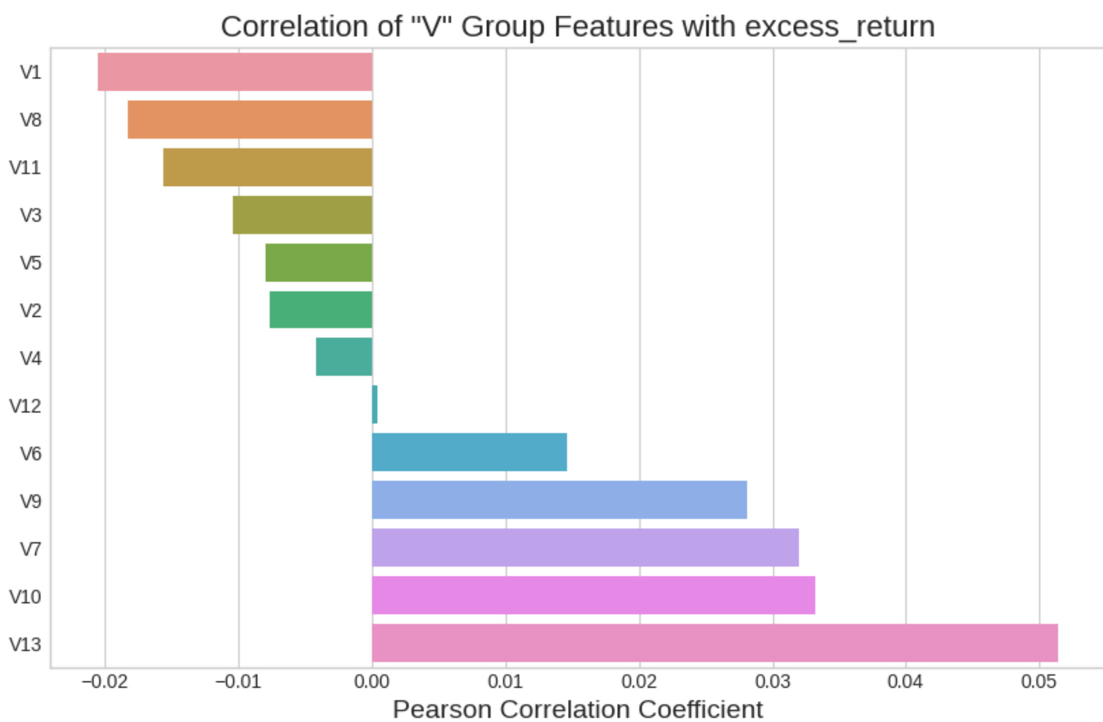
```
Analyzing feature correlations with the target variable (excess_return):
```

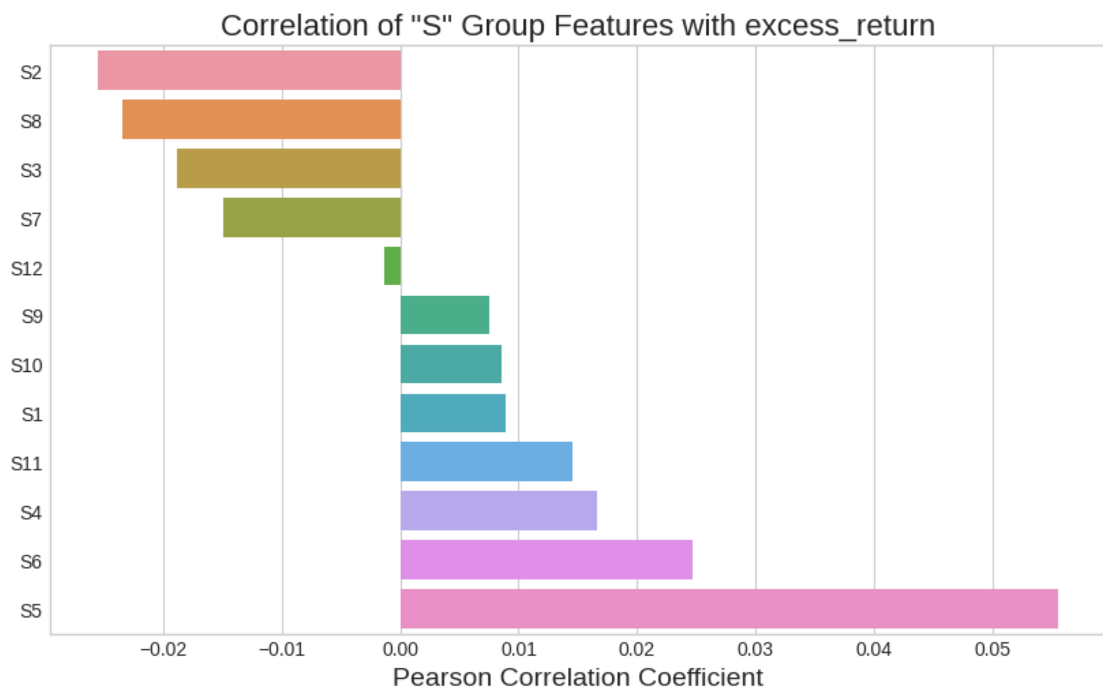


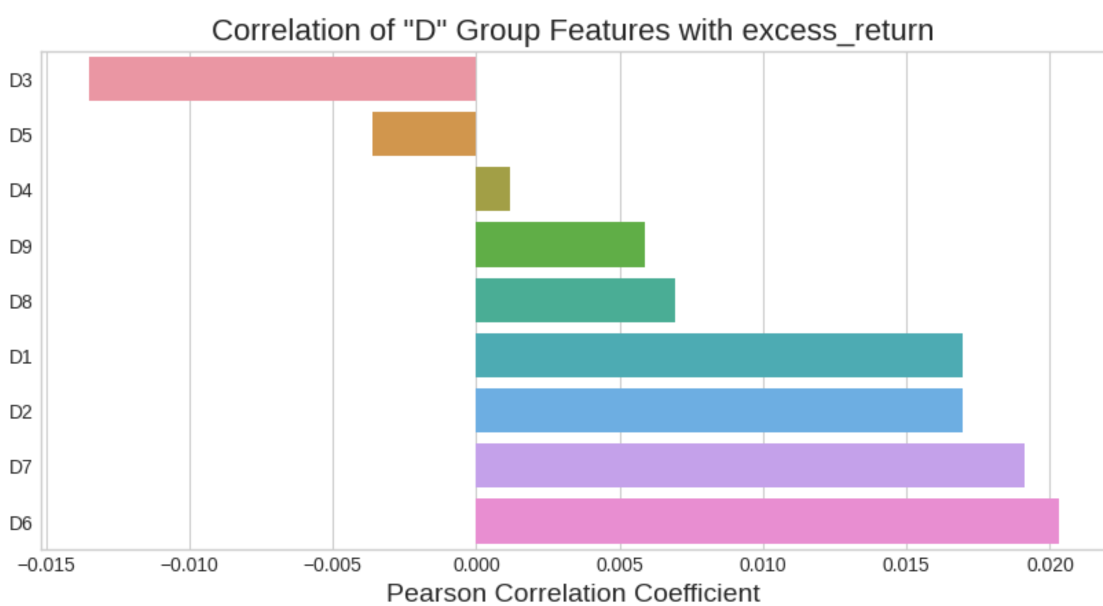

Correlation of "E" Group Features with excess_return
E3
E2
E7
E20
E10
E13
E6
E16
E17
E5
E14
E18
E4
E11
E12
E1
E15
E9
E19
E8
−0.05
−0.04
−0.03
−0.02
−0.01
0.00
0.01
0.02
0.03
Pearson Correlation Coefficient


Correlation of "I" Group Features with excess_return
I2
I5
I9
I6
I4
I8
I1
I3
I7
−0.015
−0.010
−0.005
0.000
0.005
0.010
Pearson Correlation Coefficient


Correlation of "P" Group Features with excess_return
P8
P10
P11
P12
P3
P5
P6
P7
P13
P9
P4
P1
P2
−0.06
−0.04
−0.02
0.00
0.02
0.04
Pearson Correlation Coefficient


Correlation of "V" Group Features with excess_return
V1
V8
V11
V3
V5
V2
V4
V12
V6
V9
V7
V10
V13
−0.02
−0.01
0.00
0.01
0.02
0.03
0.04
0.05
Pearson Correlation Coefficient

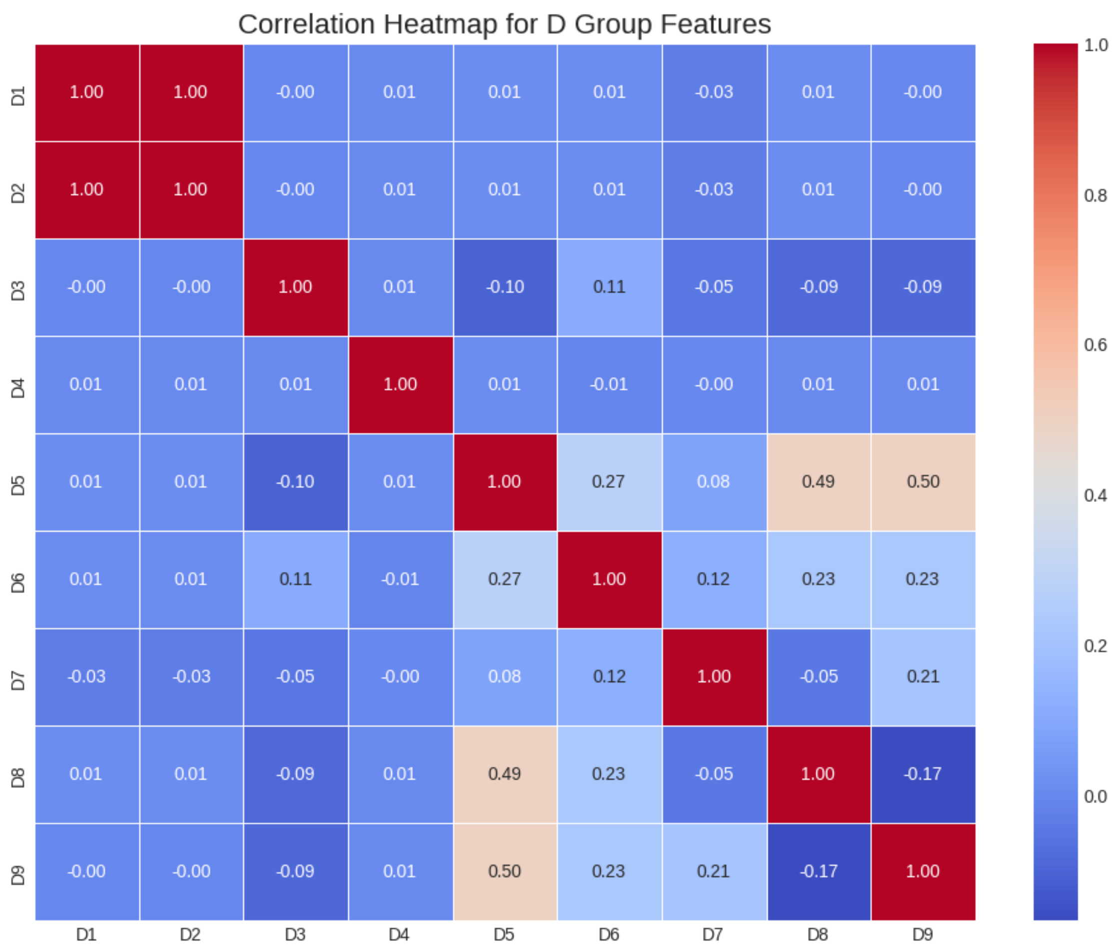

Correlation of "S" Group Features with excess_return
S2
S8
S3
S7
S12
S9
S10
S1
S11
S4
S6
S5
−0.02
−0.01
0.00
0.01
0.02
0.03
0.04
0.05
Pearson Correlation Coefficient


Correlation of "D" Group Features with excess_return
D3
D5
D4
D9
D8
D1
D2
D7
D6
−0.015
−0.010
−0.005
0.000
0.005
0.010
0.015
0.020
Pearson Correlation Coefficient

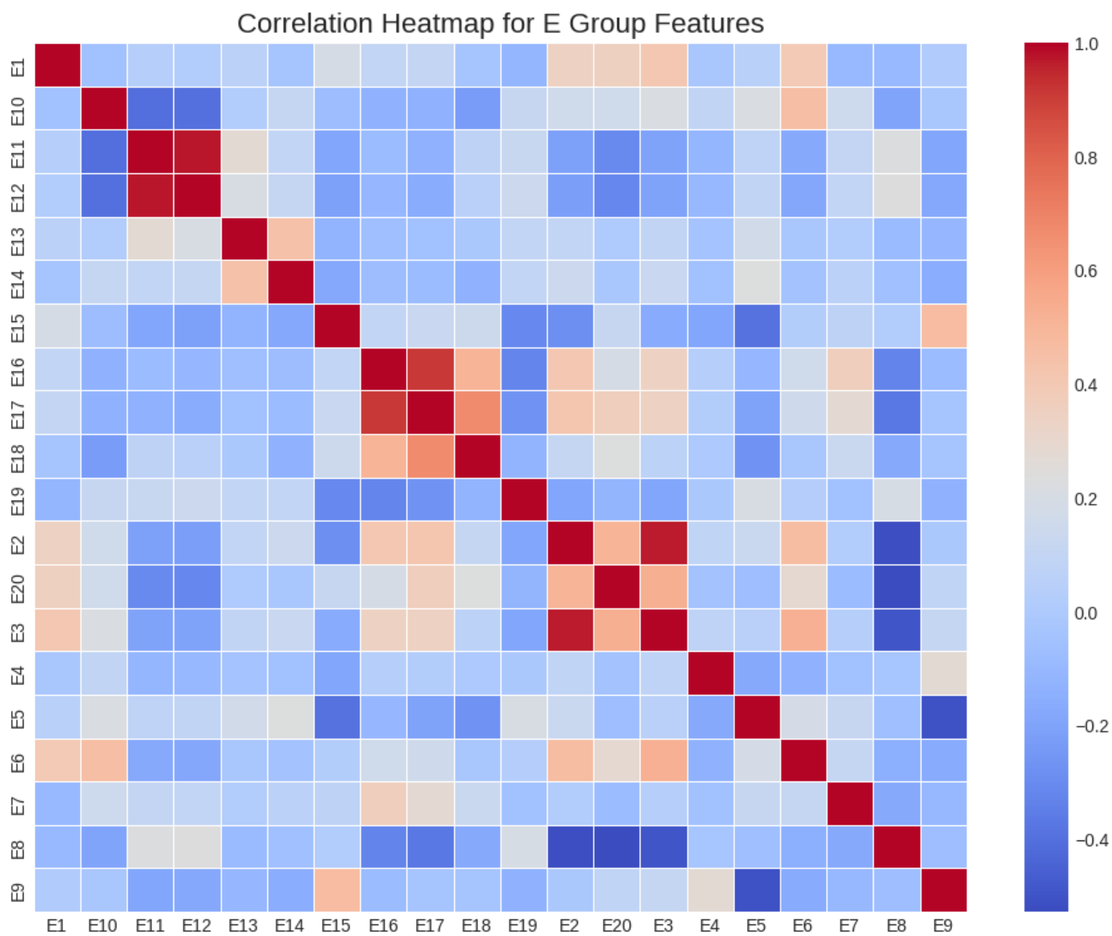
6 Correlation Heatmap

[9]:
```
df_imputed = df.fillna(method='ffill').fillna(method='bfill')

feature_categories = ['D', 'E', 'I', 'M', 'P', 'S', 'V']
feature_groups = {cat: [col for col in df_imputed.columns if col.
↪startswith(cat)] for cat in feature_categories}

for category, features in feature_groups.items():
    if len(features) < 2:
        print(f"\nGroup '{category}' has fewer than 2 features, skipping the␣
↪heatmap.")
        continue

    print(f"\nGenerating heatmap for group '{category}'...")

    corr_matrix = df_imputed[features].corr()

    show_annotations = len(features) < 15

    plt.figure(figsize=(12, 9))
    sns.heatmap(
        corr_matrix,
        annot=show_annotations,
        cmap='coolwarm',
        fmt='.2f',
        linewidths=.5
    )
    plt.title(f'Correlation Heatmap for {category} Group Features', fontsize=16)
    plt.show()
```

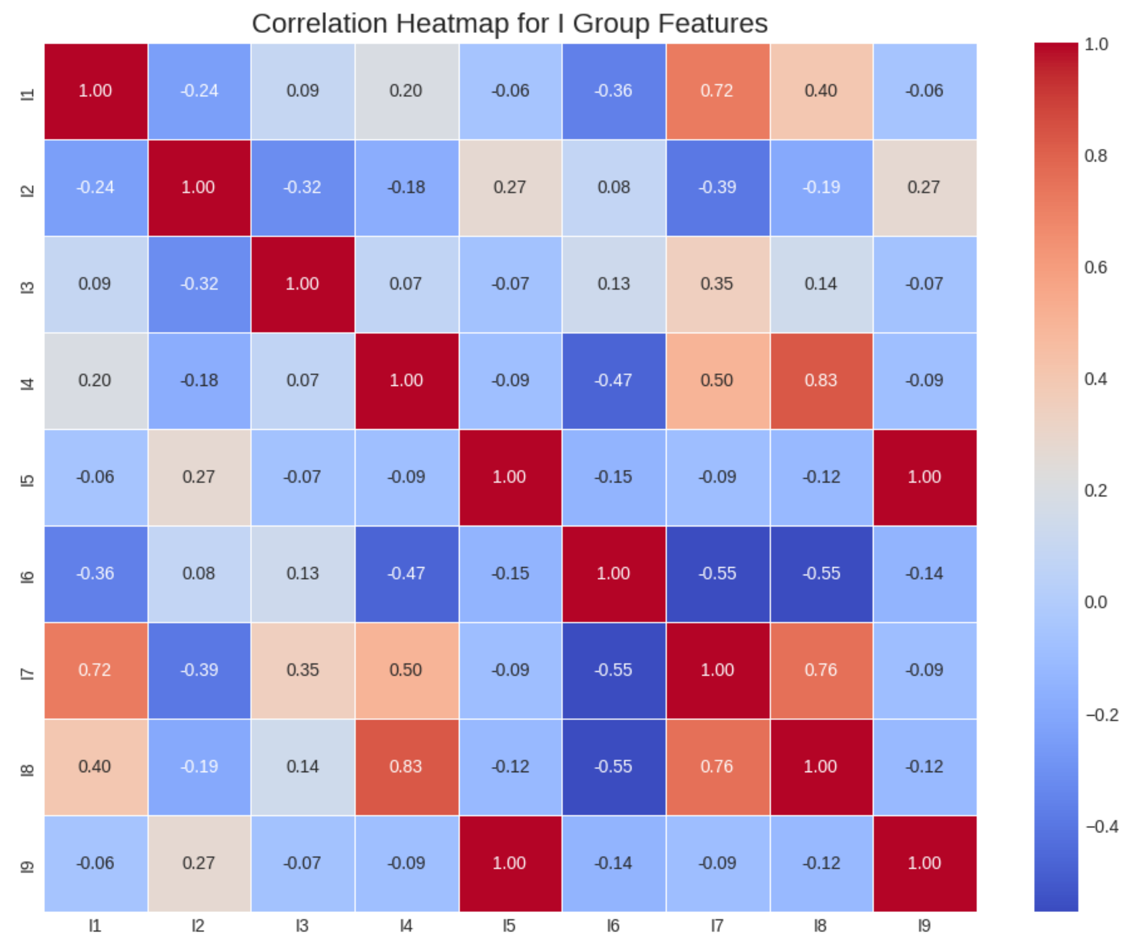
```
Generating heatmap for group 'D'...
```



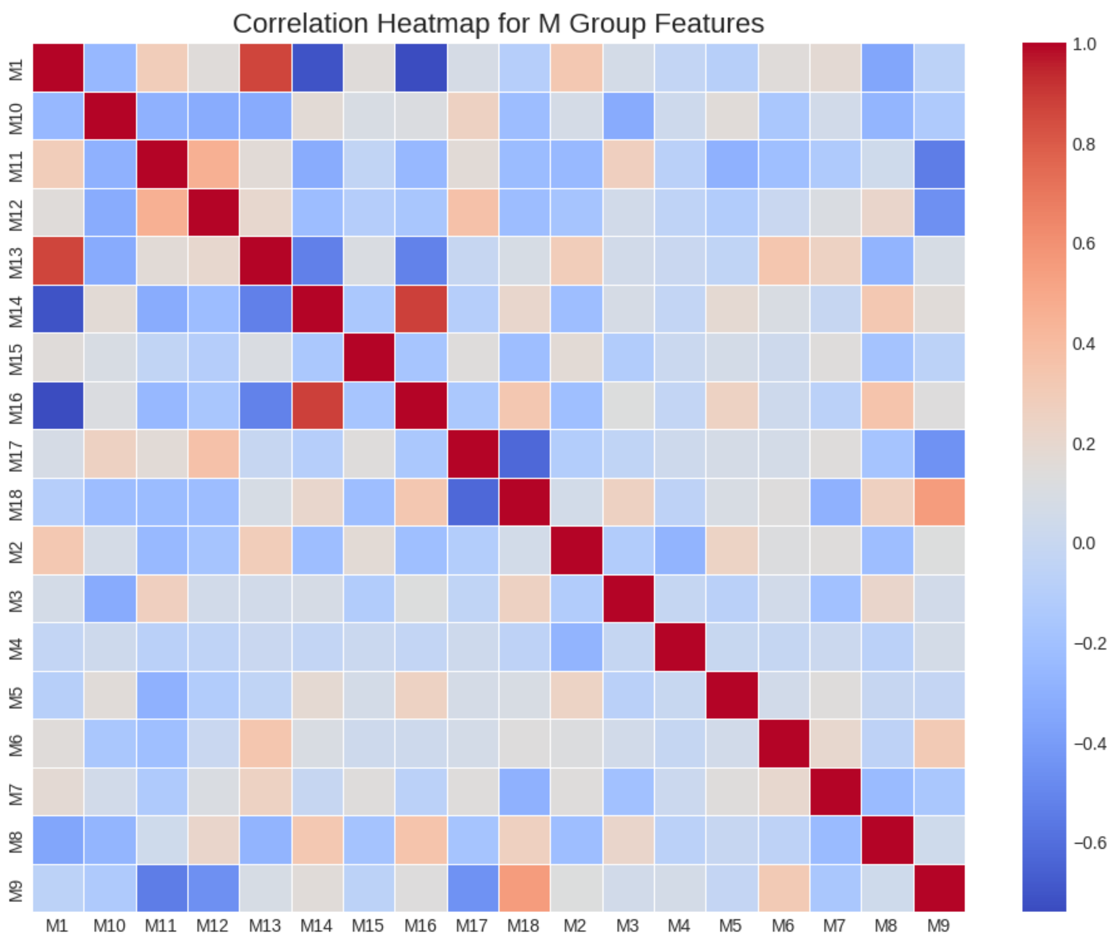

```
Generating heatmap for group 'E'...
```



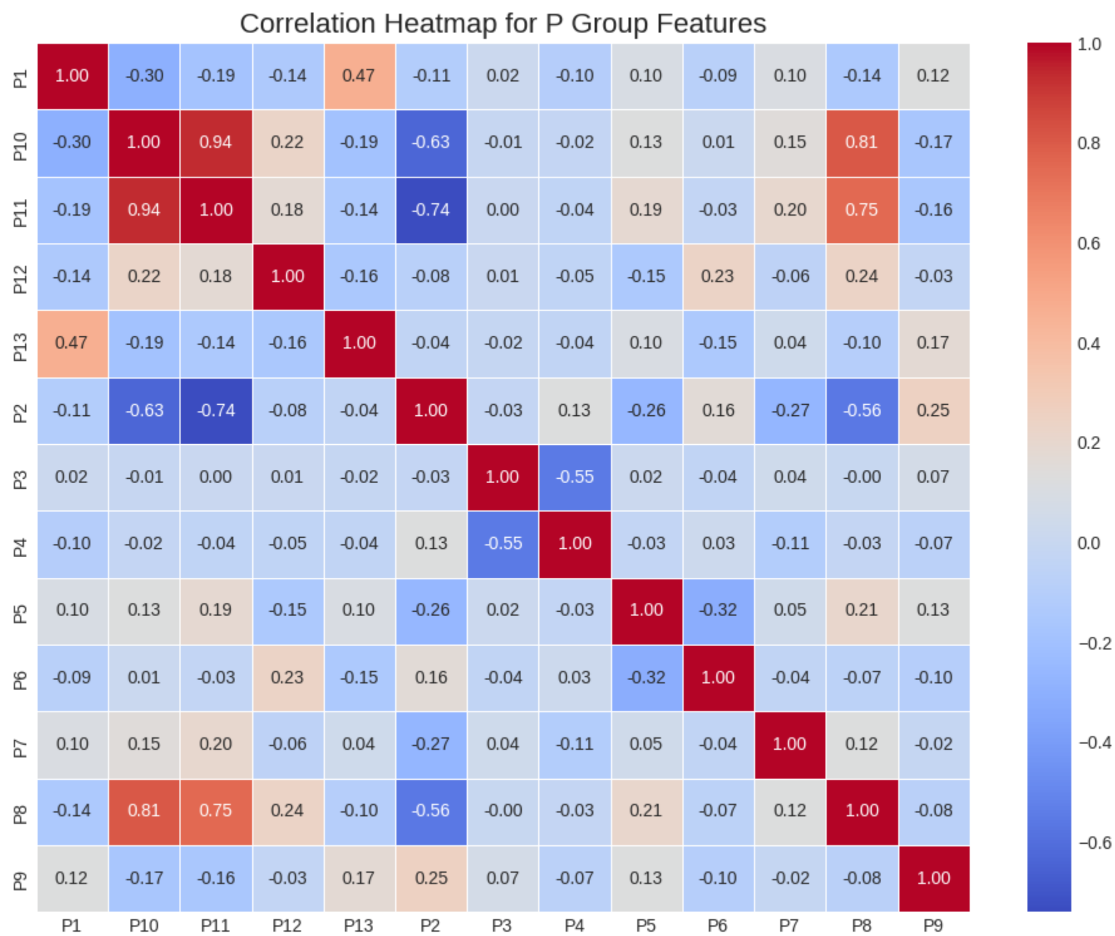

```
Generating heatmap for group 'I'...
```



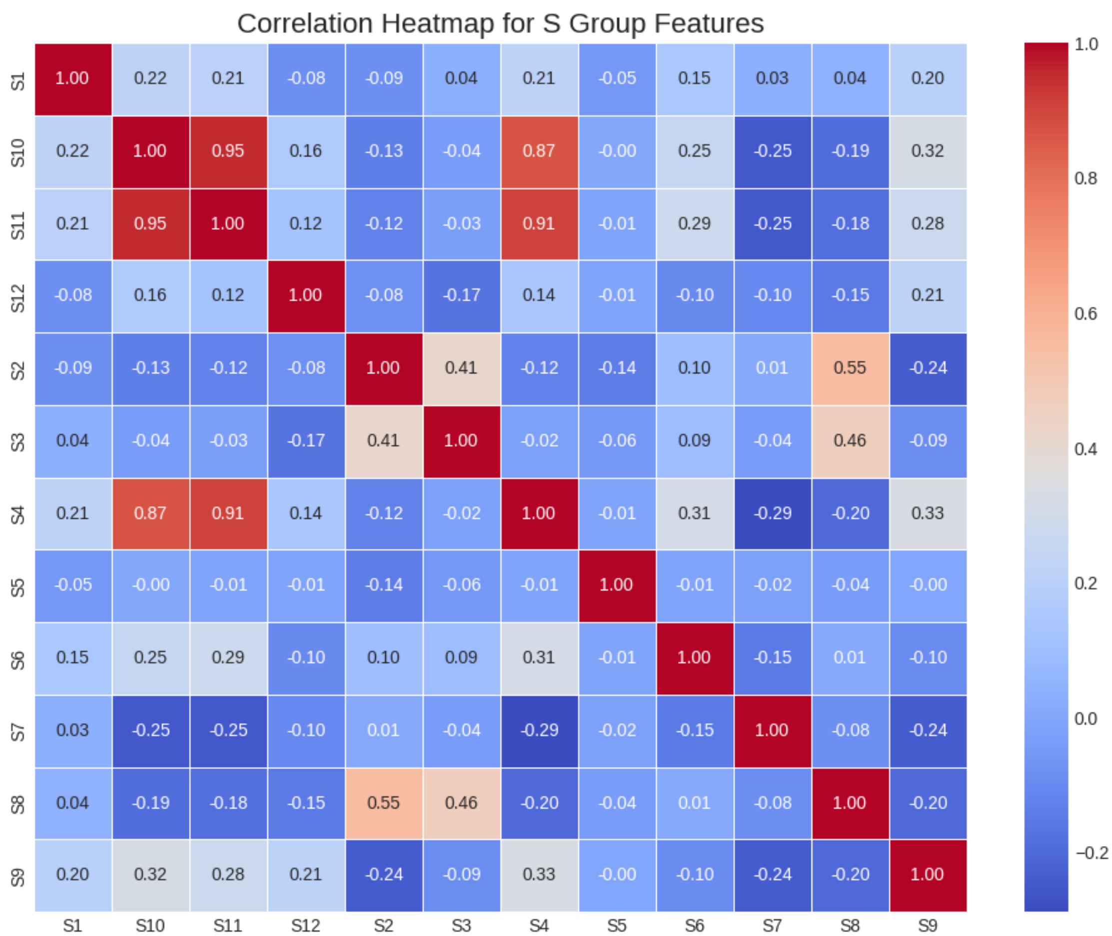

```
Generating heatmap for group 'M'...
```



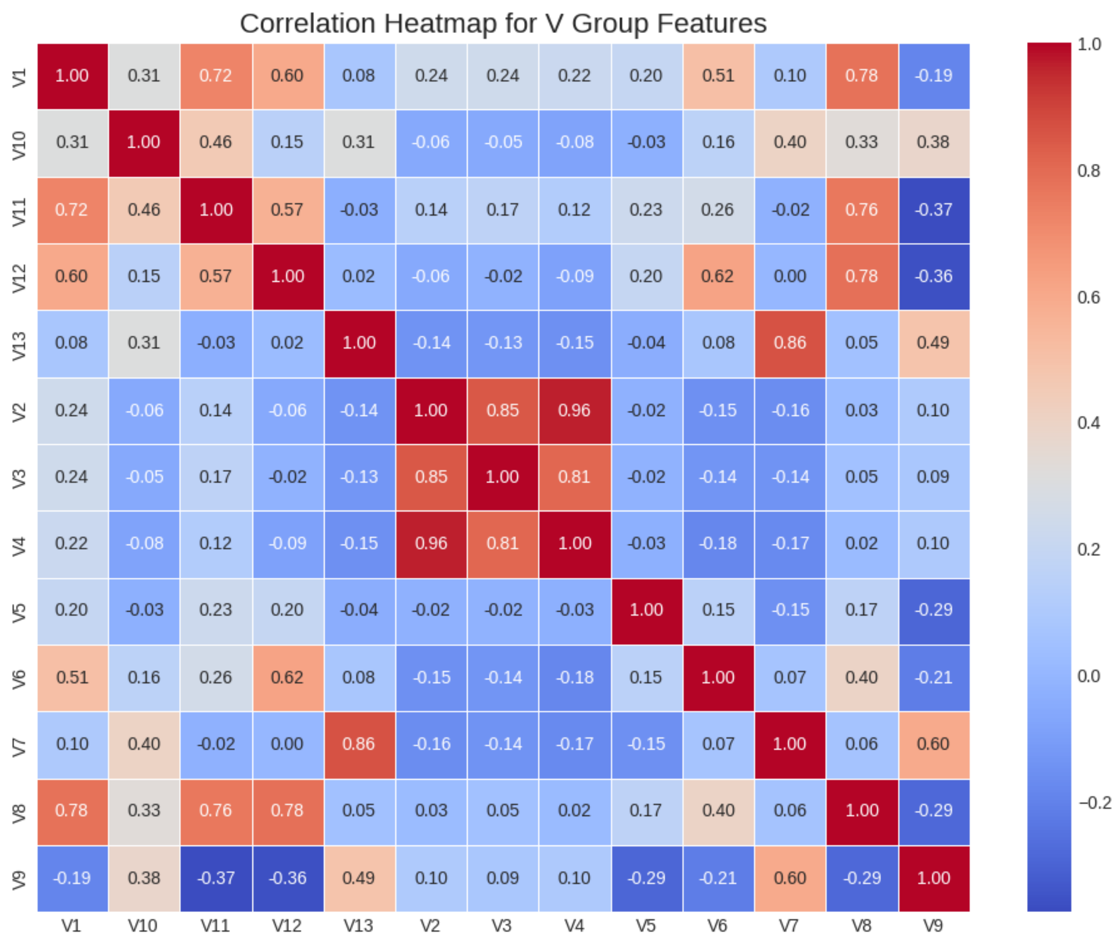

```
Generating heatmap for group 'P'...
```




```
Generating heatmap for group 'S'...
```




```
Generating heatmap for group 'V'...
```



7 Some Verdicts

[10]:
```
print(f"Dataset consist of {len(list(df))} columns: {list(df)}")
print()
print(f"Train df contains {df.shape[0]} lines and {df.shape[1]} columns")
print()
print(f"Top 5 signs by the number of passes:\n{df.isnull().mean().
↪sort_values(ascending=False).head()}")
print()
df['forward_returns'].plot(title='Visualization of target value')
print(f"Top 20 features by correlation: \n{df.
↪corrwith(df['market_forward_excess_returns']).abs().
↪sort_values(ascending=False).head(20)}")

forward_returns_data = df['forward_returns'].dropna()
stat, p_value = normaltest(forward_returns_data)
print(f"Normality test (D'Agostino): p-value = {p_value:.4f}")
```

```python
if p_value > 0.05:
    print("The data is normally distributed.")
else:
    print("The data is not normally distributed.")
```

```
Dataset consist of 98 columns: ['D1', 'D2', 'D3', 'D4', 'D5', 'D6', 'D7', 'D8',
'D9', 'E1', 'E10', 'E11', 'E12', 'E13', 'E14', 'E15', 'E16', 'E17', 'E18',
'E19', 'E2', 'E20', 'E3', 'E4', 'E5', 'E6', 'E7', 'E8', 'E9', 'I1', 'I2', 'I3',
'I4', 'I5', 'I6', 'I7', 'I8', 'I9', 'M1', 'M10', 'M11', 'M12', 'M13', 'M14',
'M15', 'M16', 'M17', 'M18', 'M2', 'M3', 'M4', 'M5', 'M6', 'M7', 'M8', 'M9',
'P1', 'P10', 'P11', 'P12', 'P13', 'P2', 'P3', 'P4', 'P5', 'P6', 'P7', 'P8',
'P9', 'S1', 'S10', 'S11', 'S12', 'S2', 'S3', 'S4', 'S5', 'S6', 'S7', 'S8', 'S9',
'V1', 'V10', 'V11', 'V12', 'V13', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8',
'V9', 'forward_returns', 'risk_free_rate', 'market_forward_excess_returns',
'excess_return']

Train df contains 8990 lines and 98 columns

Top 5 signs by the number of passes:
E7     0.7752
V10    0.6729
S3     0.6377
M1     0.6170
M14    0.6162
dtype: float64

Top 20 features by correlation:
market_forward_excess_returns    1.0000
excess_return                    1.0000
forward_returns                  1.0000
M4                               0.0665
V13                              0.0624
M1                               0.0463
S5                               0.0401
S2                               0.0377
D2                               0.0342
D1                               0.0342
M2                               0.0333
V10                              0.0327
E7                               0.0325
E11                              0.0320
V7                               0.0315
E12                              0.0308
P8                               0.0297
S12                              0.0261
I2                               0.0255
D8                               0.0247
dtype: float64
```

```
Normality test (D'Agostino): p-value = 0.0000
The data is not normally distributed.
```