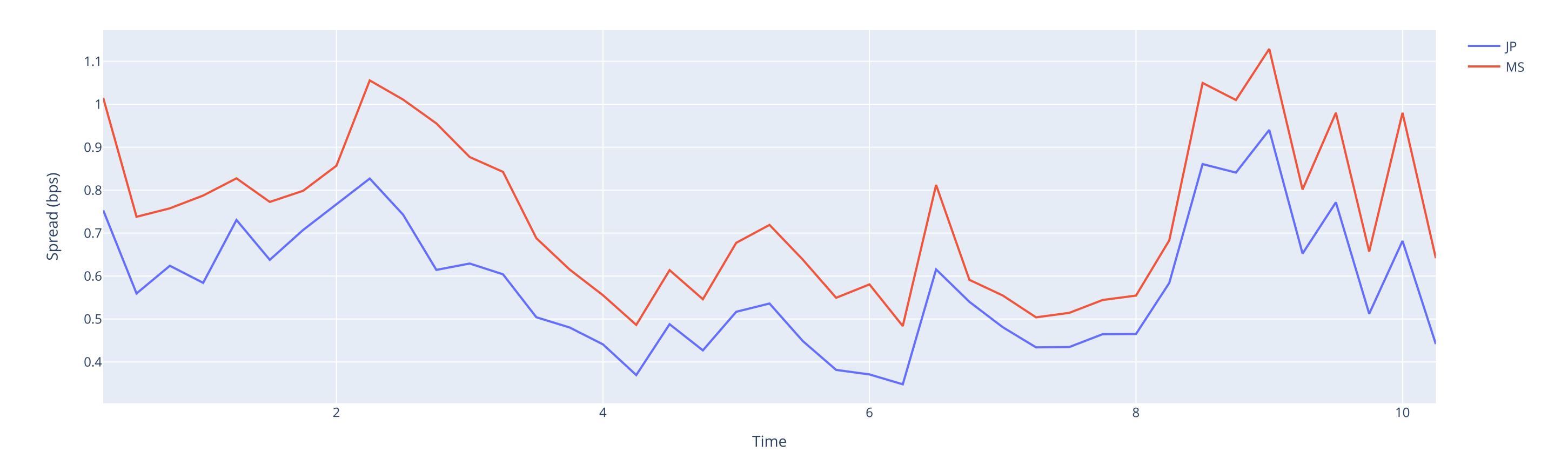
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```
Final BCVA.ipynb - Colaboratory
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.graph_objects as go
from google.colab import drive
drive.mount('/content/drive')
     Mounted at /content/drive
# Loading the CDS spread data for JP Morgan and Morgan Stanley from a CSV file
data = pd.read_csv("/content/drive/MyDrive/Combined_CDS_Spread_New.csv")
#JP is ourself
#MS is counterparty
print(data.head())
         Date JPM_Spread MS_Spread
     0 14-Jan
                   0.7532
                             1.0148
     1 14-Feb
                   0.6191
                             0.8766
     2 14-Mar
                   0.5696
                             0.8717
                             0.7380
     3 14-Apr
                   0.5595
     4 14-May
                   0.5613
                             0.7224
# Renaming columns for clarity
data.rename(columns={'JPM_Spread':'JP', 'MS_Spread':'MS'},inplace=True)
print(data.head())
                   JP
                          MS
         Date
     0 14-Jan 0.7532 1.0148
     1 14-Feb 0.6191 0.8766
     2 14-Mar 0.5696 0.8717
     3 14-Apr 0.5595 0.7380
     4 14-May 0.5613 0.7224
# Downsampling the data for analysis -Quater Wise
data = data.iloc[::3, :]
print(data.head())
                    JP
                           MS
          Date
     0 14-Jan 0.7532 1.0148
         14-Apr 0.5595 0.7380
        14-Jul 0.6240 0.7577
        14-Oct 0.5842 0.7875
     12 15-Jan 0.7306 0.8275
# Calculating hazard rates
data['JP_lambda']=data['JP']/(1-0.45) #0.45 is our RR
# Calculating hazard rates
data['MS_lambda']=data['MS']/(1-0.60) #0.60 is counterparty RR
print(data.head())
                    JP
                           MS JP_lambda MS_lambda
          Date
        14-Jan 0.7532 1.0148 1.369455
                                          2.53700
         14-Apr 0.5595 0.7380 1.017273
                                           1.84500
        14-Jul 0.6240 0.7577 1.134545
                                           1.89425
         14-Oct 0.5842 0.7875 1.062182
                                           1.96875
     12 15-Jan 0.7306 0.8275 1.328364
                                           2.06875
#Just to Make 0.25 , 0.5 -Time Steps
data['time']= ((data.index /3)+ 1 ) * 0.25
print(data.head())
                           MS JP_lambda MS_lambda time
          Date
        14-Jan 0.7532 1.0148 1.369455
                                           2.53700 0.25
        14-Apr 0.5595 0.7380 1.017273
                                         1.84500 0.50
     6 14-Jul 0.6240 0.7577 1.134545
                                         1.89425 0.75
     9 14-Oct 0.5842 0.7875 1.062182 1.96875 1.00
     12 15-Jan 0.7306 0.8275 1.328364 2.06875 1.25
# CDS Spread Visualization
fig = go.Figure()
# Add traces for 'JP' and 'MS' using the 'time' column as x-axis
fig.add_trace(go.Scatter(x=data['time'], y=data['JP'], mode='lines', name='JP'))
fig.add_trace(go.Scatter(x=data['time'], y=data['MS'], mode='lines', name='MS'))
fig.update_layout(
   title='CDS Spreads over Time',
   xaxis_title='Time',
   yaxis_title='Spread (bps)'
fig.show()
```

 $https://colab.research.google.com/drive/1QPgoS_wrAdnwwmBxfp9nxBxi_ZqPBxBf\#scrollTo=YPCxy_5XTTM3\&printMode=true$

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CDS Spreads over Time



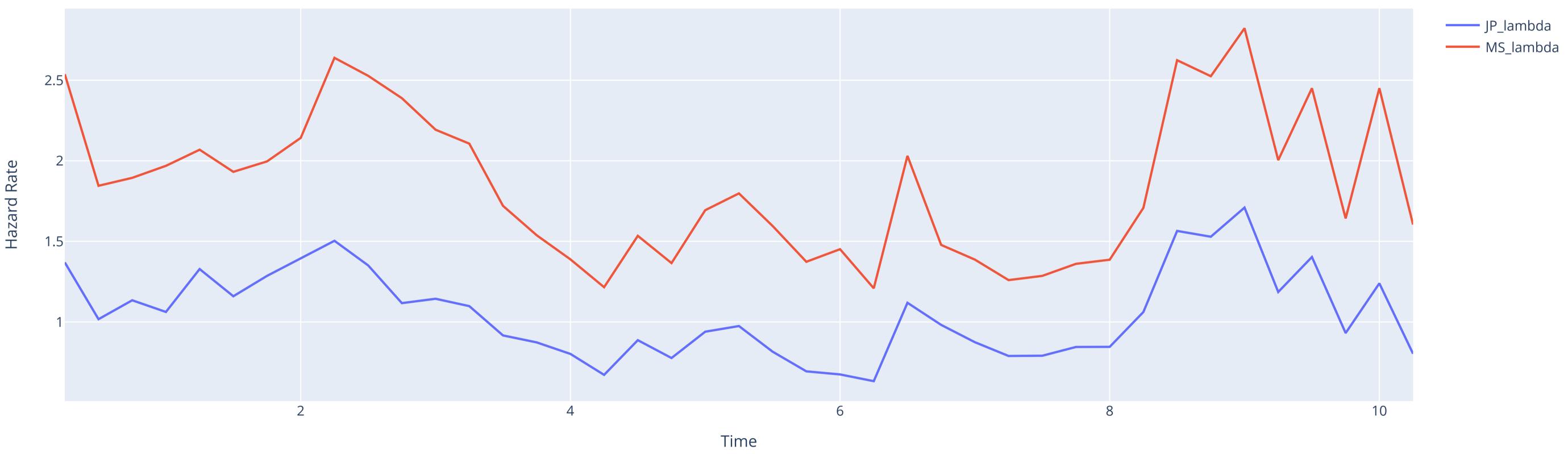
```
#Hazard Rate Plot
fig = go.Figure()

fig.add_trace(go.Scatter(x=data['time'], y=data[']P_lambda'], mode='lines', name='JP_lambda'))
fig.add_trace(go.Scatter(x=data['time'], y=data['MS_lambda'], mode='lines', name='MS_lambda'))

fig.update_layout(
   title='Hazard Rates over Time',
   xaxis_title='Time',
   yaxis_title='Hazard Rate'
)

fig.show()
```

Hazard Rates over Time



```
#Marginal PD Calculation
#data['Difference'] = data['Value'] - data['Value'].shift(-1) e^lambda1*time1 - e^lambda2*time2 (0.25 and 0.5)
#shift brings the next value
data['JP_M_PD']=np.exp(-(data['JP_lambda']*data['time'])) - np.exp(-(data['JP_lambda'].shift(-1)*data['time'].shift(-1)))
data['MS_M_PD']=np.exp(-(data['MS_lambda']*data['time'])) - np.exp(-(data['MS_lambda'].shift(-1)*data['time'].shift(-1)))
print(data.head())
                           MS JP_lambda MS_lambda time JP_M_PD MS_M_PD \
          Date
       14-Jan 0.7532 1.0148 1.369455
                                          2.53700 0.25 0.108775 0.132809
        14-Apr 0.5595 0.7380
                              1.017273
                                         1.84500 0.50 0.174288 0.155976
        14-Jul 0.6240 0.7577 1.134545
                                          1.89425 0.75 0.081326 0.101917
        14-Oct 0.5842 0.7875
                                          1.96875 1.00 0.155648 0.064306
                              1.062182
    12 15-Jan 0.7306 0.8275 1.328364
                                          2.06875 1.25 0.014436 0.020151
        JP_CumPD MS_CumPD
       0.108775 0.132809
        0.283063 0.288785
        0.364389 0.390702
        0.520037 0.455008
    12 0.534474 0.475158
# Calculating cumulative default probabilities
data['JP_CumPD']=data['JP_M_PD'].cumsum()
# Calculating cumulative default probabilities
data['MS_CumPD']=data['MS_M_PD'].cumsum()
print(data.head())
print(data.tail())
          Date
                           MS JP_lambda MS_lambda time JP_M_PD
                                                                  MS_M_PD \
        14-Jan 0.7532 1.0148
                               1.369455
                                          2.53700 0.25 0.108775 0.132809
        14-Apr 0.5595 0.7380
                               1.017273
                                          1.84500 0.50 0.174288 0.155976
        14-Jul 0.6240 0.7577
                               1.134545
                                          1.89425 0.75 0.081326 0.101917
        14-Oct 0.5842 0.7875
                                          1.96875 1.00 0.155648 0.064306
                               1.062182
                                          2.06875 1.25 0.014436 0.020151
    12 15-Jan 0.7306 0.8275
                               1.328364
        JP_CumPD MS_CumPD
        0.108775 0.132809
        0.283063 0.288785
        0.364389 0.390702
```

108 23 - Jan 0.6523 0.8015 1.186000 2.00375 9.25 0.000016

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MS JP_lambda MS_lambda time

JP_M_PD \

0.520037 0.455008

JP

12 0.534474 0.475158

Date

```
114 23-Jul 0.5122 0.6569
                                                      9.75 0.000110
                                 0.931273
                                             1.64225
     117 23-Oct 0.6818 0.9801
                                             2.45025 10.00 -0.000262
                                 1.239636
     120 24-Jan 0.4416 0.6417
                                 0.802909
                                             1.60425 10.25
                                                                 NaN
              MS_M_PD JP_CumPD MS_CumPD
     108 8.844758e-09 0.710088 0.530333
     111 -1.111220e-07 0.709976 0.530333
     114 1.111769e-07 0.710086 0.530333
     117 -7.219617e-08 0.709823 0.530333
     120
                  NaN
                            NaN
                                     NaN
#Plot Cumulative Default Probabilities:
fig = go.Figure()
fig.add_trace(go.Scatter(x=data['time'], y=data['JP_CumPD'], mode='lines', name='JP_CumPD'))
fig.add_trace(go.Scatter(x=data['time'], y=data['MS_CumPD'], mode='lines', name='MS_CumPD'))
fig.update_layout(
   title='Cumulative Default Probabilities',
   xaxis_title='Time',
   yaxis_title='Cumulative Probability'
fig.show()
```

Cumulative Default Probabilities

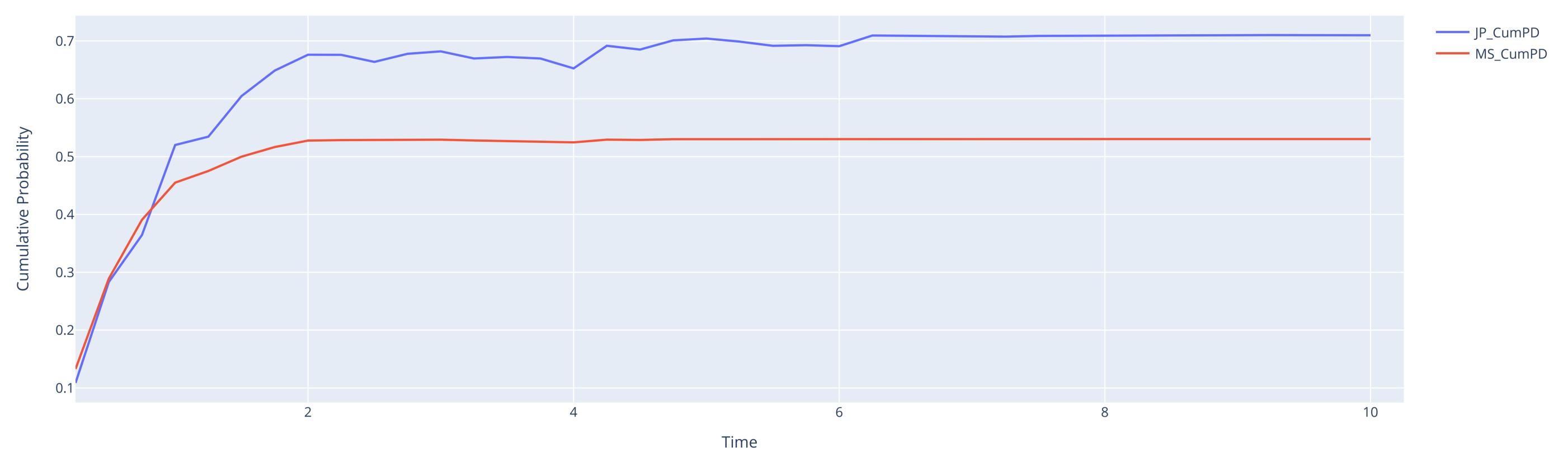
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111 23-Apr 0.7717 0.9801

1.403091

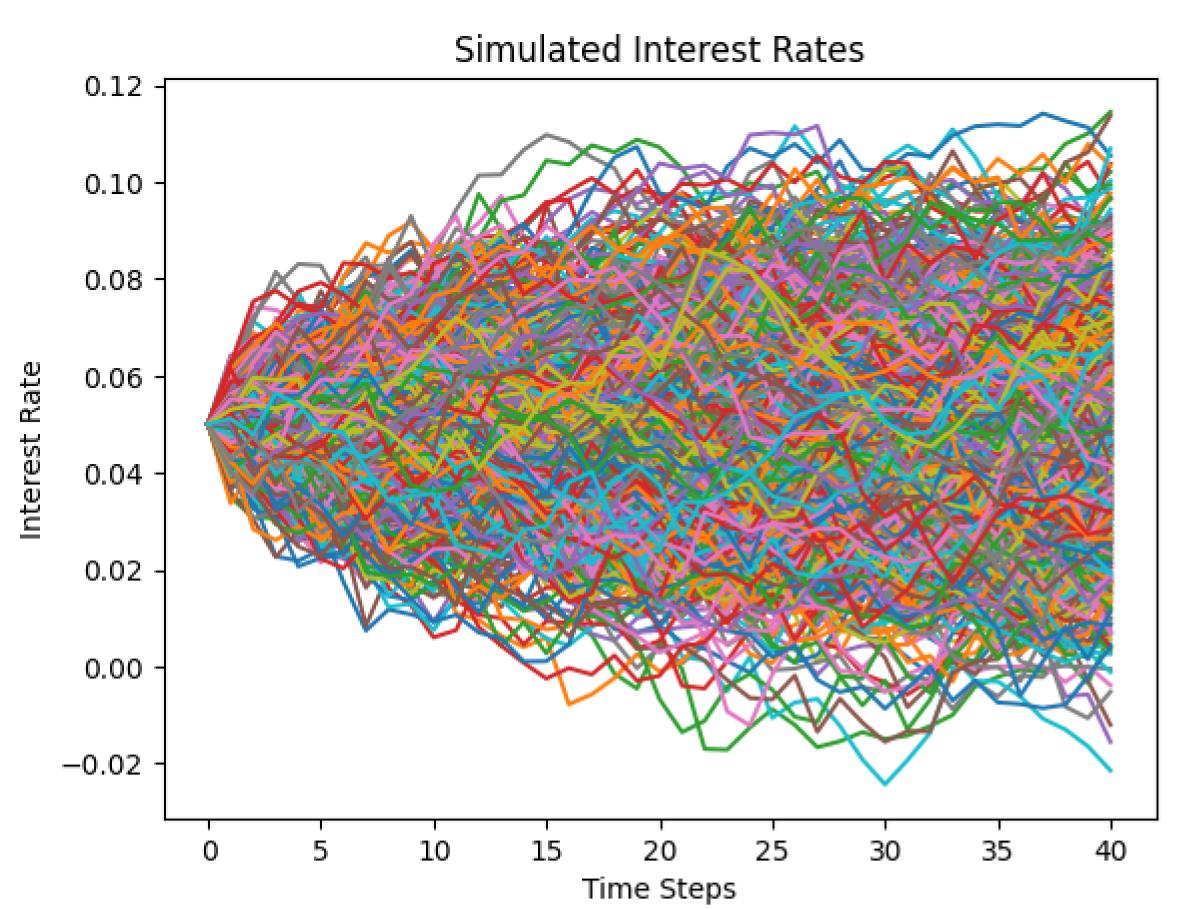
2.45025

9.50 -0.000112



```
Our_CumPD=data['JP_CumPD'].iloc[-2]
CP_CumPD=data['MS_CumPD'].iloc[-2]
print(data['MS_CumPD'].iloc[-2]) #Counterparty's cumulative PD - For cVa
print(data['JP_CumPD'].iloc[-2]) #Our cumulative PD - For dVa
     0.5303330167964186
     0.70982335843477
#Simualting Values of IRS with Vaiscek Model
# Defining a function to simulate interest rates using the Vasicek model
def simulate_vasicek(a,b,sigma,r0,T,dt,n_paths):
  n_steps=int(T/dt)
  rates=np.zeros((n_steps+1,n_paths))
  rates[0]=r0
  for step in range(1,n_steps+1):
    dw=np.random.normal(0,np.sqrt(dt), n_paths)
    rates[step]=rates[step-1] + a * (b-rates[step-1]) * dt +sigma *dw
  return rates
# Define model parameters
a = 0.1 # Mean Reversion Rate
b = 0.05 # Long-Term Mean or Equilibrium Level
sigma = 0.01 # Volatility of Interest Rates
r0 = 0.05 # Initial Interest Rate
T = 10 # Time to Maturity
dt = 0.25 \# Time Step
n_paths = 1000 # Number of Paths
# Simulate interest rates using the Vasicek model
simulated_rates = simulate_vasicek(a, b, sigma, r0, T, dt, n_paths)
# Compute discount factors using exponential functions
discount_factors = np.exp(-simulated_rates * np.arange(0, simulated_rates.shape[0])[:, None] * dt)
# Initialize simulation data dictionary
simulation_data = {'DF': []}
# Calculate average discount factors
simulation_data['DF'] = discount_factors.mean(axis=1)
```

#Vasicek model simulation plt.plot(simulated_rates) plt.title('Simulated Interest Rates') plt.xlabel('Time Steps') plt.ylabel('Interest Rate') plt.ylabel('Interest Rate')



results_df=pd.DataFrame(simulation_data,index=np.arange(0,T+dt,dt))

```
0.00 1.000000
0.25 0.987635
0.50 0.975333
0.75 0.963382
1.00 0.951484
```

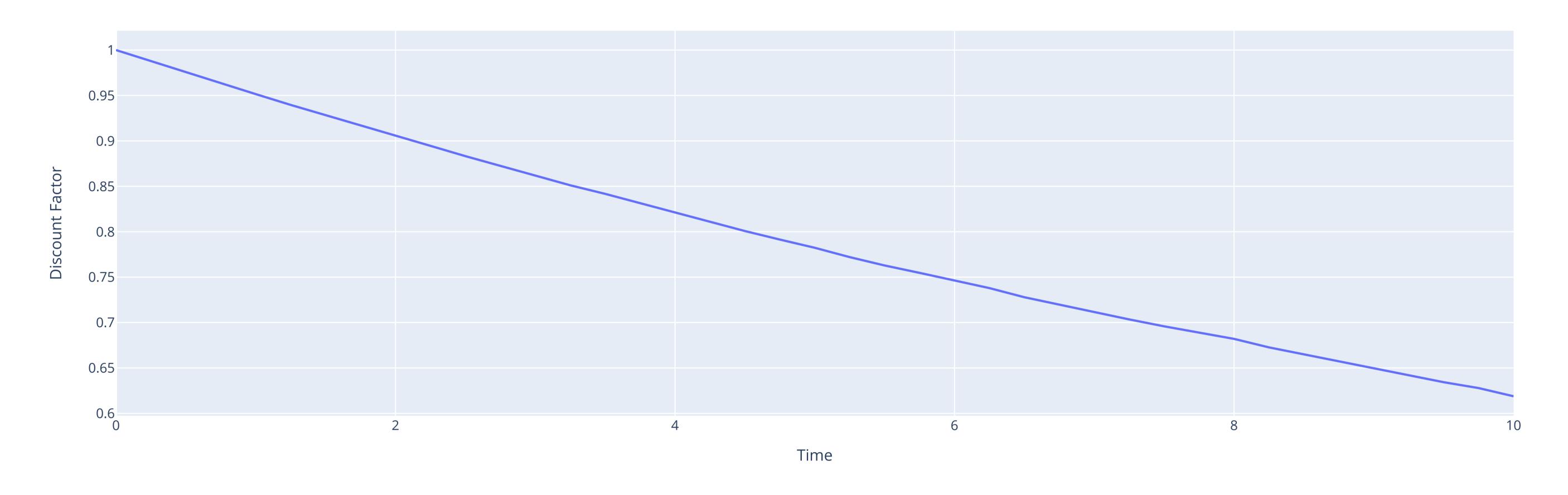
```
fig = go.Figure()

# Iterate through the columns of 'results_df' to add traces
for column in results_df.columns:
    fig.add_trace(go.Scatter(x=results_df.index, y=results_df[column], mode='lines', name=column))

# Update the layout with labels and title
fig.update_layout(
    title='Discount Factor vs. Time',
    xaxis_title='Time',
    yaxis_title='Discount Factor'
)

# Show the plot
fig.show()
```

Discount Factor vs. Time



```
# Define contract parameters
notional = 1
fixed_rate = 0.055
payment_frequency = 1
```

```
# Initialize present value array
mtm_values = np.zeros_like(simulated_rates)
```

```
# Calculate MtM values
for step in range(1, mtm_values.shape[0]):
    time_to_maturity = T - step * dt

# Calculate fixed leg present value
    fixed_leg_pv = notional * fixed_rate * np.exp(-simulated_rates[step] * time_to_maturity)

# Calculate floating leg present value
    floating_leg_pv = notional * simulated_rates[step] * np.exp(-simulated_rates[step] * time_to_maturity)

# Calculate MtM value for this step
    mtm_values[step] = fixed_leg_pv - floating_leg_pv
```

```
# Calculate expected exposure (EE)
EE = mtm_values

# Calculate average MtM across paths
average_MtM = mtm_values.mean(axis=1)
```

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```
# Create a dictionary for simulation results
data1 = {'Time': np.arange(0, T + dt, dt),
         'Average MtM': average_MtM,
         'DF': simulation_data['DF']
# Add individual run paths to the data dictionary
for path in range(n_paths):
    data1[f'Run {path + 1}'] = mtm_values[:, path]
# Create a DataFrame for the simulation results
results_df1 = pd.DataFrame(data1)
```

```
print(results_df1.head())
```

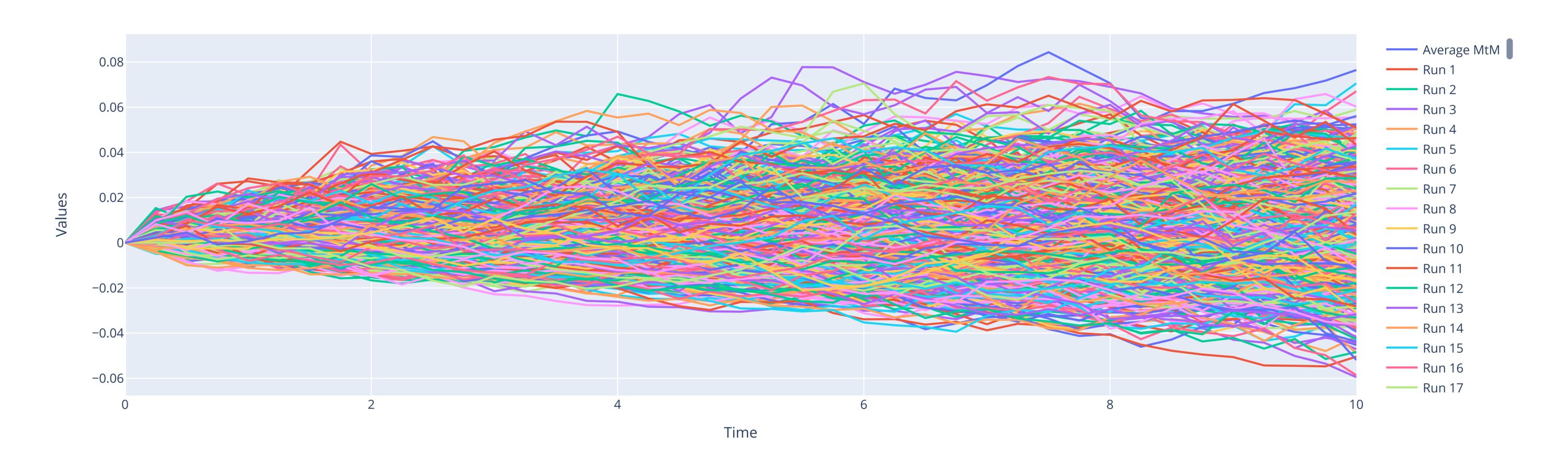
```
Time Average MtM
                                      Run 2
                              Run 1
          0.00
1 0.25
          0.003368 0.987635 0.003201 0.004301 0.000412 0.002318
2 0.50
          0.003430 0.975333 0.001627 -0.001049 -0.002436 -0.003269
3 0.75
          0.003738 0.963382 0.003414 0.000097 -0.001427 -0.001204
4 1.00
          0.003873 0.951484 0.000003 -0.000184 0.002382 0.001688
                      Run 7 ... Run 991 Run 992 Run 993 Run 994 \
     Run 5
             Run 6
0 0.000000 0.000000 0.000000
                            ... 0.000000 0.000000
                                                 0.000000 0.000000
1 0.010854 0.006010 -0.000500
                            ... 0.003643 0.008477
                                                 0.003352 0.001584
                            ... 0.007351 0.012038 0.003287 0.005806
2 0.007215 0.008497 -0.001454
                            ... -0.000440 0.007107 0.000785 0.007774
3 0.003210 0.006574 0.001986
4 0.001420 0.004274 0.005198 ... -0.000596 0.007177 -0.000143 0.008140
   Run 995 Run 996 Run 997 Run 998 Run 999 Run 1000
 . 0.003093 0.002481 -0.000078 0.008210 0.001179 0.002376
2 0.009864 0.009820 0.000013 0.004665 0.000684 0.004508
3 0.006935 0.007885 0.001127 0.009560 0.001059 -0.000828
4 0.006563 0.005982 0.000642 0.008680 0.000226 0.000613
[5 rows x 1003 columns]
```

```
fig = go.Figure()
# Add the main line for 'Time' vs. 'Average MtM'
fig.add_trace(go.Scatter(x=results_df1['Time'], y=results_df1['Average MtM'], mode='lines', name='Average MtM'))
# Select specific runs to add to the plot from 'Run 1' to 'Run 1000'
for run in range(1, 1001):
    fig.add_trace(go.Scatter(x=results_df1['Time'], y=results_df1[f'Run {run}'], mode='lines', name=f'Run {run}'))
# Add labels and a title
fig.update_layout(xaxis_title='Time', yaxis_title='Values', title='Values vs. Time')
# Show the plot
fig.show()
```

Run 3

Run 4 \

Values vs. Time



```
#Now the CVA Calculation
def create_dataframe():
   np.random.seed(987654321)
   # Generating a series of numbers from 1 to 1000
   numbers = pd.Series(range(1, 1001))
   # Generating a series of 1000 random numbers between 0 and 1
   random_numbers = pd.Series(np.random.rand(1000))
   # Creating a DataFrame with two columns
   df = pd.DataFrame({'Runs': numbers, 'Random_No': random_numbers})
   return df
```

```
# Create the DataFrame
df = create_dataframe()
df.head()
```

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Runs Random_No

0.072988

```
0.216037
               0.464753
               0.622590
               0.618388
#Adding Default Indicator
df['Default_indicator'] = (df['Random_No'] < CP_CumPD).astype(int)</pre>
df.head()
        Runs Random_No Default_indicator
               0.072988
               0.216037
               0.464753
               0.622590
               0.618388
data_df = pd.DataFrame(data)
# Function to find the corresponding time for each default
def find_time_for_default(row):
   # Find the last time where MS_CumPD is less than or equal to the random number
   filtered_data = data_df[data_df['MS_CumPD'] <= row['Random_No']]</pre>
   if not filtered_data.empty:
       return filtered_data.iloc[-1]['time']
    else:
       return None # or some default value
# Apply the function using .loc to rows in df where Default_indicator is 1
df.loc[df['Default_indicator'] == 1, 'time of default'] = df[df['Default_indicator'] == 1].apply(find_time_for_default, axis=1)
print(df.head())
        Runs Random_No Default_indicator time of default
              0.072988
                                                      NaN
          2 0.216037
                                                      0.25
          3 0.464753
                                                     1.00
          4 0.622590
                                                      NaN
          5 0.618388
                                                       NaN
# Apply the function using .loc to rows in df where Default_indicator is 1
df.loc[df['Default_indicator'] == 1, 'time of default'] = df[df['Default_indicator'] == 1].apply(find_time_for_default, axis=1)
# Set 'time of default' to 0 where it is NaN and 'Default_indicator' is 1
df.loc[(df['Default_indicator'] == 1) & (df['time of default'].isna()), 'time of default'] = 0
print(df.head())
       Runs Random_No Default_indicator time of default
                                                      0.00
              0.072988
              0.216037
                                                      0.25
              0.464753
                                                     1.00
          4 0.622590
                                                      NaN
          5 0.618388
                                                       NaN
# Ensure the data types are compatible
df['time of default'] = df['time of default'].astype(results_df1['Time'].dtype)
# Perform a left merge
merged_df = df.merge(
    results_df1[['Time', 'DF']],
   left_on='time of default',
   right_on='Time',
   how='left'
# Rename the 'DF' column to 'DF1' and drop the extra 'Time' column from the merge
merged_df.rename(columns={'DF': 'DF1'}, inplace=True)
merged_df.drop(columns=['Time'], inplace=True)
# 'merged_df' now contains the original data from 'df' with the additional 'DF1' column
print(merged_df.head())
        Runs Random_No Default_indicator time of default
                                                                DF1
              0.072988
                                                     0.00 1.000000
              0.216037
                                                     0.25 0.987635
          3 0.464753
                                                     1.00 0.951484
          4 0.622590
                                                                NaN
         5 0.618388
```

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```
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                                                                                                   Final BCVA.ipynb - Colaboratory
   def get_value(row):
       run_col = 'Run ' + str(int(row['Runs'])) # Ensure the run number is an integer
      if run_col in results_df1.columns:
           matching_row = results_df1[results_df1['Time'] == row['time of default']]
           # # Debugging: Print statements to check the process
          if matching_row.empty:
             pass
               # print(f"No matching time step for Run {row['Runs']} at time {row['time of default']}")
          else:
                     #print(f"Match found for Run {row['Runs']} at time {row['time of default']}: {matching_row[run_col].iloc[0]}")
            return matching_row[run_col].iloc[0]
       else:
        pass
           #print(f"Run column {run_col} not found")
       return None
   # Apply the function to each row in merged_df
   merged_df['value'] = merged_df.apply(get_value, axis=1)
   merged_df.head()
           Runs Random_No Default_indicator time of default
                                                                    DF1
                                                                            value
                   0.072988
                                                               1.000000 0.000000
                                                          0.00
                  0.216037
                                                          0.25 0.987635 0.004301
                                                          1.00 0.951484 0.002382
                   0.464753
                  0.622590
                                                          NaN
                                                                    NaN
                                                                             NaN
                  0.618388
                                                                    NaN
                                                          NaN
                                                                             NaN
   #Stats
   positive_count = (merged_df['value'] > 0).sum()
   negative_count = (merged_df['value'] < 0).sum()</pre>
   nan_count = merged_df['value'].isna().sum()
   print(positive_count, negative_count, nan_count)
        311 71 489
   #Consider only Positive Exposures
   merged_df['Exposure'] = merged_df['value'].apply(lambda x: max(0, x) if pd.notna(x) else 0) #Positive Exposure Only
   merged_df.head()
            Runs Random_No Default_indicator time of default
                                                                    DF1
                                                                            value Exposure
                  0.072988
                                                          0.00 1.000000 0.000000 0.000000
                                                          0.25  0.987635  0.004301  0.004301
                  0.216037
                  0.464753
                                                          1.00 0.951484 0.002382 0.002382
                  0.622590
                                                                             NaN 0.000000
                                                                    NaN
                                            0
                                                          NaN
                  0.618388
                                                                    NaN
                                                                             NaN 0.000000
                                            0
                                                          NaN
   #Final Loss Values
   CP_LGD=1-0.60 # Assuming a recovery rate of 60% for MS
   merged_df['Loss']=merged_df['DF1']*merged_df['Exposure']*CP_LGD
   merged_df.head(10)
            Runs Random_No Default_indicator time of default
                                                                    DF1
                                                                            value Exposure
                                                                                                Loss
                   0.072988
                                                          0.00 1.000000 0.000000
                                                                                  0.000000 0.000000
                                                          0.25  0.987635  0.004301  0.004301  0.001699
                  0.216037
                  0.464753
                                                          1.00 0.951484 0.002382 0.002382 0.000907
                  0.622590
                                                                             NaN 0.000000
                                                          NaN
                                                                    NaN
                                                                                                NaN
                  0.618388
                                                          NaN
                                                                    NaN
                                                                             NaN 0.000000
                                                                                                NaN
                  0.427379
                                                          0.75  0.963382  0.006574  0.006574  0.002533
                                                          0.00 1.000000 0.000000 0.000000 0.000000
                  0.111334
                  0.526045
                                                          4.00 0.820450 0.015666 0.015666 0.005141
                  0.269190
                                                          0.25  0.987635  0.004060  0.004060  0.001604
             10
                  0.640339
                                                          NaN
                                                                    NaN
                                                                             NaN 0.000000
                                                                                                NaN
                                            0
   df321 = merged_df[['Runs', 'Loss']] # Select the 'Runs' and 'Loss' columns
   # Define a color array based on the 'Loss' values
   colors = ['blue' if loss == 0 else 'green' for loss in df321['Loss']]
   # Create a scatter plot with reversed axes and conditional coloring
  fig = go.Figure(data=go.Scatter(x=df321['Loss'], y=df321['Runs'], mode='markers', marker=dict(color=colors)))
   fig.update_traces(marker=dict(size=5)) # Adjust marker size
  fig.update_layout(title='Loss Value vs. Run No')
  fig.update_xaxes(title_text='Loss Value') # X-axis label
   fig.update_yaxes(title_text='Run No')
                                              # Y-axis label
```

https://colab.research.google.com/drive/1QPgoS_wrAdnwwmBxfp9nxBxi_ZqPBxBf#scrollTo=YPCxy_5XTTM3&printMode=true

Show the plot

fig.show()

Loss Value vs. Run No



```
CVA=merged_df['Loss'].mean() *1000000 #1 million notional principal
print("CVA=",CVA)
```

CVA= 1267.5962565868372

#Now we will calculate DVA

Create the DataFrame
df1 = create_dataframe()

df1.head()

RunsRandom_No010.072988120.216037230.464753340.622590450.618388

df1['Default_indicator'] = (df1['Random_No'] < Our_CumPD).astype(int)
df1.head()</pre>

```
      Runs
      Random_No
      Default_indicator

      0
      1
      0.072988
      1

      1
      2
      0.216037
      1

      2
      3
      0.464753
      1

      3
      4
      0.622590
      1

      4
      5
      0.618388
      1
```

```
def find_time_for_default(row):
    # Find the last time where MS_CumPD is less than or equal to the random number
    filtered_data = data_df[data_df['MS_CumPD'] <= row['Random_No']]
    if not filtered_data.empty:
        return filtered_data.iloc[-1]['time']
    else:
        return None # or some default value</pre>
```

Apply the function using .loc to rows in df where Default_indicator is 1
df1.loc[df1['Default_indicator'] == 1, 'time of default'] = df1[df1['Default_indicator'] == 1].apply(find_time_for_default, axis=1)
df1.head()

```
        Runs
        Random_No
        Default_indicator
        time of default

        0
        1
        0.072988
        1
        NaN

        1
        2
        0.216037
        1
        0.25

        2
        3
        0.464753
        1
        1.00

        3
        4
        0.622590
        1
        10.00

        4
        5
        0.618388
        1
        10.00
```

```
# Apply the function using .loc to rows in df where Default_indicator is 1
df1.loc[df1['Default_indicator'] == 1, 'time of default'] = df1[df1['Default_indicator'] == 1].apply(find_time_for_default, axis=1)

# Set 'time of default' to 0 where it is NaN and 'Default_indicator' is 1
df1.loc[(df1['Default_indicator'] == 1) & (df1['time of default'].isna()), 'time of default'] = 0

df1.head(10)
```

```
Final BCVA.ipynb - Colaboratory
         Runs Random_No Default_indicator time of default
                                                         0.00
                0.072988
                                                         0.25
               0.216037
                0.464753
                                                        1.00
                0.622590
                                                        10.00
                0.618388
                                                        10.00
                0.427379
                                                        0.75
                0.111334
                                                        0.00
                0.526045
                                                         4.00
                0.269190
                                                        0.25
          10
                0.640339
                                                        10.00
# Ensure the data types are compatible
df1['time of default'] = df1['time of default'].astype(results_df1['Time'].dtype)
# Perform a left merge
merged_df1 = df1.merge(
    results_df1[['Time', 'DF']],
   left_on='time of default',
    right_on='Time',
    how='left'
# Rename the 'DF' column to 'DF1' and drop the extra 'Time' column from the merge
merged_df1.rename(columns={'DF': 'DF1'}, inplace=True)
merged_df1.drop(columns=['Time'], inplace=True)
```

'merged_df1' now contains the original data from 'df' with the additional 'DF1' column

merged_df1['value'] = merged_df1.apply(get_value, axis=1) merged_df1.head(10)

Ru	ıns	Random_No	Default_indicator	time of default	DF1	value
0	1	0.072988	1	0.00	1.000000	0.000000
1	2	0.216037	1	0.25	0.987635	0.004301
2	3	0.464753	1	1.00	0.951484	0.002382
3	4	0.622590	1	10.00	0.618833	-0.041663
4	5	0.618388	1	10.00	0.618833	0.026033
5	6	0.427379	1	0.75	0.963382	0.006574
6	7	0.111334	1	0.00	1.000000	0.000000
7	8	0.526045	1	4.00	0.820450	0.015666
8	9	0.269190	1	0.25	0.987635	0.004060
9	10	0.640339	1	10.00	0.618833	-0.015970

#Stats positive_count = (merged_df1['value'] > 0).sum() negative_count = (merged_df1['value'] < 0).sum()</pre> nan_count = merged_df1['value'].isna().sum() print(positive_count, negative_count, nan_count)

437 161 273

 $merged_df1['Exposure'] = merged_df1['value'].apply(lambda x: x if x < 0 else 0) #Negative Exposure only$ merged_df1.head(10)

Runs Random_No Default_indicator time of default value Exposure DF1 0.00 1.000000 0.000000 0.000000 0.072988 0.216037 0.25 0.987635 0.004301 0.000000 0.464753 1.00 0.951484 0.002382 0.000000 0.622590 10.00 0.618833 -0.041663 -0.041663 10.00 0.618833 0.026033 0.000000 0.618388 0.427379 0.75 0.963382 0.006574 0.000000 0.111334 0.000000 0.000000 0.00 1.000000 0.526045 4.00 0.820450 0.015666 0.000000 0.25 0.987635 0.004060 0.000000 0.269190 0.640339 10.00 0.618833 -0.015970 -0.015970

Our_LGD=1-0.45 #JP

merged_df1['Loss']=merged_df1['DF1']*merged_df1['Exposure']*Our_LGD

merged_df1.head(10)

	Runs	Random_No	Default_indicator	time of default	DF1	value	Exposure	Loss
0	1	0.072988	1	0.00	1.000000	0.000000	0.000000	0.000000
1	2	0.216037	1	0.25	0.987635	0.004301	0.000000	0.000000
2	3	0.464753	1	1.00	0.951484	0.002382	0.000000	0.000000
3	4	0.622590	1	10.00	0.618833	-0.041663	-0.041663	-0.014180
4	5	0.618388	1	10.00	0.618833	0.026033	0.000000	0.000000
5	6	0.427379	1	0.75	0.963382	0.006574	0.000000	0.000000
6	7	0.111334	1	0.00	1.000000	0.000000	0.000000	0.000000
7	8	0.526045	1	4.00	0.820450	0.015666	0.000000	0.000000
8	9	0.269190	1	0.25	0.987635	0.004060	0.000000	0.000000
9	10	0.640339	1	10.00	0.618833	-0.015970	-0.015970	-0.005435

```
df3210 = merged_df1[['Runs', 'Loss']] # Select the 'Runs' and 'Loss' columns

# Define a color array based on the 'Loss' values
colors = ['blue' if loss == 0 else 'green' for loss in df3210['Loss']]

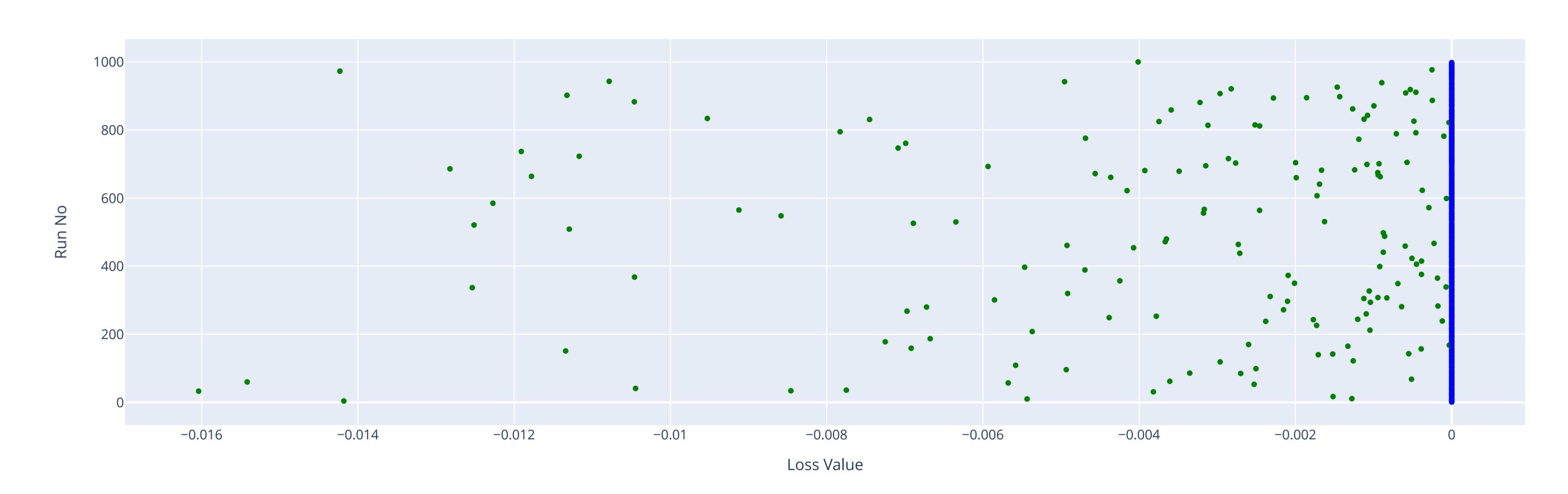
# Create a scatter plot with reversed axes and conditional coloring
fig = go.Figure(data=go.Scatter(x=df3210['Loss'], y=df3210['Runs'], mode='markers', marker=dict(color=colors)))

fig.update_traces(marker=dict(size=5)) # Adjust marker size
fig.update_layout(title='Loss Value vs. Run No')
fig.update_xaxes(title_text='Loss Value') # X-axis label
fig.update_yaxes(title_text='Run No') # Y-axis label
```

```
Loss Value vs. Run No
```

Show the plot

fig.show()



```
DVA=merged_df1['Loss'].mean() *1000000 #1 million notional principal
print("DVA=",DVA)
```

DVA= -836.7706148216657

```
print(merged_df1)
```

```
Runs Random_No Default_indicator time of default
                                                           DF1
                                                                   value \
           0.072988
                                                       1.000000 0.000000
           0.216037
                                                       0.987635 0.004301
                                                       0.951484 0.002382
           0.464753
           0.622590
                                                       0.618833 -0.041663
           0.618388
                                                       0.618833 0.026033
                                                10.00
                                                       0.987635 0.002481
           0.206384
           0.900697
                                                  NaN
                                                           NaN
           0.493368
                                                 1.25 0.939594 0.009694
           0.858213
     999
                                                  NaN
                                                           NaN
                                                                     NaN
                                                       0.618833 -0.011792
    1000
           0.684922
                                                10.00
                  Loss
     Exposure
    0.000000 0.000000
    0.000000 0.000000
    0.000000 0.000000
    -0.041663 -0.014180
     0.000000 0.000000
    0.000000 0.000000
996 0.000000
                   NaN
    0.000000 0.000000
998 0.000000
999 -0.011792 -0.004014
[1000 rows x 8 columns]
```

print(merged_df1)

```
Runs Random_No Default_indicator time of default
                                                           DF1
                                                                   value \
           0.072988
                                                 0.00 1.000000 0.000000
           0.216037
                                                 0.25 0.987635 0.004301
           0.464753
                                                 1.00 0.951484 0.002382
                                                10.00 0.618833 -0.041663
           0.622590
                                                      0.618833 0.026033
           0.618388
                                                10.00
                • • •
     996
           0.206384
                                                 0.25 0.987635 0.002481
996
     997
           0.900697
                                                           NaN
                                                  NaN
                                                                     NaN
                                                      0.939594 0.009694
997
     998
           0.493368
                                                 1.25
           0.858213
                                                           NaN
998
     999
                                                  NaN
           0.684922
                                                10.00 0.618833 -0.011792
999 1000
     Exposure
                  Loss
    0.000000 0.000000
    0.000000 0.000000
    0.000000 0.000000
   -0.041663 -0.014180
    0.000000 0.000000
    0.000000 0.000000
996 0.000000
                  NaN
997 0.000000 0.000000
998 0.000000
999 -0.011792 -0.004014
[1000 rows x 8 columns]
```

print(merged_df1)

https://colab.research.google.com/drive/1QPgoS_wrAdnwwmBxfp9nxBxi_ZqPBxBf#scrollTo=YPCxy_5XTTM3&printMode=true

1/28/24, 7:11 PM Final BCVA.ipynb - Colaboratory

• • •	• • •	• • •	• • •	• • •	• • •	• •
0.002481	0.987635	0.25	1	0.206384	996	995
NaN	NaN	NaN	0	0.900697	997	996
0.009694	0.939594	1.25	1	0.493368	998	997
NaN	NaN	NaN	0	0.858213	999	998
-0.011792	0.618833	10.00	1	0.684922	1000	999

Exposure Loss
0 0.000000 0.000000
1 0.000000 0.000000
2 0.000000 0.000000