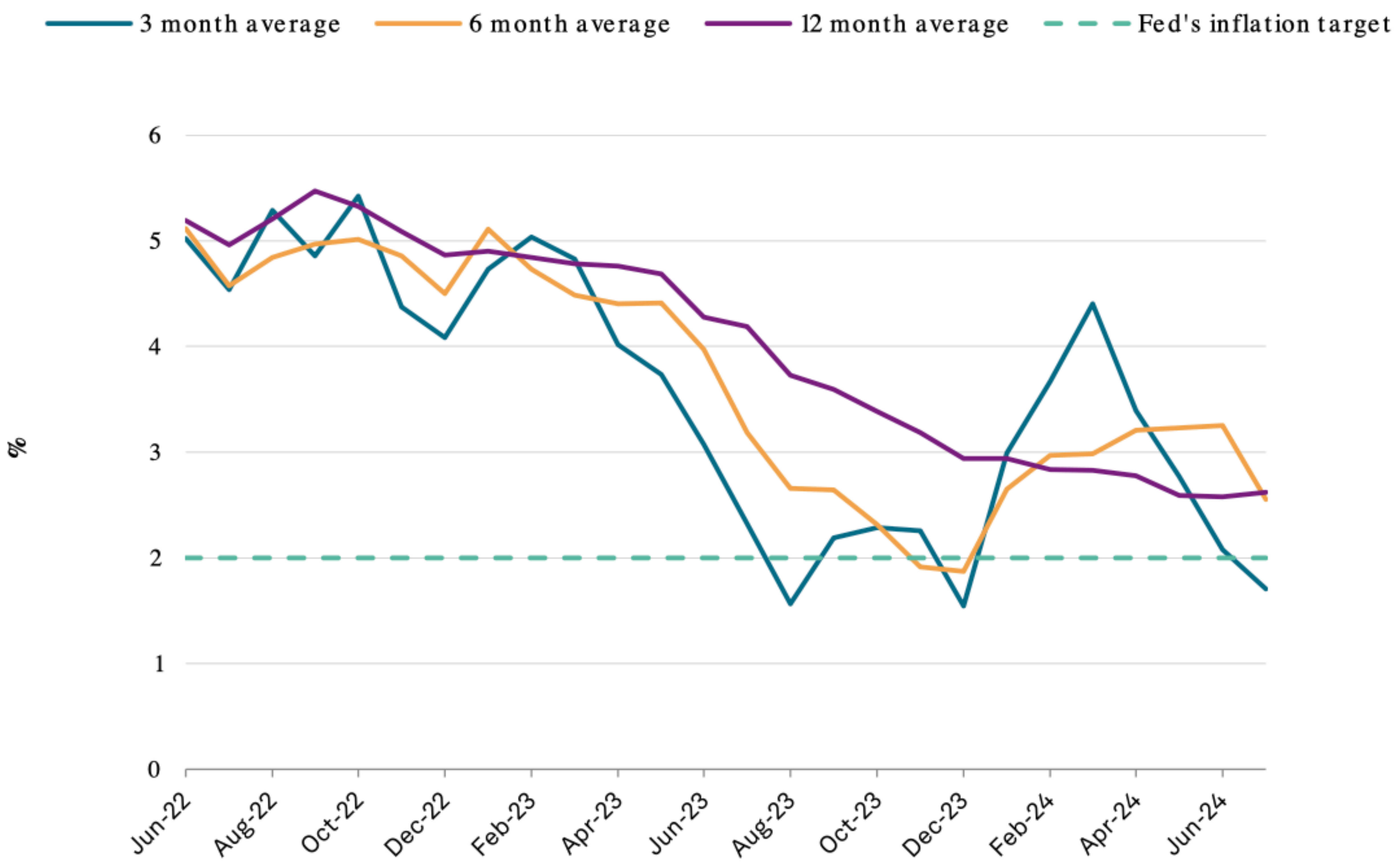
Market Outlook & CAPE/SoP

Jack

Economic and Market Outlook

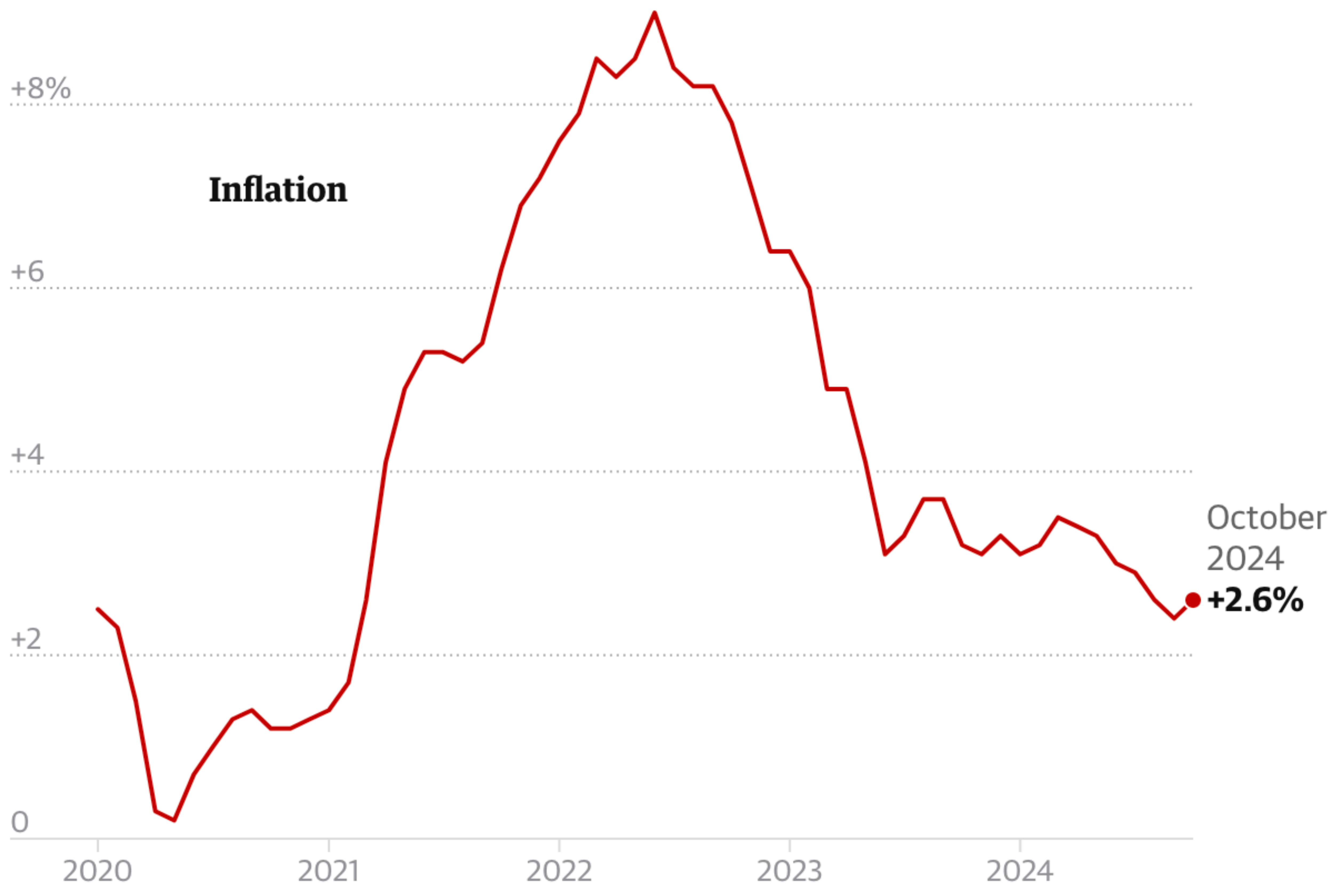
Global Macro

Consumer's personal consumption expenditure inflation (excluding food and energy)



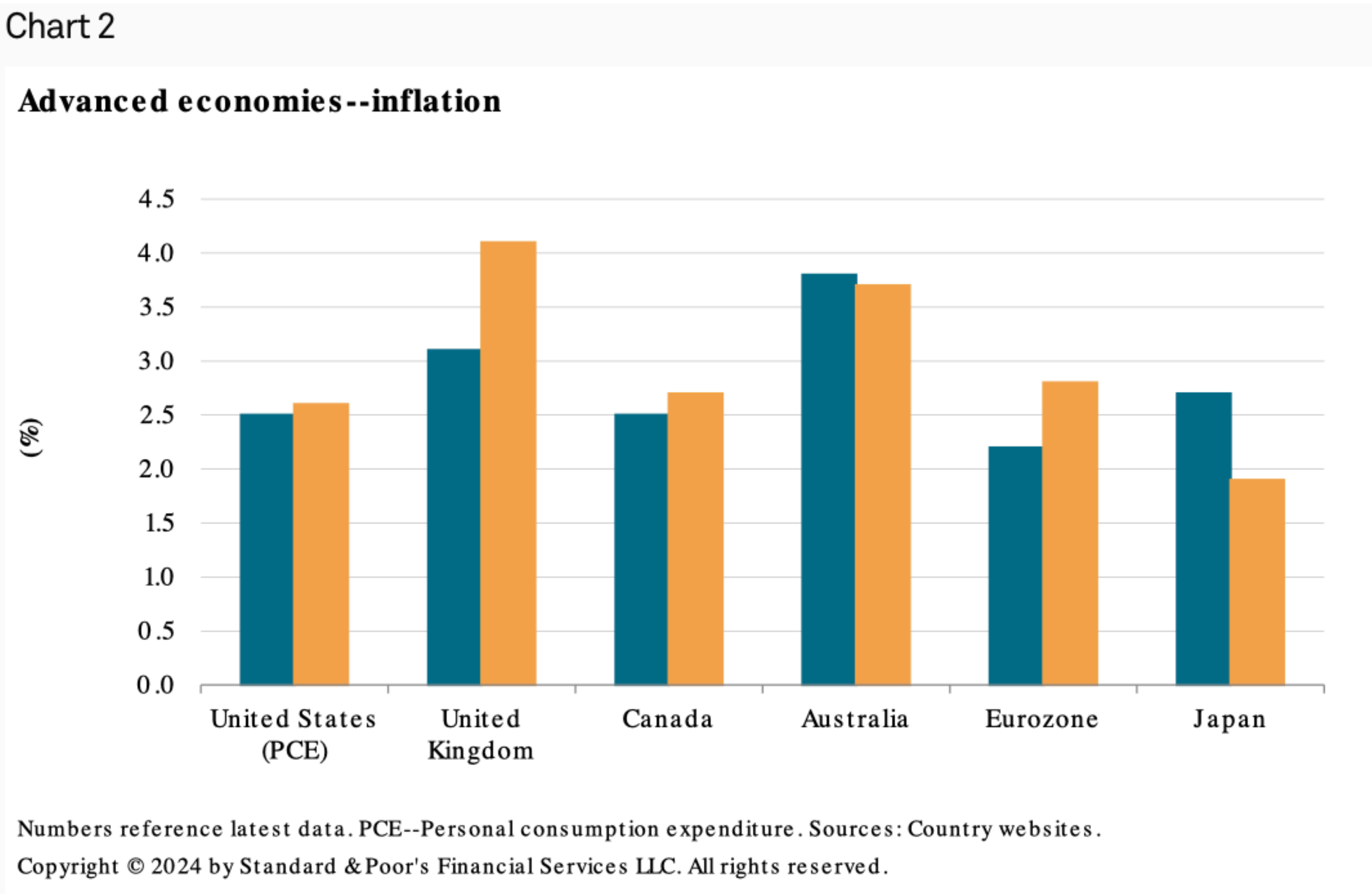
Sources: Bureau of Labor Statistics and S&P Global Ratings calculations. Data through July 2024.

- Inflation is moving towards 2.0% goal in the United States



- Recent inflation has ticked up after steady decline
- Under Trump, inflation could rise as much as 5.1%, according to Budget Lab at Yale

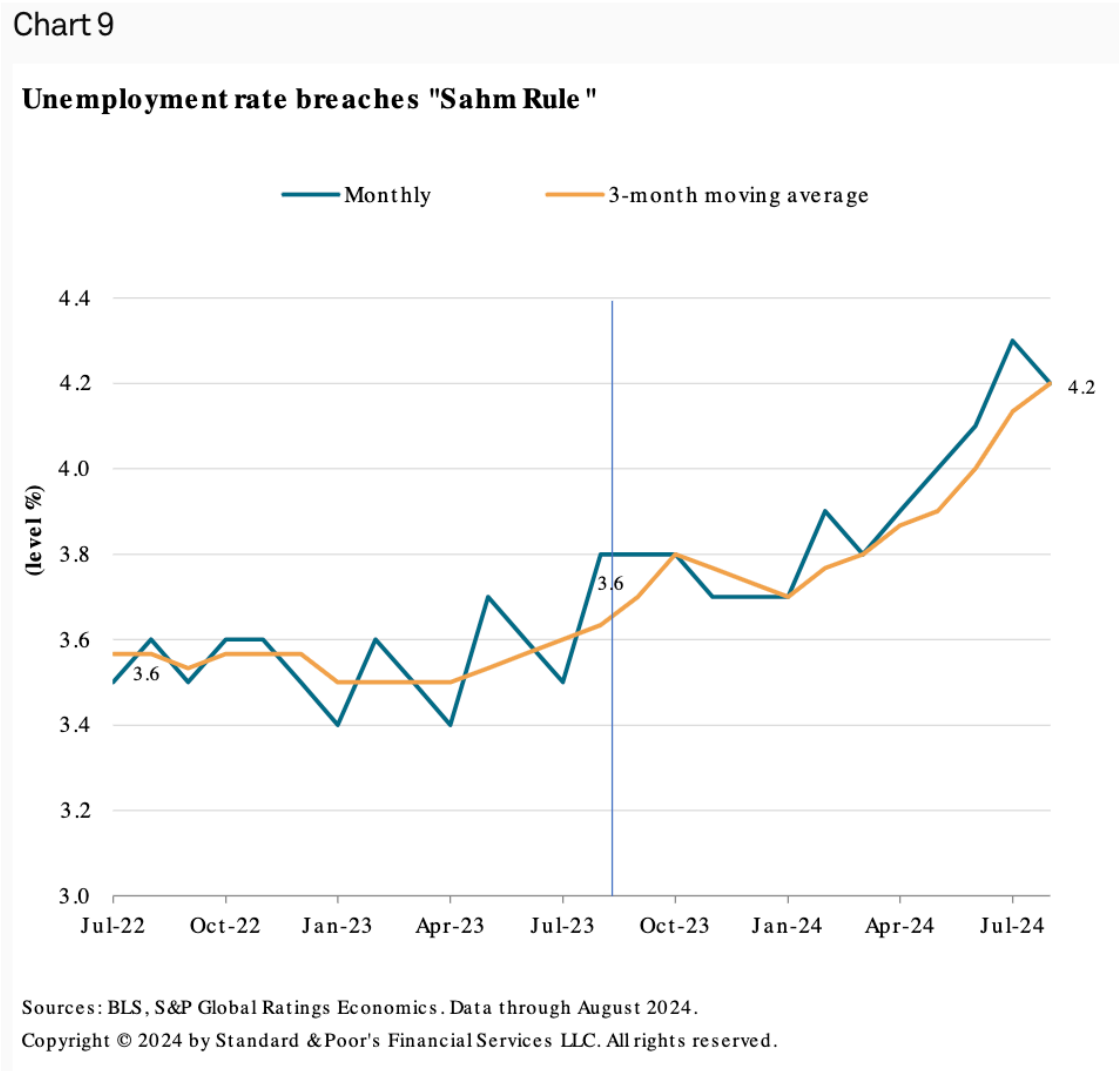
- Inflation around the world is heading towards the target of 2.0%
- The UK is still behind
- European inflation hit a record low headline measure in October



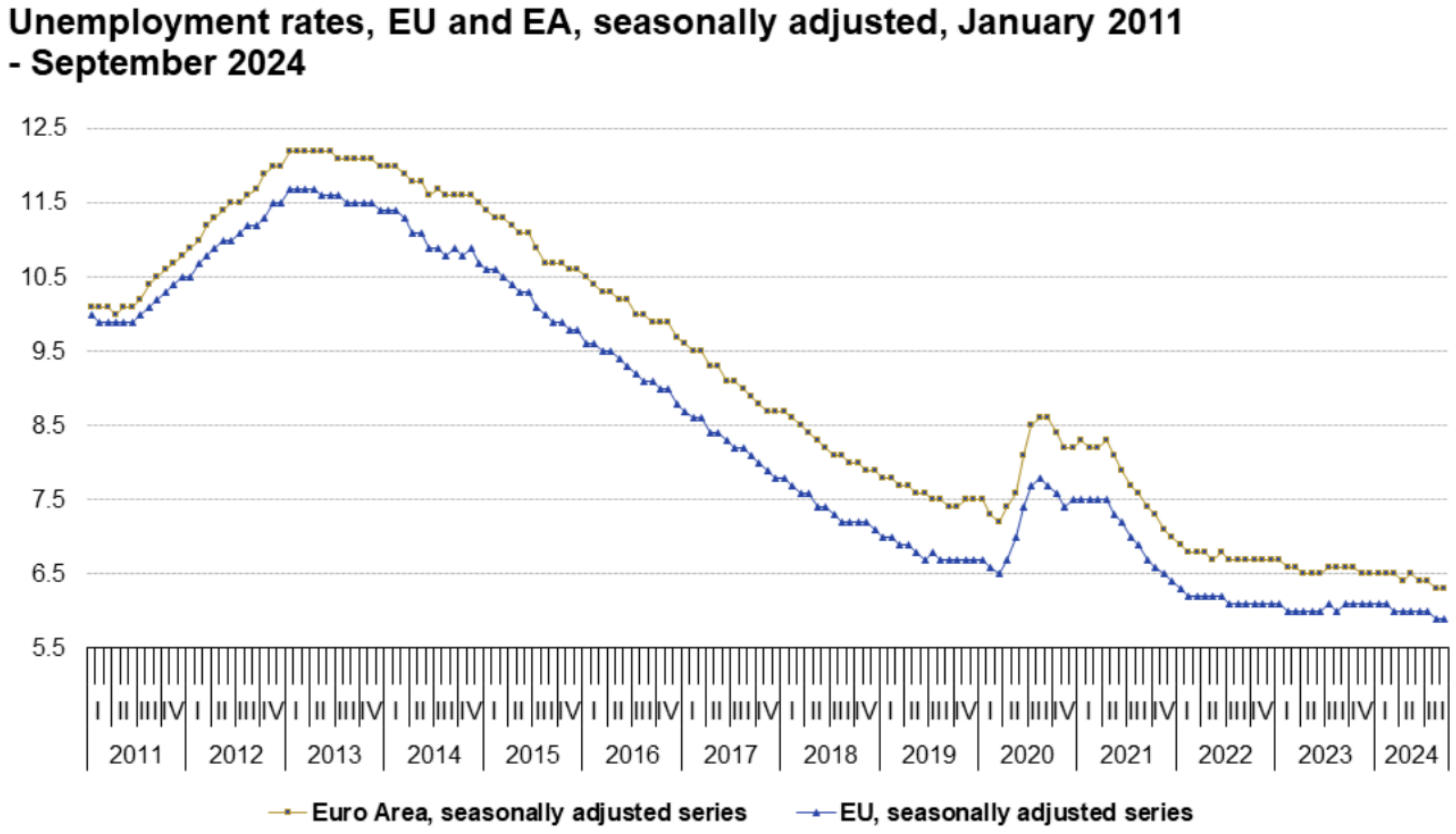
- US Unemployment hit 4.2% in September again, sits now at 4.1%

- Canada's unemployment rate sits at an unhealthy 6.5% as of October

- Canada's unemployment rate projected to hit 7% in early 2025



- EU unemployment sits at 5.9%, compared to 6.1% in September 2023



- US GDP grew by 2.8% in Q3 2024, slightly below expectations
- Expectation of a 2.0% growth in Q4, down from 3.2% Q4 growth in 2023
- China's GDP expanded 4.6% in Q3, expected to grow another 4.6% in Q4, down from earlier forecasts of 4.8%
- Eurozone experienced a 0.4% GDP growth in Q3, higher than the expected 0.2%

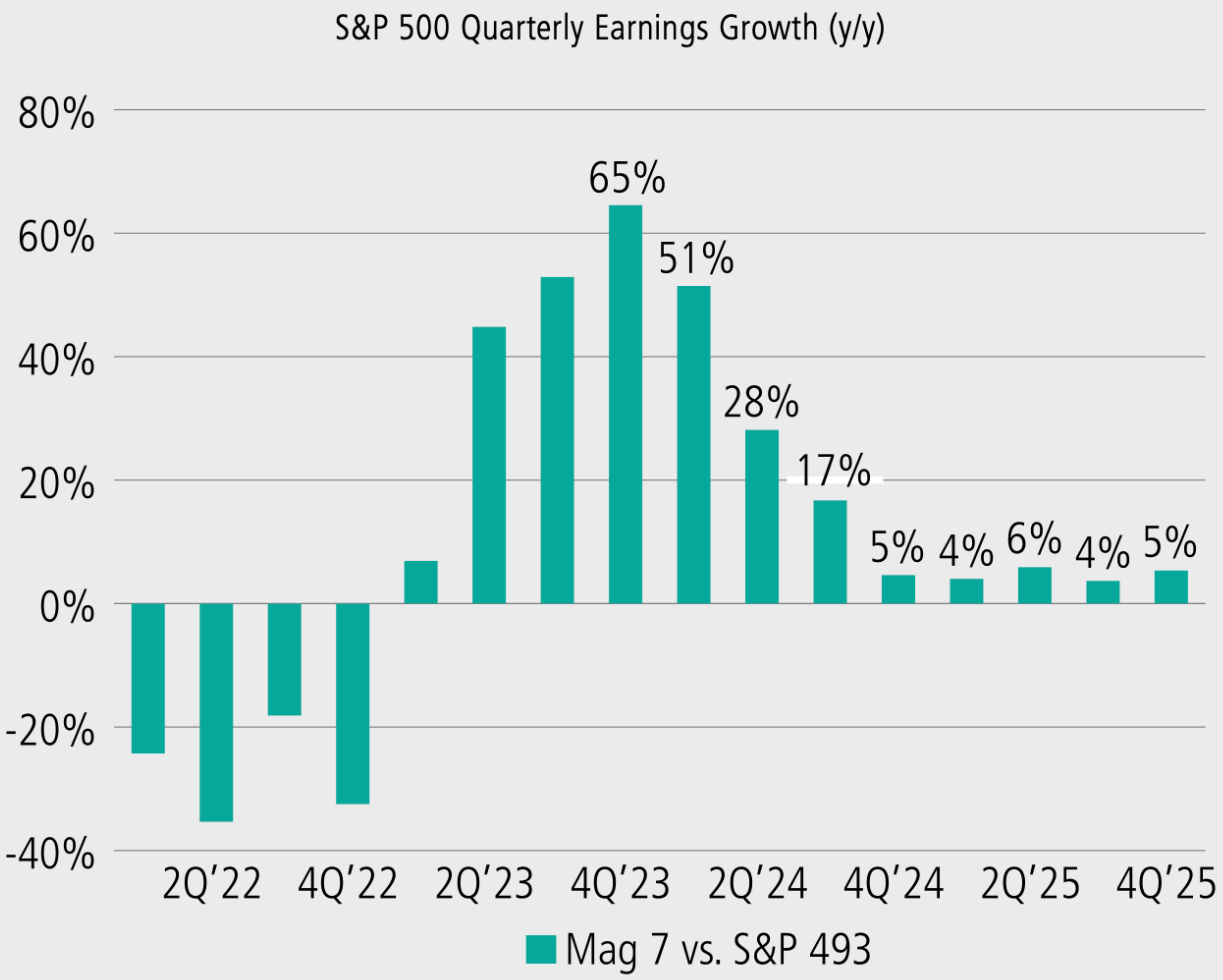
Economic and Market Outlook

Global Equity

- Market cap of Mag7, consisting of Apple, Amazon, Alphabet, Microsoft, Meta, Nvidia, Tesla, have receded since last quarter

- Still trading at a 28% premium, according to Neuberger Berman

Figure 6: The Mag 7's Growth Scarcity Premium May Continue To Diminish



- According to Forbes, Mag7 returned 90% in 2023 compared to S&P500's overall 24%

- This year, Mag7 are up ~30% compared to the S&P 500's 20%

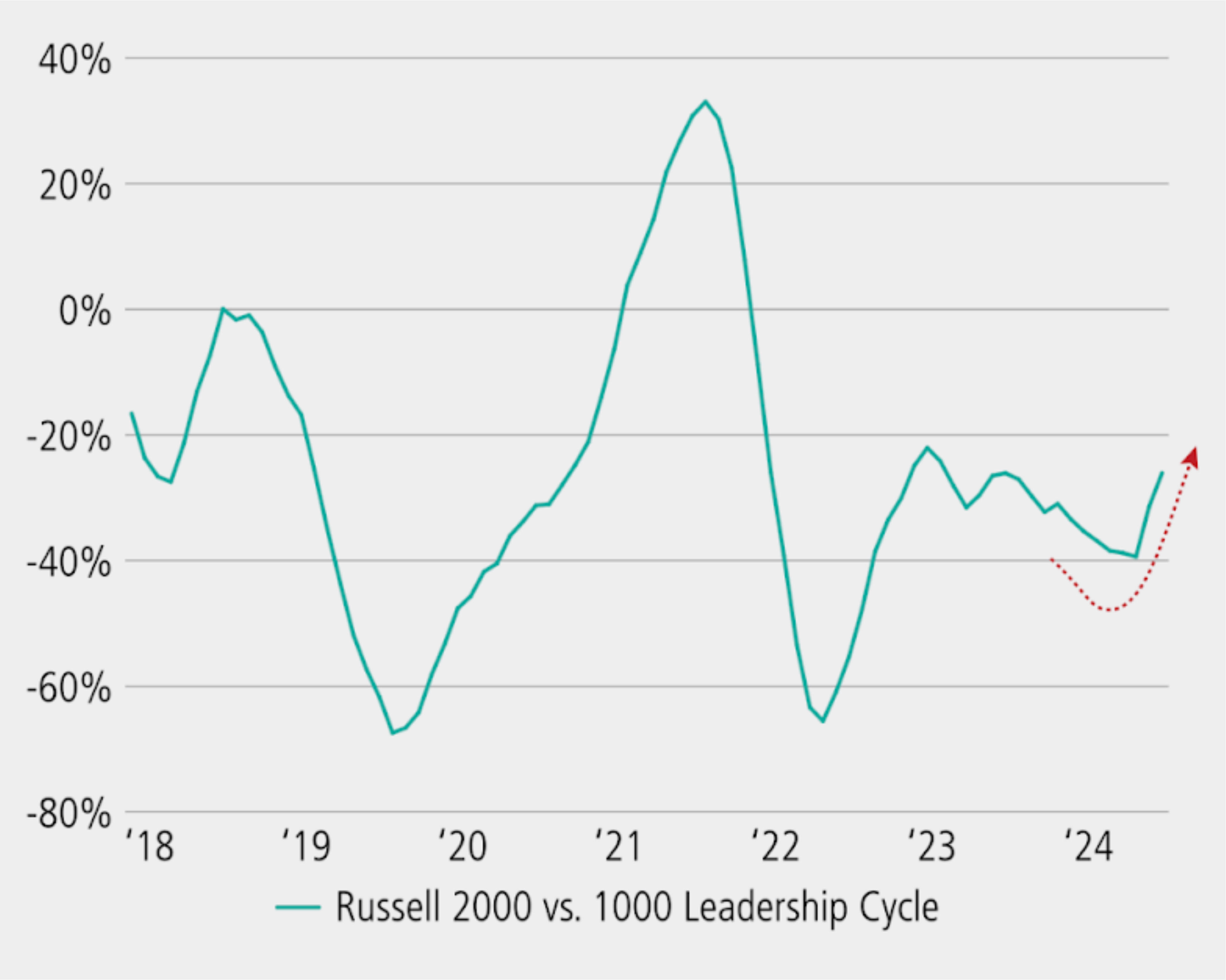
- This is a shift away from Mag7 that has positive effects for the market

- As of more recently, S&P 500 concentration in Tech & Comm remains elevated at 39.8%

- Down from 41.8% earlier this year in June

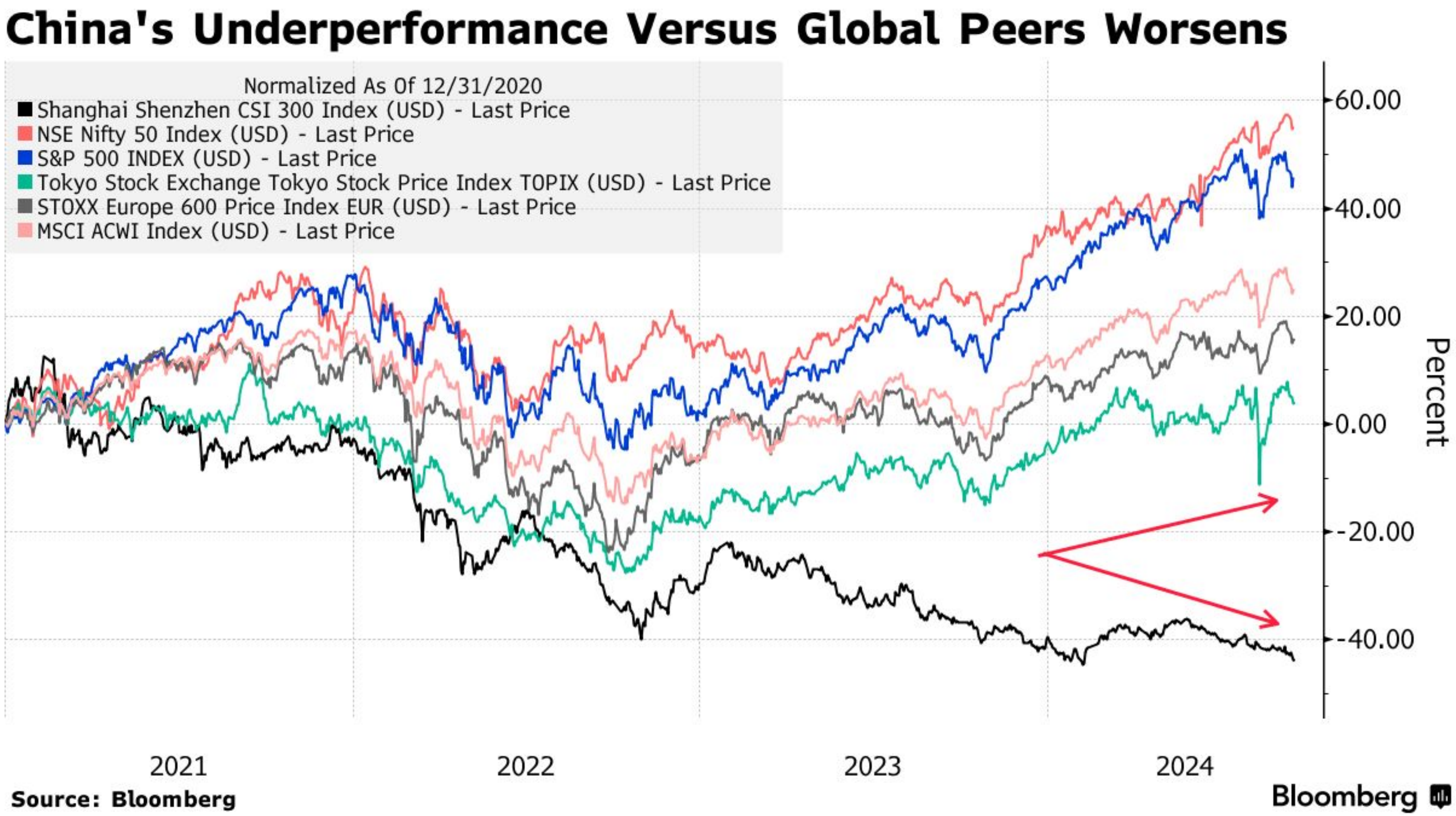
- Since July 1, the Russell 1000 Value Index has outpaced Russell 1000 Growth Index by 624 bps according to NB

- Increase in performance by Russell 2000 small-cap Index compared to Russell 1000 large-cap



- STOXX Europe 12-month P/E, excluding UK, show that European equities are being traded at below average valuations
- Reports show that European stocks closed 2% lower daily, constituting their biggest daily decline since August
- Mining stocks led the losses, dropping 4%
- Tech stock managed to inch up 0.04%

- Chinese underperformance continues in the equity market due to the housing recession



Economic and Market Outlook

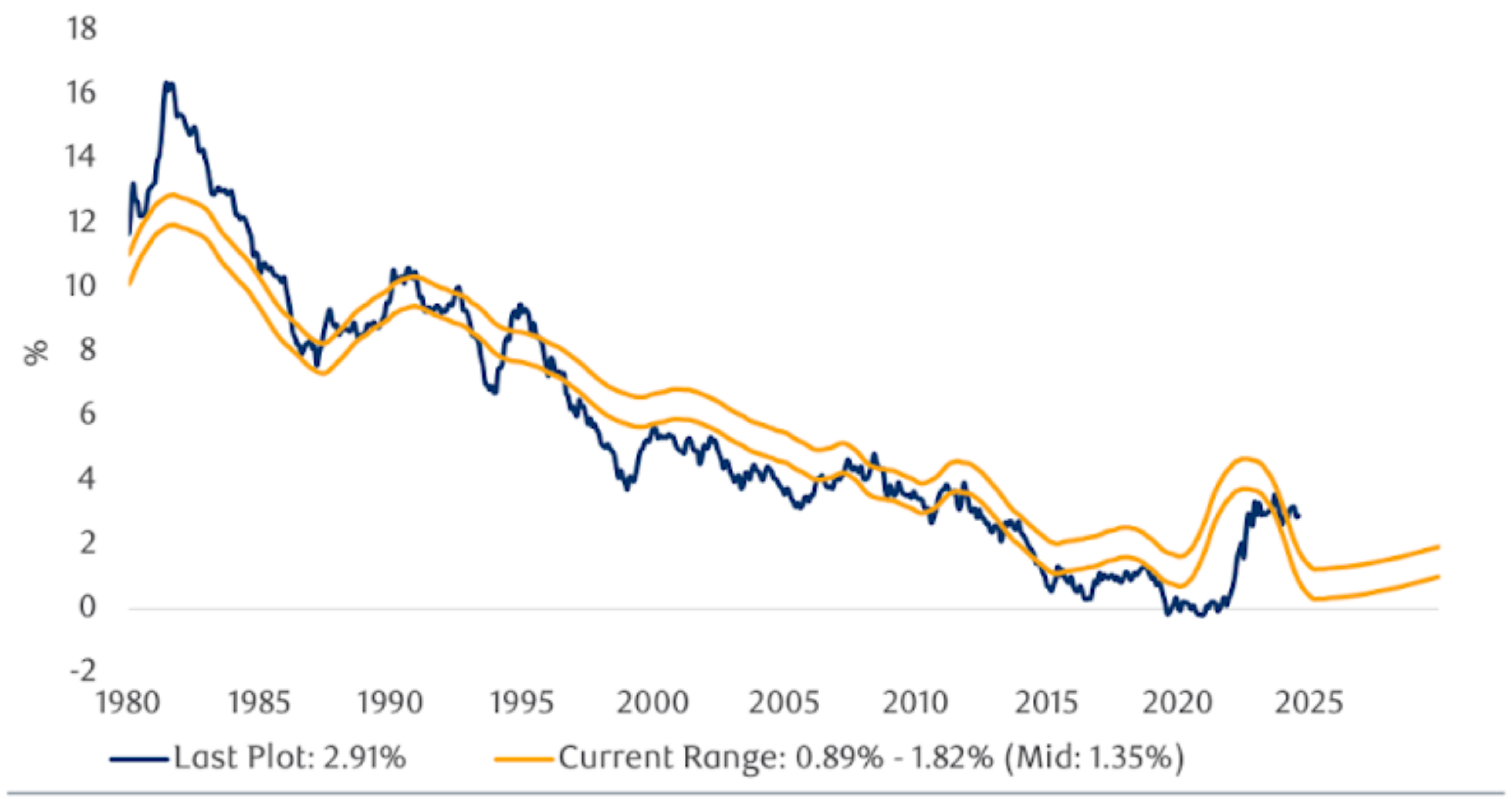
Rate Treasury

- Bank of Canada introduced substantial rate cut of 50 bps to 3.75 in late October
- US Fed Reserve cuts rates by 50 bps in mid-September and 25 bps in early November
- ECB cut rates by 25 bps in September, as did the Bank of England
- PBC cut rates by 50 bps for existing mortgages to combat housing crash

U.S. 10-Year T-Bond Yield
Equilibrium range

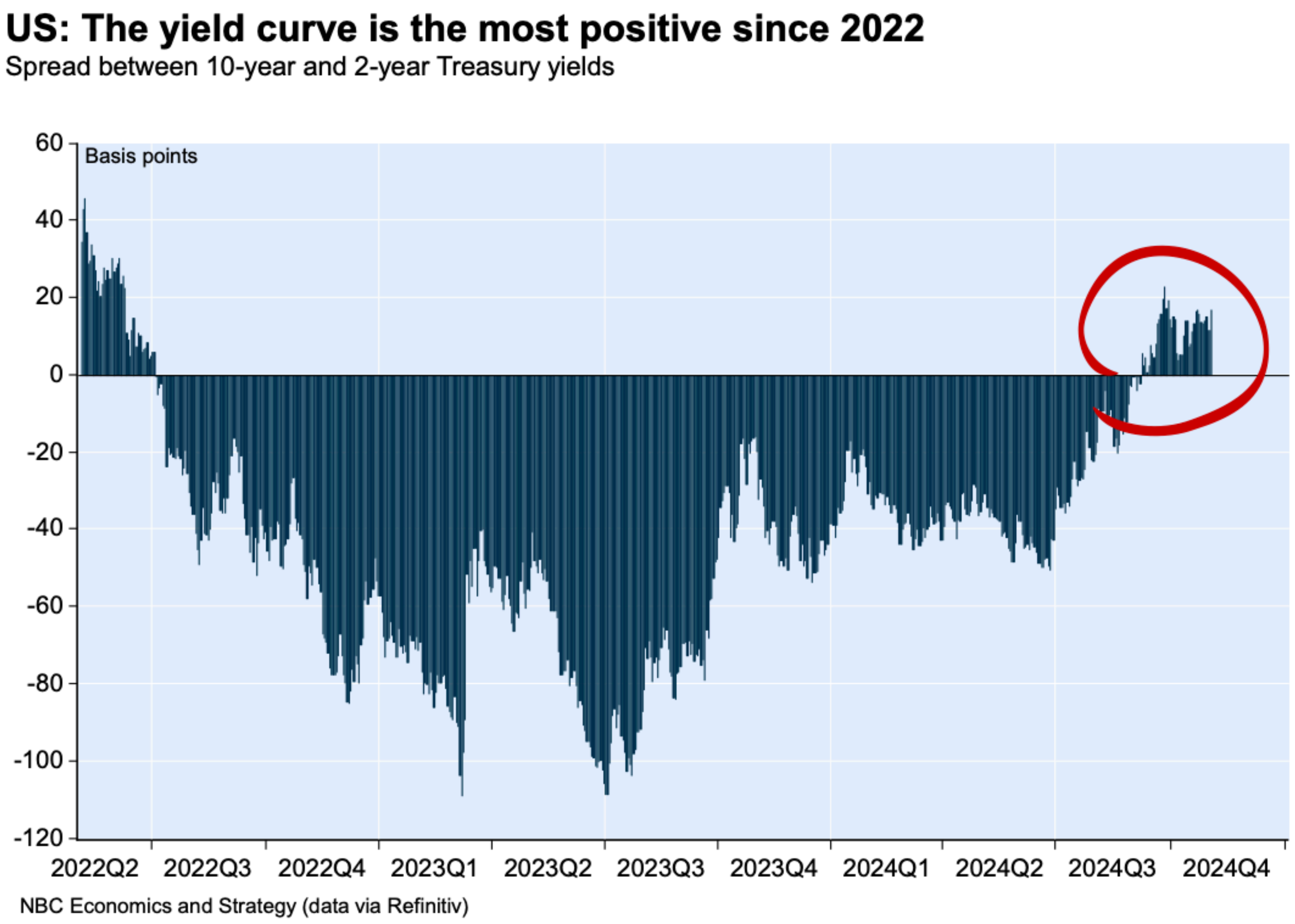
Note: As of August 30, 2024. Source: RBC GAM

Eurozone 10-Year Bond Yield
Equilibrium range



Note: As of August 30, 2024. Source: RBC GAM

- In September, 10Y US treasury yield dropped to 3.63%, notable decrease from 3.80/3.90% range through August
- By late October, approached 4.28%
- As of now, sits at 4.47%



- Characteristic of healthy yield curve

- More rate hikes by the Bank of Japan will pressure Japanese yield curve flatter
- Due to higher interest rates decreasing the demand for existing bonds
- 10Y Eurozone yield at 2.97%, compared to 3.49% last year

Economic and Market Outlook

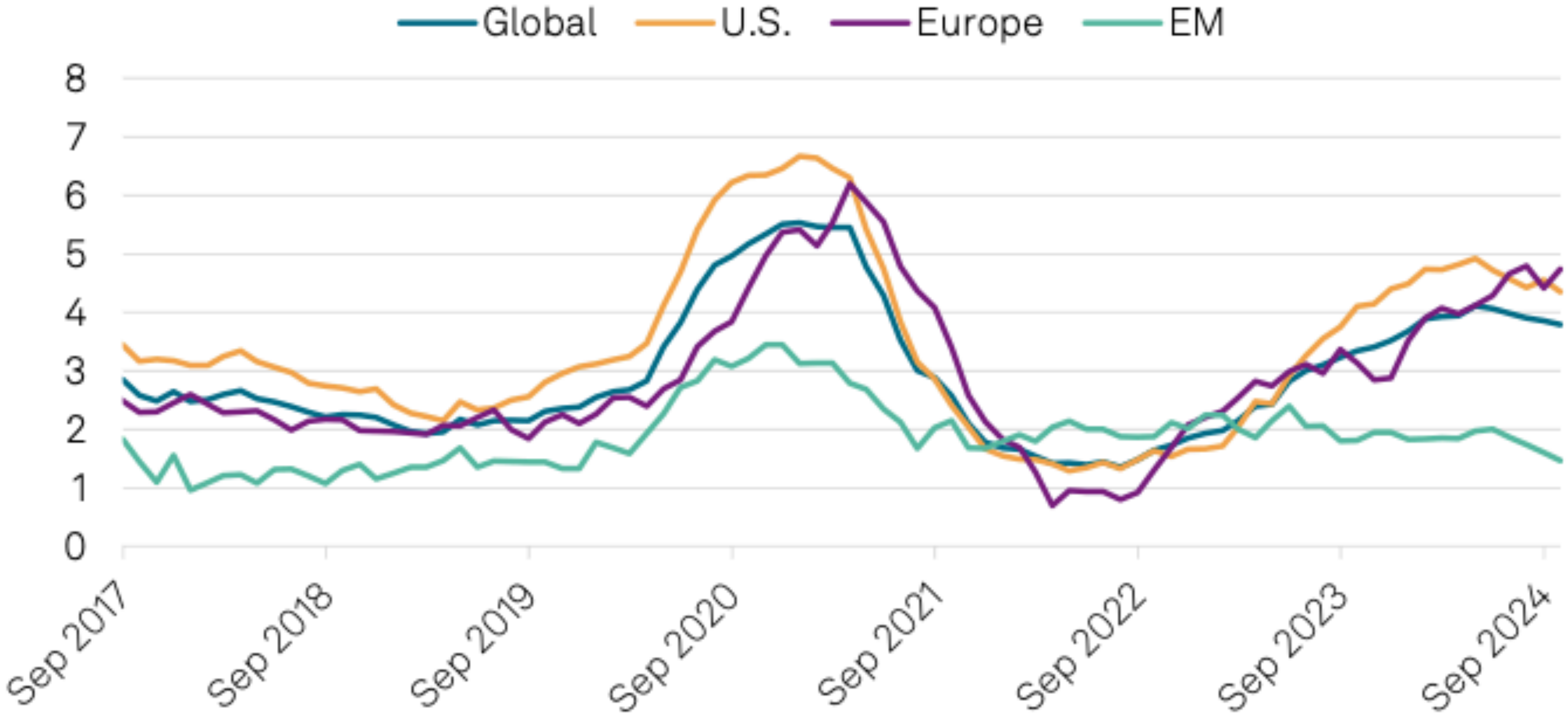
Corporate Yield

- Under current robust economic conditions, stronger grade credit securities should not wane into 2025

- For more volatile securities and vulnerable companies, speculative grade debt has been high going into Q3, Q4 due to high interest rates

Default rates may have peaked in most regions

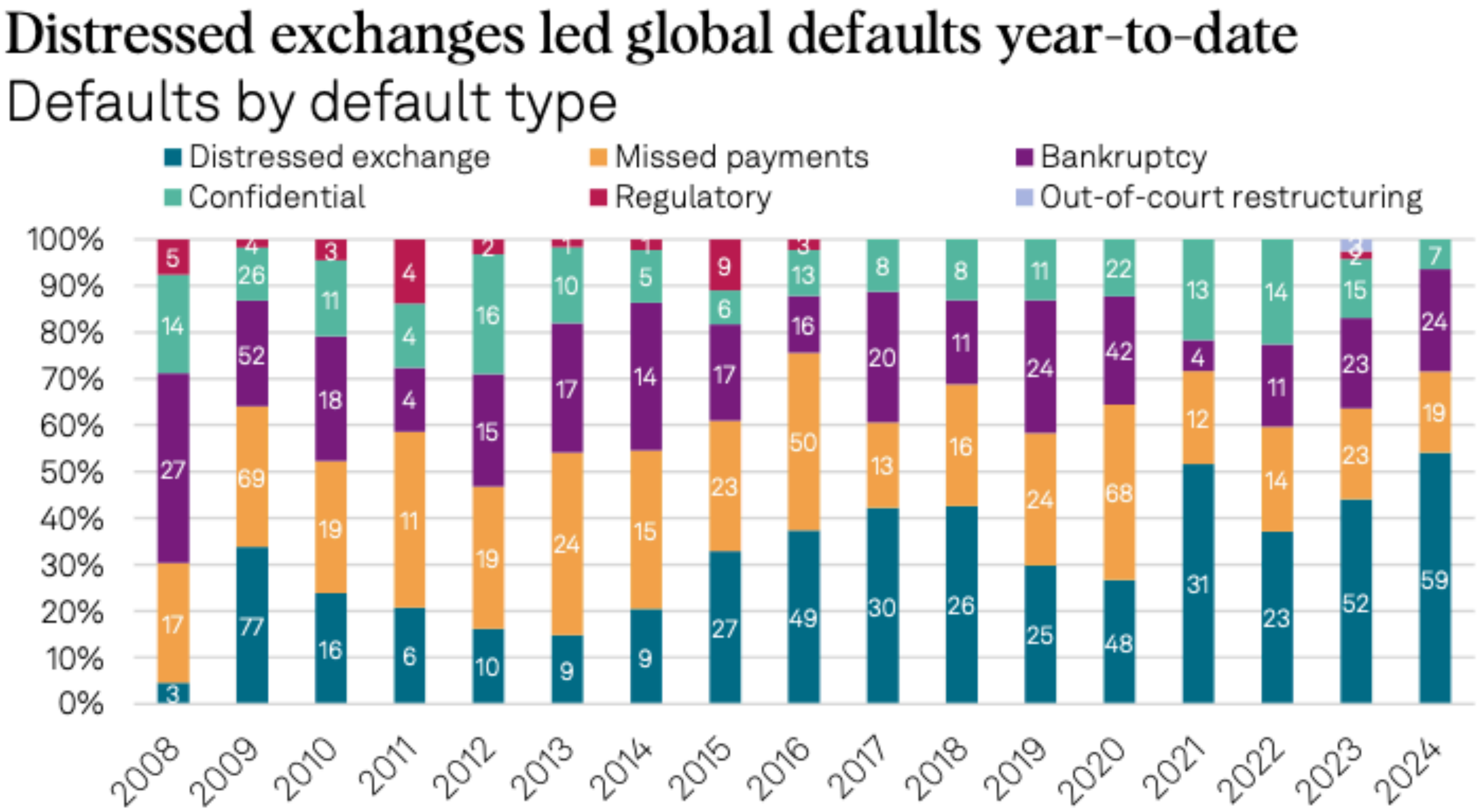
Trailing-12-month speculative-grade default rate (%)



- Gradual curbing around September 2024

- Corporate defaults decreased to 41 in Q2 from 31 in Q3

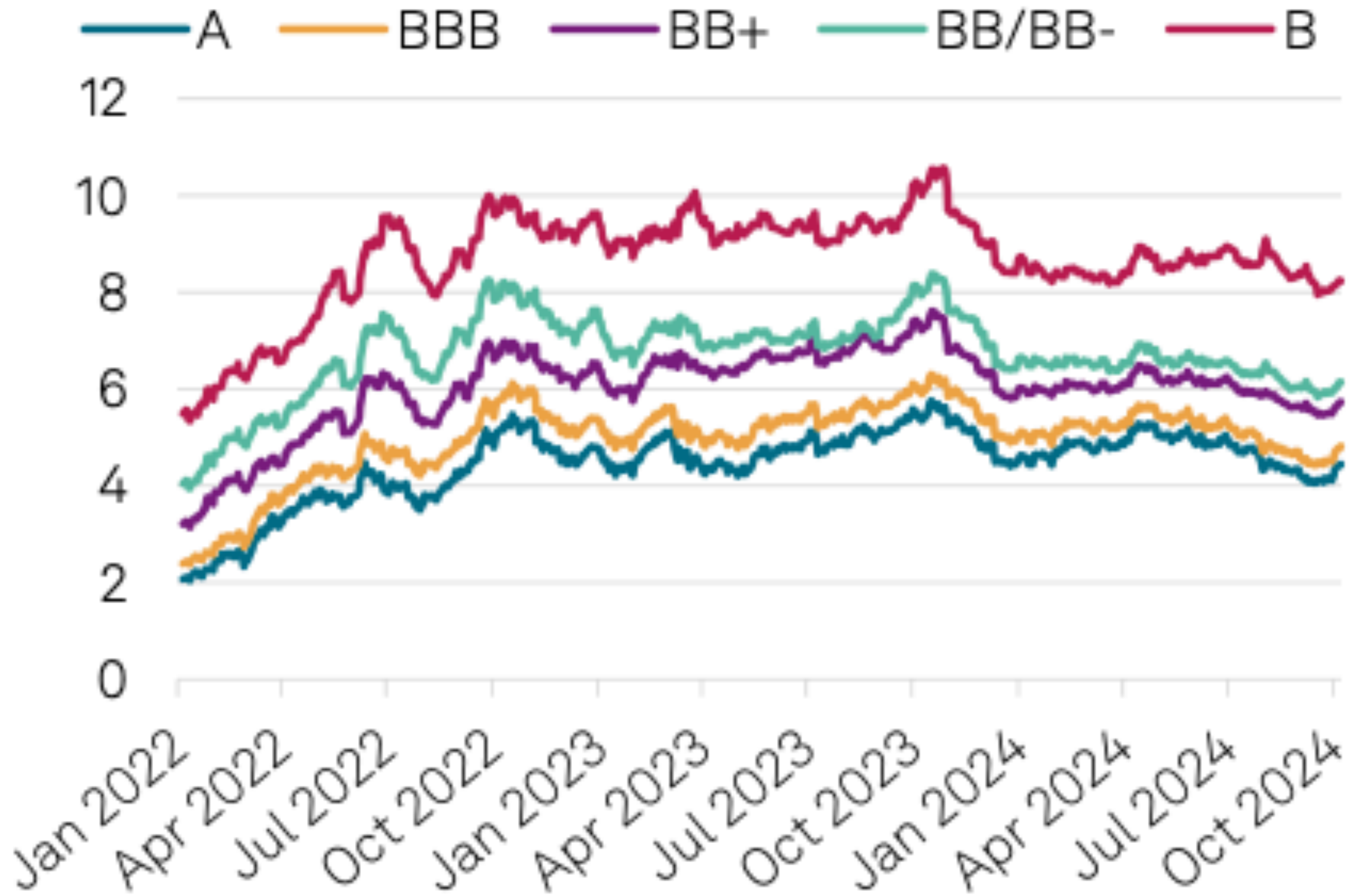
- In Europe, YtD defaults hitting record highs seen previously only in 2008, the number of defaults has dropped by 2 points, suggesting a gradual reversal



- Distressed defaults driving default rate

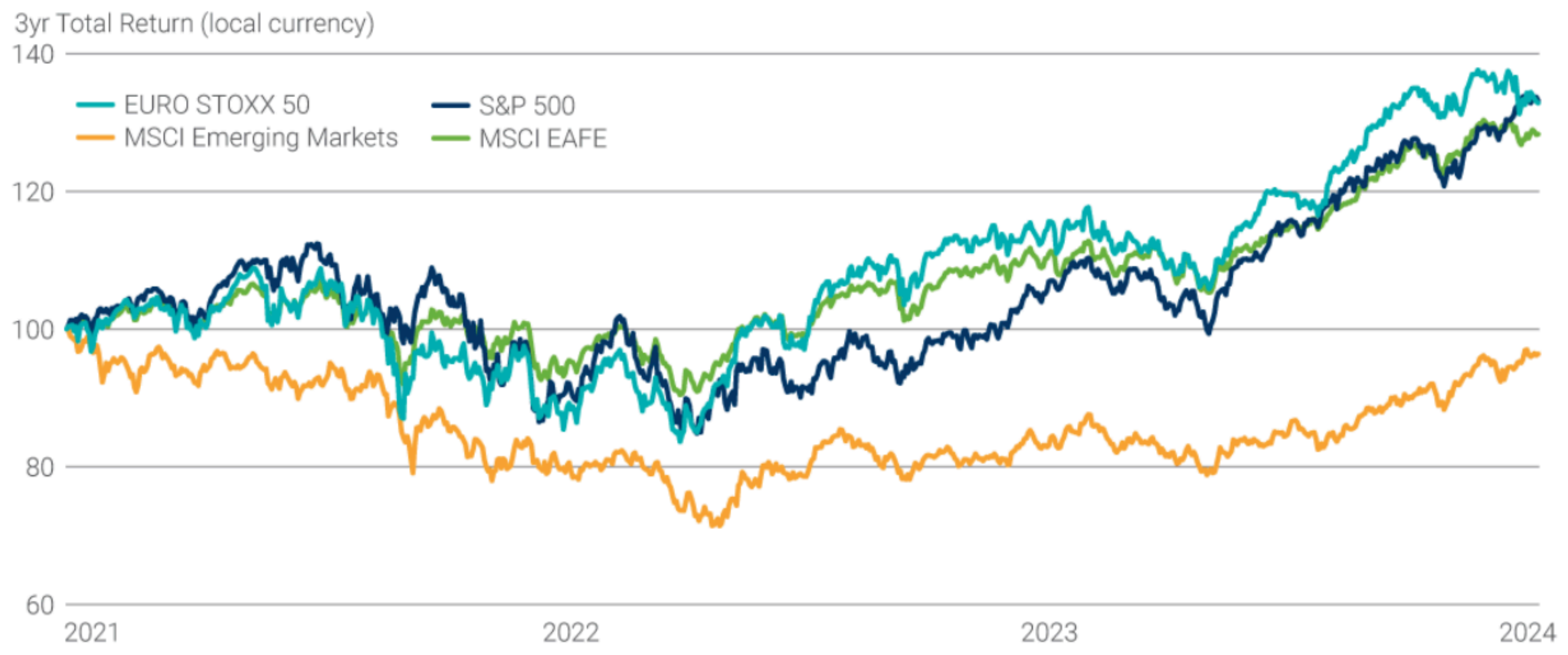
- Result of slowing economic growth

Rising uncertainties are affecting U.S. corporate rates (%)



- Corporate rates at various grades are volatile, with a consistent gradual decrease

Exhibit 4: European Corporate Bond Yields are Falling but Remain Elevated



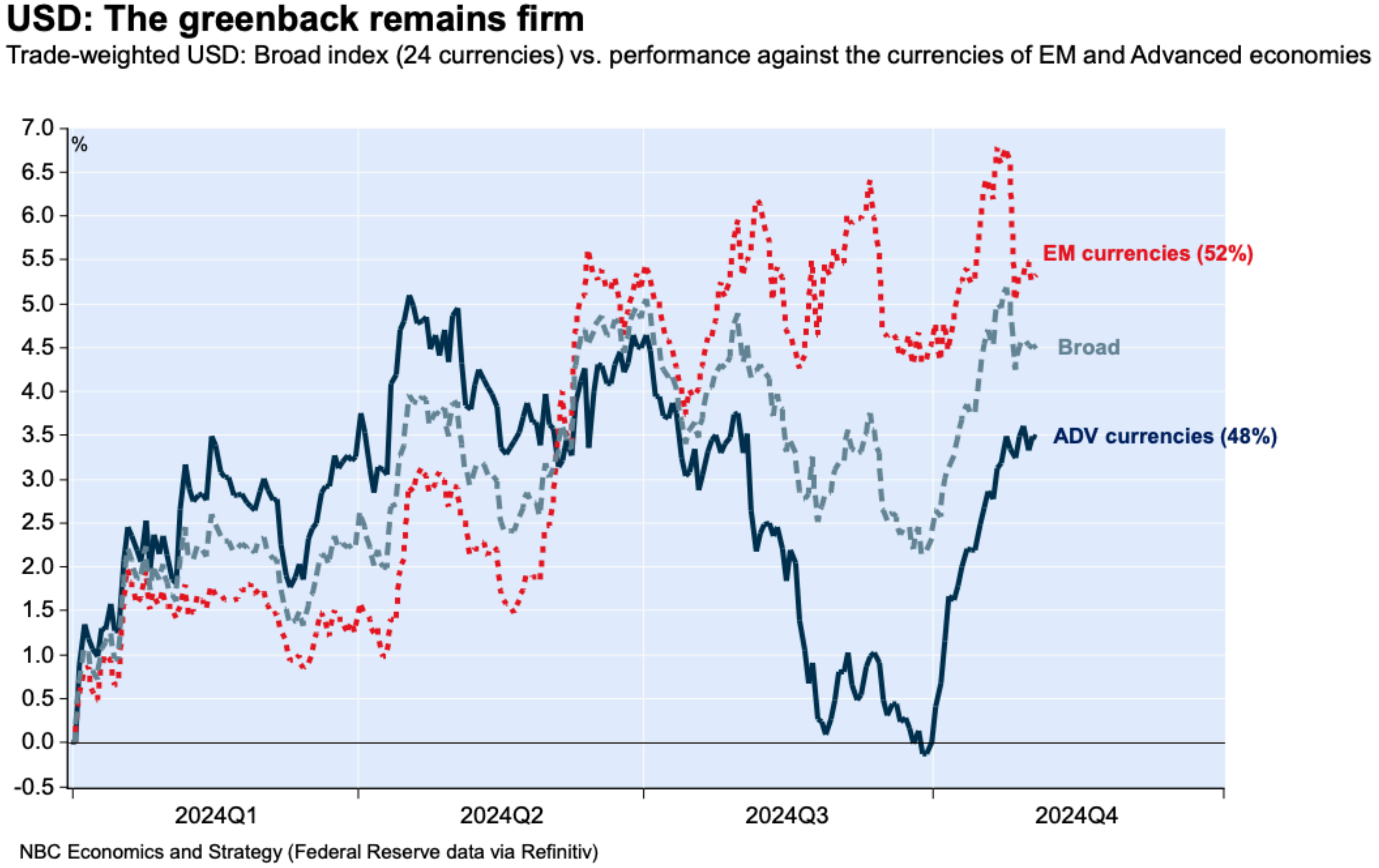
As at 30 September 2024
Source: LSEG Datastream

- Global outstanding corporate debt is up 3.2% since the beginning of the year, sitting at $24.3 trillion

Economic and Market Outlook

FOREX

- Into November, the weighted broad-dollar index is 4.5% higher than at the start of the year



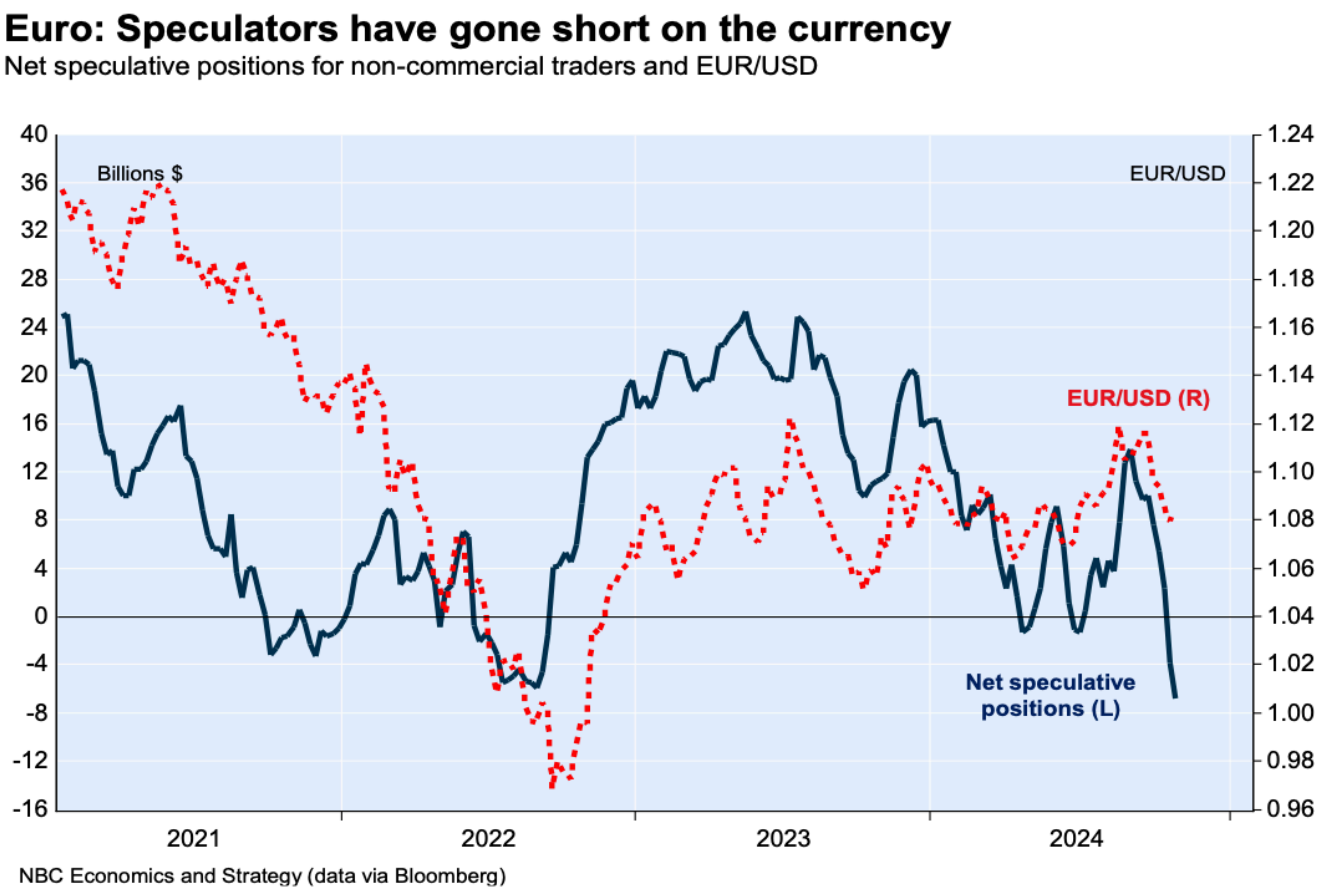
- This appreciation is likely due to strong GDP growth throughout 2024
- As of today, the index sits at 106.88, compared to the 104.20-104.30 range in late October
- Note that most developed countries are following suit in cutting interest rates, hence not making the US rate any less relatively attractive

- The Canadian dollar has struggled, reaching its worst levels since the pandemic at 1.406 CAD on the greenback, expected to hit 1.450 at the end of the month

- Explained by Canada's weak GDP growth

- Into Q4 of 2024, Canada's GDP growth is projected to hit 1.0% at most, short of the BoC's revised estimate of 1.5%

- Well short of the 2.1%-2.8% estimated growth potential



- The Euro has crashed, sitting at 1.05 USD/EURO, slumping more than 6% in September

- Could hit 1.00 USD/EURO

- EUR/USD is the most traded pair globally by far, making up 23$ of the FOREX, compared to runner up of USD/JPY at 14%

- This is likely due to fears over the upcoming Trump presidency, primarily tariff scares

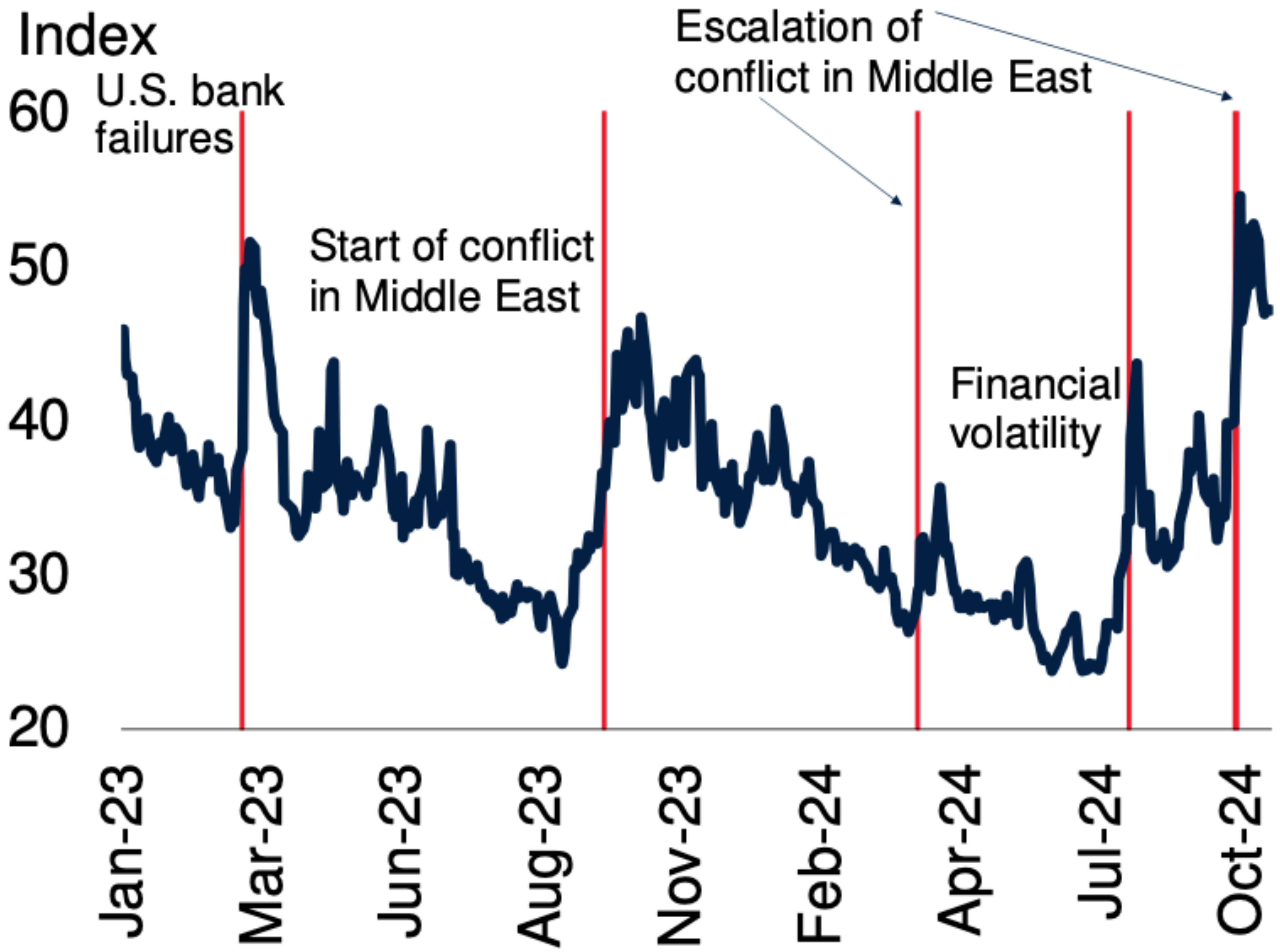
- Similarly, Mexican Peso has fallen by 6% and the Korean Won by 5.4% according to Reuters

- After stimulus measures, Chinese Yuan strengthened to 6.995 on the greenback in late September, the strongest since May 2023, and sits now at 7.245, again over fears of Trump presidency

Economic and Market Outlook

Commodities

- Geopolitical tensions have led to unstable oil prices in recent months
- Brent oil shot to a record $90/barrel earlier this year in April, now sitting at an elevated $73/barrel



- Even with high prices earlier this year and high volatility, oil price has been declining. This can be attributed to 3 reasons.

- Reason 1: Global consumption of oil is decelerating.

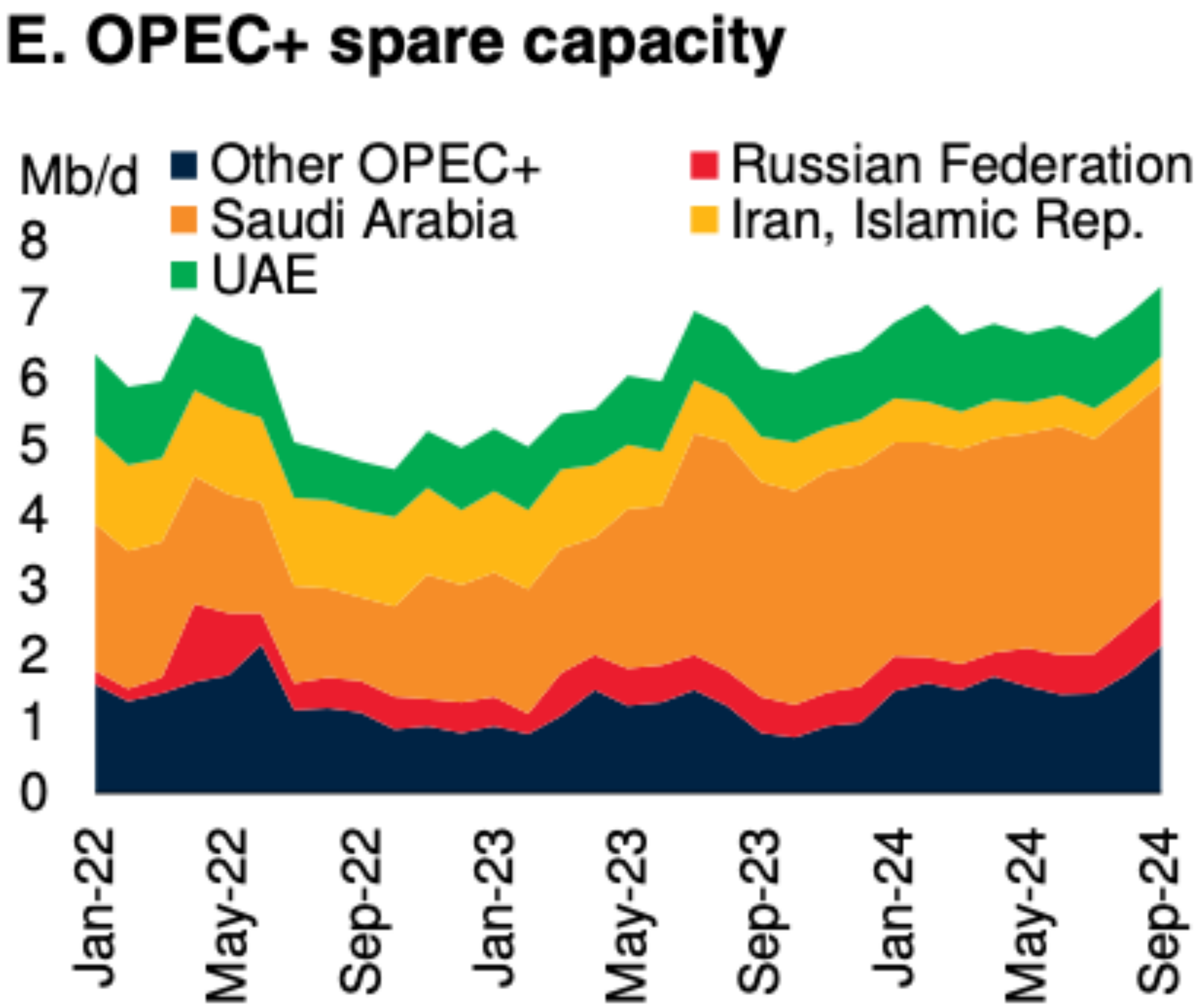
- In 2023, global oil demand increased by roughly 2 million barrels per day. In 2024, this figure sits at 1 million barrels per day.

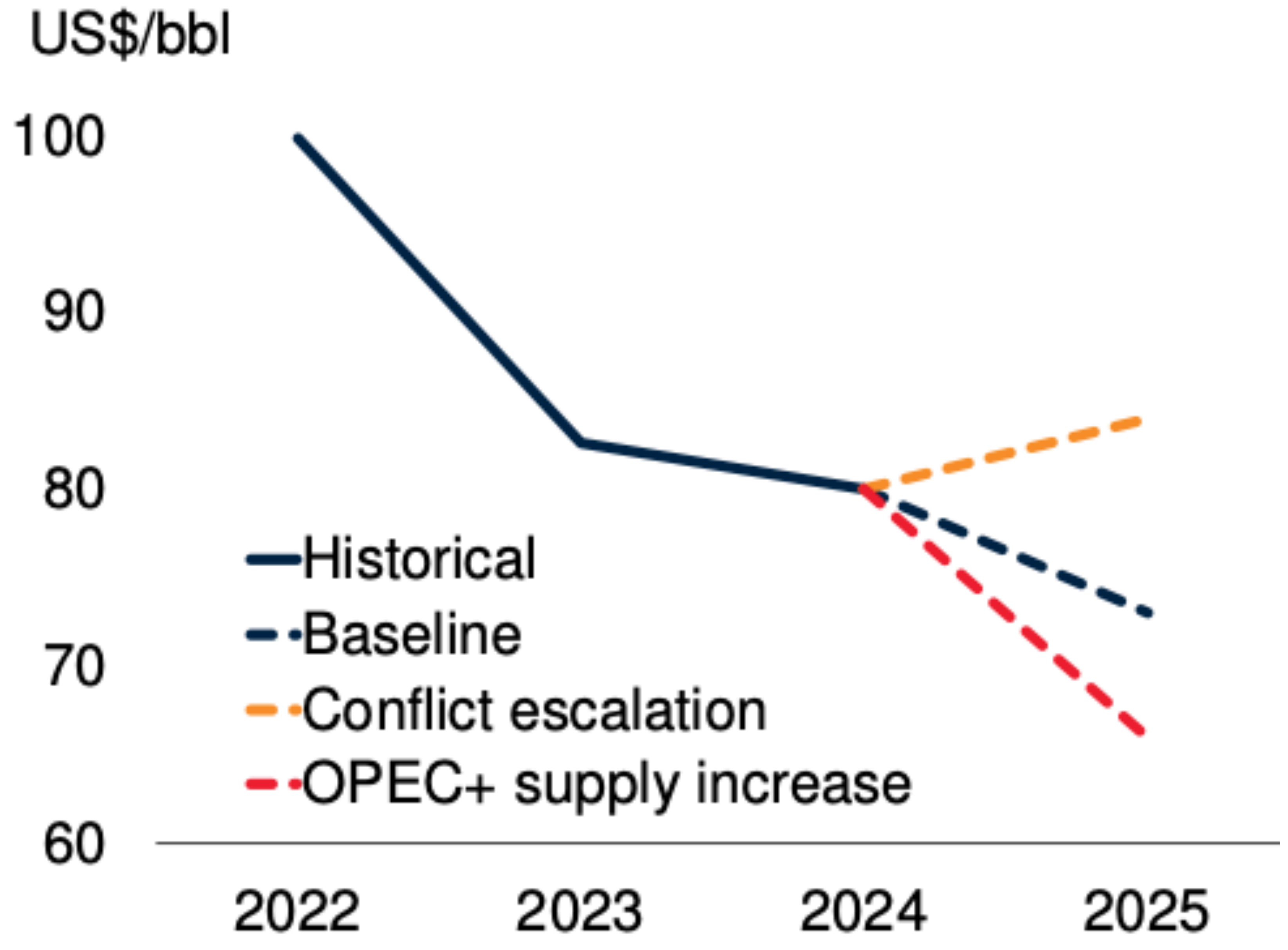
- A strong driver is China's recent contraction in oil demand, with China being the engine of global oil consumption

- Reason 2: Global oil supply continues to diversify

- Market share of non-OPEC+ producers is gradually increasing

- Reason 3: OPEC+ holds spare oil capacity of roughly 7% of current global consumption, a high, leading to potentially more supply in an already well-supplied market





- The World Bank's natural gas price index increased by 10% in Q3 of 2024
- Demand for American natural gas has hit a record high, undermining energy transition efforts
- European natural gas prices have been rising sharply, largely due to concerns over relations with Russia with the Russian-Ukraine war still waging
- As such, the European natural gas benchmark increased by 15% in Q3 of 2024
- Chinese consumption rose by 10% in the last quarter, and overall natural gas demand has increased by 2.8% through 2024

- In metal markets, prices have climbed in late September due to stimulus measures in China that are leading to increased economic activity

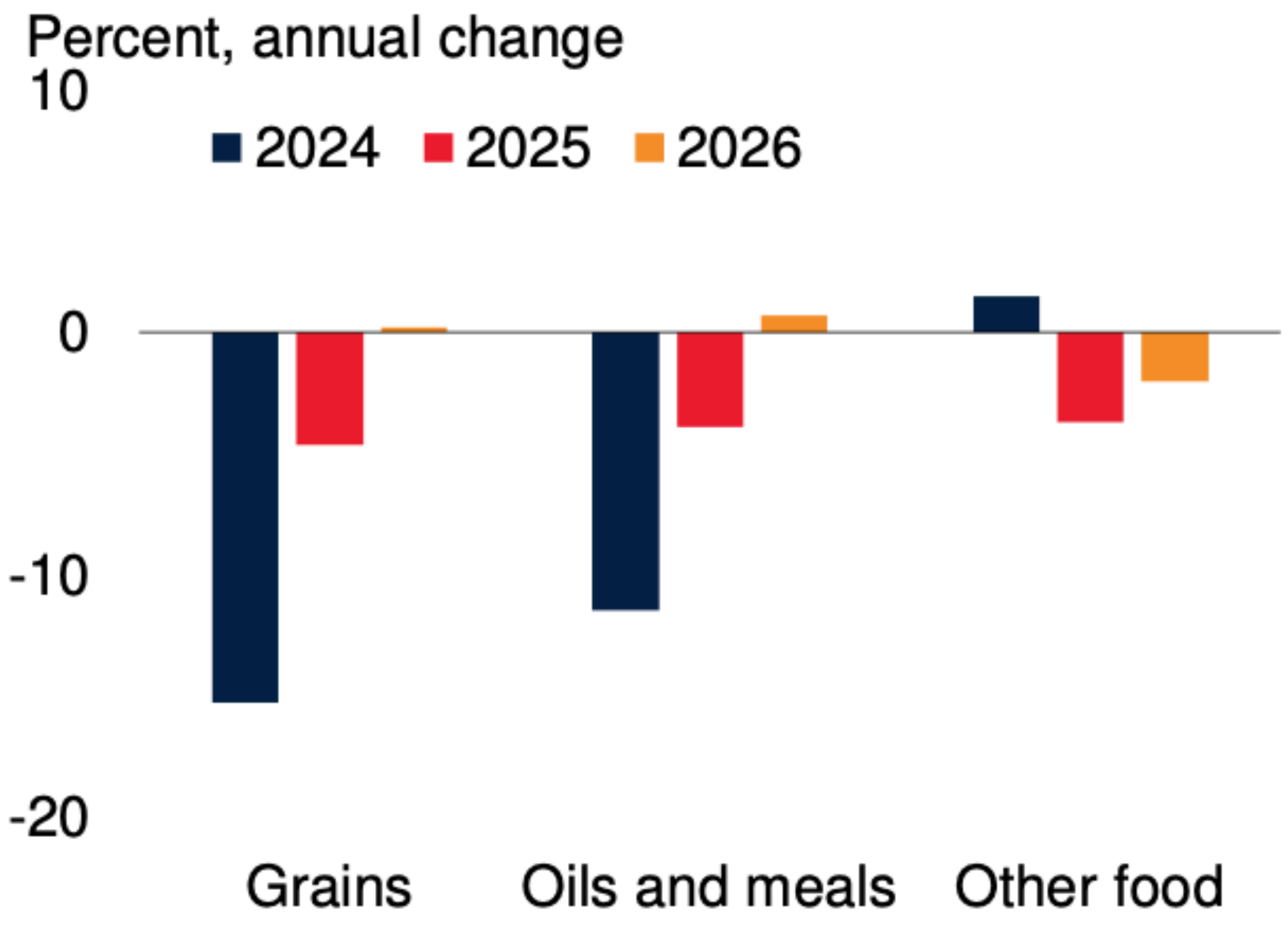
- From positive outlook and sustained demand, the World Bank base metals price index was up 10% in September

- Gold prices sit 27% above their December 2023 level, while iron has underperformed

- As a result of favourable climate conditions, supply for agricultural goods is remaining steady

- Prices are expected to fall by 4% within the next year

- The global agriculture market size has grown considerably in recent years, from $13,272.75 billion in 2023 to $14,356.23 billion in 2024 at a CAGR of 8.2%.



CAPE Ratio

- The CAPE ratio has been used since 1926, but was popularized by economist and Nobel laureate Robert Shiller in his 2000 book Irrational Exuberance

- Used to valuate equity

- Cyclically adjusted P/E ratio smoothens out P/E by considering a 10-year average of EPS, adjusted for inflation

- Strengths: more stable than P/E ratio, offering stronger predictive power for longer term equities

- Weaknesses: assumes mean reversion, structural changes unaccounted for (accounting, regulatory/policy, payout ratios), recessions and one-offs unaccounted for

- Weigand and Irons (2007) investigated market P/E and CAPE and its predictive power in future stock returns, aggregate earnings, and interest rates
- Found that the relation between the above ratios and future earnings/returns are similar except when P/E is very high

- Aras and Yilmaz (2008) demonstrated that investors in emerging markets could forecast future returns with solid accuracy for a 1-year period using the B/M ratio, with P/E playing a more minor role

- Davis et al. (2012) showed that valuation metrics such as P/E indeed have had an inverse relationship with future return, reaching similar conclusions using trailing 12-month earnings similar to the CAPE ratio

- Liem and Basana (2012) examined the relationship between P/E ratio and stock returns listed on the Indonesian Stock Exchange.

- Demonstrated that 6-month returns differ between low and high P/E stocks, while for longer periods there is no difference with various P/E values

- Goal: Replicate Shiller's result that the CAPE10 ratio has relatively high predictive power, particularly for forecasting 10-year returns

- Goal: Replicate Shiller's result that in times when CAPE <= 15.00, there are consistently higher returns over the next 10 years

We begin our empirical work by regressing real and excess stock returns on some explanatory variables that are known in advance (at the start of year t). For real returns, we consider the following variables:[2] the log dividend-price ratio, $\delta_t \equiv d_{t-1} - p_t$ (the dividend is lagged one year to ensure that it is known at the start of year t); the lagged dividend-growth rate, Δd_{t-1}; log earnings-price ratio $\epsilon_t \equiv e_{t-1} - p_t$; and two log earnings-price ratios based on moving averages of earnings. The latter two are a ten-year moving average of log real earnings minus current log real price, $\epsilon_t^{10} \equiv ((e_{t-1} + \cdots + e_{t-10})/10) - p_t$, and a thirty-year moving average of log real earnings minus current log real price, $\epsilon_t^{30} \equiv ((e_{t-1} + \cdots + e_{t-30})/30 - p_t$.

```python
df = pd.read_excel('ie_data.xls',sheet_name='Data',skiprows=7)
df.drop(df.tail(1).index,inplace=True)
df.columns = ['','S&P Comp Price','Dividend','Earnings',
              'CPI','','GS10 Interest Rate',
              '','','',
              '','','',
              '', '', '', '', '', '','','','']
df = df[['S&P Comp Price','Dividend','Earnings','CPI','GS10 Interest Rate']]

df['Real Price'] = df['S&P Comp Price'] * 315.67975 / df['CPI']
df['Real Earnings'] = df['Earnings'] * 315.67975 / df['CPI']
df['Real Dividend'] = df['Dividend'] * 315.67975 / df['CPI']

df['Real Earnings MA10'] = df['Real Earnings'].shift(-1).rolling(window=120).mean()
df.replace([np.inf, -np.inf], np.nan, inplace=True)
df.dropna(inplace=True)
df['CAPE10'] = np.log(df['Real Earnings MA10'])- np.log(df['Real Price'])

df['Real Earnings MA30'] = df['Real Earnings'].shift(-1).rolling(window=360).mean()
df.replace([np.inf, -np.inf], np.nan, inplace=True)
df.dropna(inplace=True)
df['CAPE30'] = np.log(df['Real Earnings MA30'])- np.log(df['Real Price'])

df['Dividend Growth Rate'] = (df['Real Dividend'] / df['Real Dividend'].shift(-1)).shift(1)
df['log D/P'] = np.log(df['Real Dividend'].shift(-1) / df['Real Price'])
df['log P/E'] = np.log(df['Real Price'] / df['Real Earnings'])

df.replace([np.inf, -np.inf], np.nan, inplace=True)
df.dropna(inplace=True)
df
```

```
/var/folders/yk/l64w5c2s01l4zktkbrqwbf1r0000gn/T/ipykernel_26997/2567069366.py:17: FutureWar
ed in a future version. To retain the old behavior, explicitly call `result.infer_objects(co
e.no_silent_downcasting', True)`
  df.replace([np.inf, -np.inf], np.nan, inplace=True)
```

	S&P Comp Price	Dividend	Earnings	CPI	GS10 Interest Rate	Real Price	Real Earnings	Real Dividend
479	9.050000	0.470000	0.730000	9.229089	3.974167	309.554026	24.969551	16.076286

[237]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.408
Model:	OLS	**Adj. R-squared:**	0.405
Method:	Least Squares	**F-statistic:**	112.4
Date:	Sun, 10 Nov 2024	**Prob (F-statistic):**	2.67e-90
Time:	19:09:57	**Log-Likelihood:**	-874.64
No. Observations:	820	**AIC:**	1761.
Df Residuals:	814	**BIC:**	1790.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.1396	1.849	0.616	0.538	-2.490	4.769
x1	0.2996	0.183	1.633	0.103	-0.061	0.660
x2	0.3716	0.186	2.002	0.046	0.007	0.736
x3	5.5128	1.887	2.922	0.004	1.809	9.216
x4	0.3756	0.176	2.137	0.033	0.031	0.721
x5	-0.8655	0.113	-7.670	0.000	-1.087	-0.644

Omnibus:	16.012	**Durbin-Watson:**	0.023
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	16.452
Skew:	0.327	**Prob(JB):**	0.000268
Kurtosis:	3.233	**Cond. No.**	606.

```python
X1 = df[['CAPE10','Dividend Growth Rate','log D/P','log P/E']]
y1 = df['CAPE30']
X1 = sm.add_constant(X1)
VIF_cape30 = 1 / (1 - sm.OLS(y1,X1).fit().rsquared)
print(f"VIF_cape30: {VIF_cape30}")

X2 = df[['CAPE30','Dividend Growth Rate','log D/P','log P/E']]
y2 = df['CAPE10']
X2 = sm.add_constant(X2)
VIF_cape10 = 1 / (1 - sm.OLS(y2,X2).fit().rsquared)
print(f"VIF_cape10: {VIF_cape10}")

X3 = df[['CAPE10','CAPE30','log D/P','log P/E']]
y3 = df['Dividend Growth Rate']
X3 = sm.add_constant(X3)
VIF_dgr = 1 / (1 - sm.OLS(y3,X3).fit().rsquared)
print(f"VIF_dgr: {VIF_dgr}")

X4 = df[['CAPE10','Dividend Growth Rate','CAPE30','log P/E']]
y4 = df['log D/P']
X4 = sm.add_constant(X4)
VIF_logdp = 1 / (1 - sm.OLS(y4,X4).fit().rsquared)
print(f"VIF_logdp: {VIF_logdp}")

X5 = df[['CAPE10','Dividend Growth Rate','log D/P','CAPE30']]
y5 = df['log P/E']
X5 = sm.add_constant(X5)
VIF_logpe = 1 / (1 - sm.OLS(y5,X5).fit().rsquared)
print(f"VIF_logpe: {VIF_logpe}")
```

```
VIF_cape30: 15.187975922517715
VIF_cape10: 13.843680546677996
VIF_dgr: 1.1481151163294614
VIF_logdp: 6.893169887857735
VIF_logpe: 2.845353855891372
```

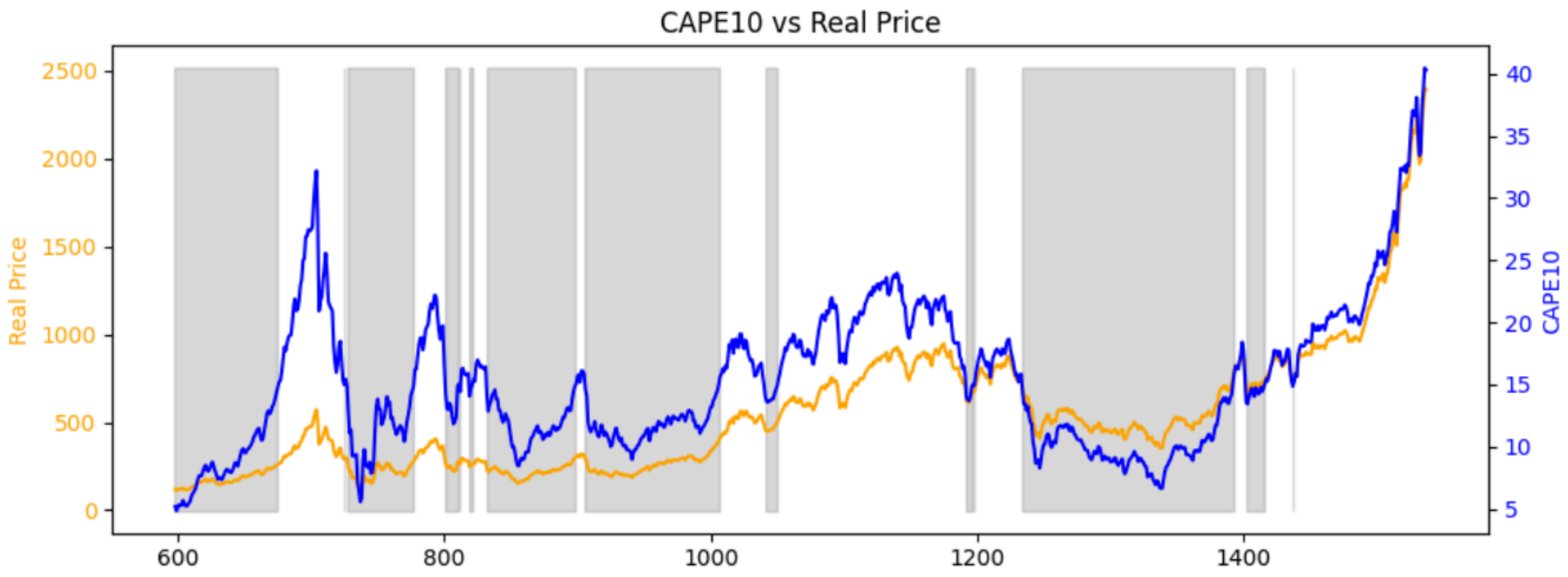
- With just CAPE10,

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            15yr_forward   R-squared:                       0.332
Model:                             OLS   Adj. R-squared:                  0.331
Method:                  Least Squares   F-statistic:                     466.1
Date:                 Fri, 15 Nov 2024   Prob (F-statistic):           3.09e-84
Time:                         19:44:29   Log-Likelihood:                -1248.6
No. Observations:                  940   AIC:                             2501.
Df Residuals:                      938   BIC:                             2511.
Df Model:                            1
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.4941      0.083     42.273      0.000       3.332       3.656
CAPE10        -0.1094      0.005    -21.589      0.000      -0.119      -0.099
==============================================================================
Omnibus:                        77.720   Durbin-Watson:                   0.012
Prob(Omnibus):                   0.000   Jarque-Bera (JB):               95.896
Skew:                            0.778   Prob(JB):                     1.50e-21
Kurtosis:                        3.160   Cond. No.                         45.4
==============================================================================
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             7yr_forward   R-squared:                       0.143
Model:                             OLS   Adj. R-squared:                  0.142
Method:                  Least Squares   F-statistic:                     156.4
Date:                 Fri, 15 Nov 2024   Prob (F-statistic):           2.71e-33
Time:                         19:44:29   Log-Likelihood:                -840.47
No. Observations:                  940   AIC:                             1685.
Df Residuals:                      938   BIC:                             1695.
Df Model:                            1
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          2.0052      0.054     37.451      0.000       1.900       2.110
CAPE10        -0.0410      0.003    -12.504      0.000      -0.047      -0.035
==============================================================================
Omnibus:                        77.085   Durbin-Watson:                   0.017
Prob(Omnibus):                   0.000   Jarque-Bera (JB):               95.593
Skew:                            0.781   Prob(JB):                     1.75e-21
Kurtosis:                        3.007   Cond. No.                         45.4
==============================================================================
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            10yr_forward   R-squared:                       0.159
Model:                             OLS   Adj. R-squared:                  0.158
Method:                  Least Squares   F-statistic:                     177.6
Date:                 Fri, 15 Nov 2024   Prob (F-statistic):           3.16e-37
Time:                         19:44:29   Log-Likelihood:                -938.65
No. Observations:                  940   AIC:                             1881.
Df Residuals:                      938   BIC:                             1891.
Df Model:                            1
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          2.2356      0.059     37.613      0.000       2.119       2.352
CAPE10        -0.0485      0.004    -13.326      0.000      -0.056      -0.041
==============================================================================
Omnibus:                        57.089   Durbin-Watson:                   0.014
Prob(Omnibus):                   0.000   Jarque-Bera (JB):               65.652
Skew:                            0.637   Prob(JB):                     5.54e-15
Kurtosis:                        2.768   Cond. No.                         45.4
==============================================================================
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            25yr_forward   R-squared:                       0.160
Model:                             OLS   Adj. R-squared:                  0.159
Method:                  Least Squares   F-statistic:                     178.8
Date:                 Fri, 15 Nov 2024   Prob (F-statistic):           1.89e-37
Time:                         19:44:29   Log-Likelihood:                -1491.5
No. Observations:                  940   AIC:                             2987.
Df Residuals:                      938   BIC:                             2997.
Df Model:                            1
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.8064      0.107     35.563      0.000       3.596       4.016
CAPE10        -0.0877      0.007    -13.371      0.000      -0.101      -0.075
==============================================================================
Omnibus:                       105.986   Durbin-Watson:                   0.015
Prob(Omnibus):                   0.000   Jarque-Bera (JB):               47.701
Skew:                            0.366   Prob(JB):                     4.38e-11
Kurtosis:                        2.174   Cond. No.                         45.4
==============================================================================
```



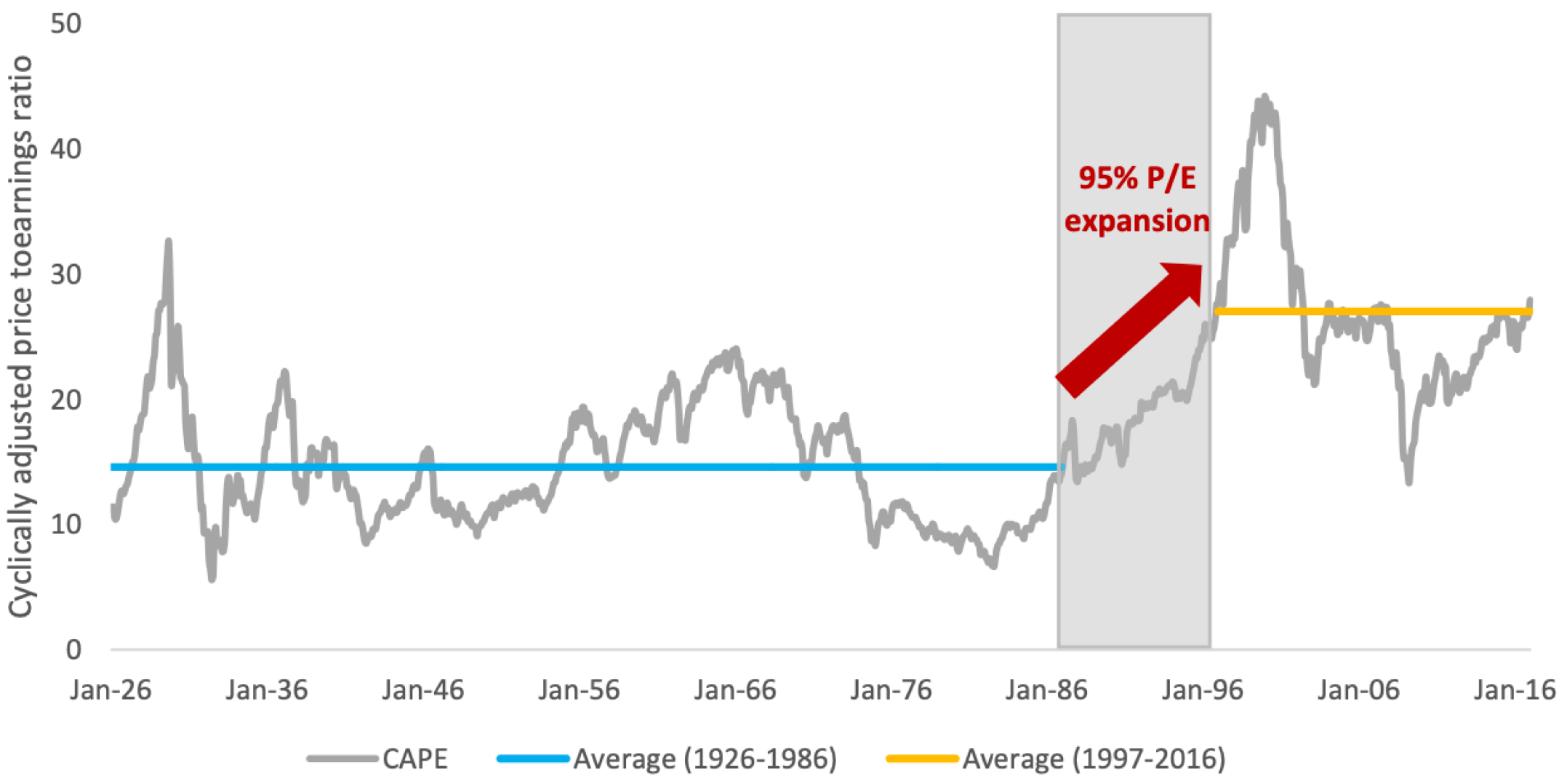

```python
df1['20yr_forward_window'] = df1['Real Price'].rolling(window = 240).mean().shift(179
df1.dropna(inplace = True)

condition = df1['CAPE10'] <= 15
subset_smaller = df1[condition].reset_index(drop=True)
subset_larger = df1[~condition].reset_index(drop=True)

print('Larger CAPE mean: ', np.mean(subset_larger['20yr_forward_window']))
print('Smaller CAPE mean: ', np.mean(subset_smaller['20yr_forward_window']))
print ('---------------------------------------')
print('Larger CAPE median: ', np.median(subset_larger['20yr_forward_window']))
print('Smaller CAPE median: ', np.median(subset_smaller['20yr_forward_window']))
print ('---------------------------------------')
print('Larger CAPE std: ', np.std(subset_larger['20yr_forward_window']))
print('Smaller CAPE std: ', np.std(subset_smaller['20yr_forward_window']))
```

```
Larger CAPE mean:  428.8270746216655
Smaller CAPE mean:  462.61511898344463
---------------------------------------
Larger CAPE median:  274.1379168384396
Smaller CAPE median:  454.324563989553
---------------------------------------
Larger CAPE std:  207.6130167471679
Smaller CAPE std:  129.74679819939846
```

SoP Valuation

- “The accuracy of the U.S. stock return forecasts based on the cyclically-adjusted CAPE ratio has deteriorated since 1985”

Figure 3: *Which mean will the CAPE ratio revert to?*



Source: Calculations based on the data obtained from Robert Shiller website, at aida.wss.yale.edu/~shiller/data.htm.

- Strengths: Clearer breakdown of returns into fundamental bits: changes in valuation, earnings growth, D/P
- Reduces estimation bias by considering directly measure components

the CAPE ratio itself. Specifically, we estimate a vector autoregressive (VAR) model with twelve monthly lags of the form:

$$(2)\ X_t = \alpha + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_{12} X_{t-12} + \varepsilon_t,$$

where $\boldsymbol{X_t}$ is a vector of the five variables in the VAR model in logarithmic form, including:

- CAPE real earnings yield, or $1/CAPE$
- Real 10-year bond yields, or nominal Treasury yield less an estimated 10-year expected inflation rate (see Appendix)
- Year-over-year CPI inflation rate
- Realized S&P500 price volatility, over trailing 12 months, and
- Realized volatility of changes in our real bond yield series, over trailing 12 months.[5]

```
df['10yr_forward'] = df['Real Price'].shift(-120) / df['Real Price']
df.replace([np.inf, -np.inf], np.nan, inplace=True)
df.dropna(inplace=True)

X = df[['delta_CPI','delta_Yield','delta_Earnings','delta_D/P']].to_numpy()
y = df['1/CAPE10'].to_numpy()
X = sm.add_constant(X)
model = sm.OLS(y,X).fit()
model.summary()
```

OLS Regression Results

Step 2: *Impute stock returns from the CAPE earnings yield forecasts*

Rather than estimating equation (1), we calculate future returns directly based on their three components, thereby reducing estimation bias. We adapt the framework of Bogle and Nolan (2015) and Ferreira and Santa-Clara (2011) in imputing monthly stock returns by their "sum of parts" identity:

$$(3)\ r_{t+1} \equiv \%\Delta PE_{t+1} + \%\Delta E_{t+1} + DP_{t+1}$$

where %ΔPE is the percentage change in P/E ratio, %ΔE is earnings growth, and DP is the

```
df['1/CAPE10'] = 1 / df['CAPE10']

df['Yield_10_later'] = df['10 Year Annualized Bonds Real Return'].shift(-120)
df['delta_Yield'] = 100 * (df['Yield_10_later'] - df['10 Year Annualized Bonds Real Return']) / df['10 Year Annualized Bonds Real Return']

df['Earnings_10_later'] = df['Real Earnings'].shift(-120)
df['delta_Earnings'] = 100 * (df['Earnings_10_later'] - df['Real Earnings'])/ df['Real Earnings']

df['D/P'] = df['Real Dividend'] / df['Real Price']
df['D/P_10_later'] = df['D/P'].shift(-120)
df['delta_D/P'] = 100 * (df['D/P_10_later'] - df['D/P']) / df['D/P']
df.dropna()
```

```python
df['10yr_forward'] = (df['Real Price'].shift(-120) / df['Real Price']) * 100
df.replace([np.inf, -np.inf], np.nan, inplace=True)
df.dropna(inplace=True)

df['1/CAPE10_lag1'] = df['1/CAPE10'].shift(-1)
df['1/CAPE10_lag2'] = df['1/CAPE10'].shift(-2)
df['1/CAPE10_lag3'] = df['1/CAPE10'].shift(-3)
df['1/CAPE10_lag4'] = df['1/CAPE10'].shift(-4)
df['1/CAPE10_lag5'] = df['1/CAPE10'].shift(-5)
df['1/CAPE10_lag6'] = df['1/CAPE10'].shift(-6)
df['1/CAPE10_lag7'] = df['1/CAPE10'].shift(-7)
df['1/CAPE10_lag8'] = df['1/CAPE10'].shift(-8)
df['1/CAPE10_lag9'] = df['1/CAPE10'].shift(-9)
df['1/CAPE10_lag10'] = df['1/CAPE10'].shift(-10)
df['1/CAPE10_lag11'] = df['1/CAPE10'].shift(-11)
df['1/CAPE10_lag12'] = df['1/CAPE10'].shift(-12)

df.replace([np.inf, -np.inf], np.nan, inplace=True)
df.dropna(inplace=True)

X = df[['1/CAPE10_lag1','1/CAPE10_lag2','1/CAPE10_lag3','1/CAPE10_lag4',
       '1/CAPE10_lag5','1/CAPE10_lag6','1/CAPE10_lag7','1/CAPE10_lag8',
       '1/CAPE10_lag9','1/CAPE10_lag10','1/CAPE10_lag11','1/CAPE10_lag12']].to_numpy()
y = df['1/CAPE10'].to_numpy()
X = sm.add_constant(X)
model = sm.OLS(y,X).fit()

predicted_values = []
for i in range(len(X)):
    prediction = model.predict(X[i])
    predicted_values.append(prediction[0])

df['Predicted_1/CAPE10'] = predicted_values

df.replace([np.inf, -np.inf,0], np.nan, inplace=True)
df.dropna(inplace=True)
df
```

```
df['CAPE10_after_forecast'] = 1 / df['Predicted_1/CAPE10']
df['CAPE10_after_forecast_shifted'] = df['CAPE10_after_forecast'].shift(1)

df.replace([np.inf, -np.inf,0], np.nan, inplace=True)
df.dropna(inplace=True)

df['deltaP/E_after'] = 100 * (df['CAPE10_after_forecast_shifted'] -
                            df['CAPE10_after_forecast'])/df['CAPE10_after_forecast']

X = df[['deltaP/E_after','delta_Earnings','D/P']].to_numpy()
y = df['10yr_forward'].to_numpy()
X = sm.add_constant(X)
model = sm.OLS(y,X).fit()
model.summary()
```

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.527
Model:	OLS	**Adj. R-squared:**	0.525
Method:	Least Squares	**F-statistic:**	199.1
Date:	Sat, 16 Nov 2024	**Prob (F-statistic):**	1.08e-86
Time:	16:51:29	**Log-Likelihood:**	-2768.6
No. Observations:	539	**AIC:**	5545.
Df Residuals:	535	**BIC:**	5562.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-37.5542	8.463	-4.437	0.000	-54.179	-20.929
x1	0.1636	0.400	0.409	0.683	-0.622	0.950
x2	0.7336	0.037	19.764	0.000	0.661	0.807
x3	2856.1665	159.269	17.933	0.000	2543.297	3169.036

Omnibus:	72.134	**Durbin-Watson:**	0.047
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	148.503
Skew:	0.756	**Prob(JB):**	5.66e-33
Kurtosis:	5.080	**Cond. No.**	4.65e+03