02 - Naive Baseline Models

Before building sophisticated models (GARCH, LSTM, Transformer), we must establish how good simple approaches can be. This provides insight into whether or not increasingly complex models are justified.

Importance of Baselines

- **In machine learning:** Complex models often barely beat naive baselines
- **In volatility forecasting:** High persistence makes "tomorrow = today" quite powerful
- **For this project:** These baselines set the bar that GARCH/LSTM/Transformer must clear

Baselines Tested

- **Persistence** - Tomorrow = Today (leverages autocorrelation)
- **Rolling means** - Smooth recent history (5, 10, 21 days)
- **Global mean** - Historical average (tests mean reversion)

Key Finding Preview

Persistence achieves RMSE = 0.000698, which is very low.

This is because `rv_21` is strongly autocorrelated (ACF = 0.31 from `NB01`), which means volatility changes slowly. Simple persistence uses this very fact to provide extremely close predictions.

Imports and Configuration

In [1]:
```
import os
from pathlib import Path
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pathlib import Path
from sklearn.metrics import mean_squared_error, mean_absolute_error

plt.style.use("seaborn-v0_8")
```

In [2]:
```
# Paths
PROCESSED_DIR = Path("../data/processed")
RESULTS_DIR = Path("../results/baselines/")
FIG_DIR = Path("../results/figures/baselines")
```

```
RESULTS_DIR.mkdir(parents=True, exist_ok=True)
FIG_DIR.mkdir(parents=True, exist_ok=True)
```

Load Data

In [3]:
```
df = pd.read_csv(PROCESSED_DIR / "modeling_dataset.csv")
df["Date"] = pd.to_datetime(df["Date"])

df = df.sort_values("Date").reset_index(drop=True)

print(df.head(), "\n")
print(df.tail(), "\n")
print(df.isna().sum())

target_col = "rv_21"
```

```
        Date         Open         High          Low        Close    Adj Close  \
0 2000-02-02  1409.280029  1420.609985  1403.489990  1409.119995  1409.119995   
1 2000-02-03  1409.119995  1425.780029  1398.520020  1424.969971  1424.969971   
2 2000-02-04  1424.969971  1435.910034  1420.630005  1424.369995  1424.369995   
3 2000-02-07  1424.369995  1427.150024  1413.329956  1424.239990  1424.239990   
4 2000-02-08  1424.239990  1441.829956  1424.239990  1441.719971  1441.719971   

       Volume  log_return     rv_21  
0  1038600000   -0.000114  0.016190  
1  1146500000    0.011185  0.013915  
2  1045100000   -0.000421  0.013915  
3   918100000   -0.000091  0.013916  
4  1047700000    0.012198  0.012880   

           Date         Open         High          Low        Close  \
6496 2025-12-01  6812.299805  6843.649902  6799.939941  6812.629883   
6497 2025-12-02  6830.959961  6851.549805  6806.709961  6829.370117   
6498 2025-12-03  6815.290039  6862.419922  6810.430176  6849.720215   
6499 2025-12-04  6866.470215  6866.470215  6827.120117  6857.120117   
6500 2025-12-05  6866.319824  6895.779785  6858.290039  6870.399902   

        Adj Close      Volume  log_return     rv_21  
6496  6812.629883  4549370000   -0.005338  0.009322  
6497  6829.370117  4582290000    0.002454  0.009320  
6498  6849.720215  4736780000    0.002975  0.009336  
6499  6857.120117  4872440000    0.001080  0.008938  
6500  6870.399902  4944560000    0.001935  0.008916   

Date          0
Open          0
High          0
Low           0
Close         0
Adj Close     0
Volume        0
log_return    0
rv_21         0
dtype: int64
```

Train-Test Split

Split strategy: 80/20 chronological (no shuffling)

Reasons for preserving chronology:

- Time series have temporal dependencies which are broken by shuffling
- Models must forecast the future, not interpolate the past
- Simulates real-world deployment i.e. train on history, predict tomorrow

The test set includes extreme volatility regime (COVID), testing whether baselines handle shocks or just track stable periods.

In [4]:
```
split_ratio = 0.8
split_index = int(len(df) * split_ratio)

train = df.iloc[:split_index].copy()
test = df.iloc[split_index:].copy()

print("Train period: ", train["Date"].min(), "to", train["Date"].max())
print("Test period: ", test["Date"].min(), "to", test["Date"].max())
print("Test observations:", len(test))
print("Years of test data:", round(len(test) / 252, 2))

y_train = train[target_col].values
y_test = test[target_col].values
dates_test = test["Date"].values
```

```
Train period:  2000-02-02 00:00:00 to 2020-10-01 00:00:00
Test period:  2020-10-02 00:00:00 to 2025-12-05 00:00:00
Test observations: 1301
Years of test data: 5.16
```

Baseline Models

We now construct the following baselines-

- Persistence: forecast tomorrow as today.
- Rolling mean with window 5.
- Rolling mean with window 10.
- Rolling mean with window 21.
- Global mean of the training set.

These baselines are simple but informative. They show how much structure an advanced model must capture to outperform naive strategies.

Persistence Model

Forecast rule: `rv_21(t+1) = rv_21(t)`

We know that `rv_21` has strong autocorrelation. This means:

- If volatility is high today, it's likely high tomorrow
- Slow-moving series means yesterday is informative

In [5]:
```
train["persistence"] = train[target_col].shift(1)
test["persistence"] = test[target_col].shift(1)

# First test forecast uses the last training value
test.loc[test.index[0],"persistence"] = train[target_col].iloc[-1]
```

Rolling Mean Baselines

Forecast rule: Forecast = average of last N observations

Window choices:

- **5 days:** ~1 trading week (responsive to recent changes)
- **10 days:** ~2 trading weeks (balanced)
- **21 days:** ~1 trading month (matches `rv_21` construction)

We use the final training rolling mean as a constant forecast across the entire test set. This is leak-free but static, so it doesn't adapt to volatility regime changes.

This is intentionally simplistic. Walk-forward rolling means (updating with each test observation) would perform better but will complicate direct comparison with GARCH/neural models which make true out-of-sample forecasts.

In [6]:
```
for w in [5, 10, 21]:
    roll_name = f"roll_mean_{w}"
    train[roll_name] = train[target_col].rolling(w).mean()

    last_roll_value = train[roll_name].iloc[-1]
    test[roll_name] = last_roll_value
```

Global Mean Baseline

Forecast rule: `rv_21(t+1) = mean(training rv_21)`

What this tests:

- **Assumption:** Volatility always reverts to its long-run average
- **Forecast:** Constant (~1% volatility) regardless of current level

When this works well:

- Stable periods (volatility near historical average)

- Long forecast horizons (short-term noise averages out)

When this fails:

- Regime shifts (2008 crisis, COVID spike)
- Persistent deviations from mean

From `NB01`, we know volatility is mean-reverting but also highly autocorrelated. Global mean captures the first property but not the second.

In [7]:
```
global_mean = y_train.mean()
test["global_mean"] = global_mean
```

Evaluation Metrics

We compute RMSE and MAE for each baseline. These metrics provide complementary views of forecast performance.

In [8]:
```
results = []

baseline_cols = ["persistence", "roll_mean_5", "roll_mean_10", "roll_mean_21", "glo

for col in baseline_cols:
    preds = test[col].values
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    mae = mean_absolute_error(y_test, preds)

    results.append({
        "model": col,
        "rmse": rmse,
        "mae": mae
    })

metrics_df = pd.DataFrame(results)
print(metrics_df)

best_model = metrics_df.loc[metrics_df['rmse'].idxmin(), 'model']
best_rmse = metrics_df['rmse'].min()

print("\n=== Baseline Summary ===\n")
print(f"Lowest RMSE comes from: {best_model}")
print(f"RMSE value: {best_rmse:.6f}")
```

```
          model      rmse       mae
0   persistence  0.000698  0.000351
1   roll_mean_5  0.007216  0.006536
2  roll_mean_10  0.006772  0.006086
3  roll_mean_21  0.005747  0.005011
4   global_mean  0.004536  0.003477

=== Baseline Summary ===

Lowest RMSE comes from: persistence
RMSE value: 0.000698
```

Interpretation

Performance Ranking:

1. **Persistence:** RMSE = 0.000698 (best)
2. **Global mean:** RMSE = 0.004536
3. **Rolling mean (21):** RMSE = 0.005747
4. **Rolling mean (10):** RMSE = 0.006772
5. **Rolling mean (5):** RMSE = 0.007216 (worst)

Key Insights:

Persistence dominates

- Better than all other baselines by a large margin
- Confirms `NB01` finding: high autocorrelation (ACF = 0.31) makes "tomorrow = today" powerful
- This is the bar GARCH/LSTM/Transformer must clear

Global mean outperforms rolling means

- Rolling means are too smooth (lag reality) while global mean captures the right average level
- Shows that *smoothing ≠ better forecasting* for volatile series

Shorter windows hurt more

- 5-day rolling worst (RMSE = 0.007216)
- 21-day rolling better (RMSE = 0.005747)
- This is because shorter windows over-react to noise while longer windows remain closer to stable mean

Absolute errors are small

- All RMSEs < 0.008 (`rv_21` typically ranges between 0.5% - 3%)
- However, relative differences are huge (10× between best and worst)

Plots

Baseline Forecasts

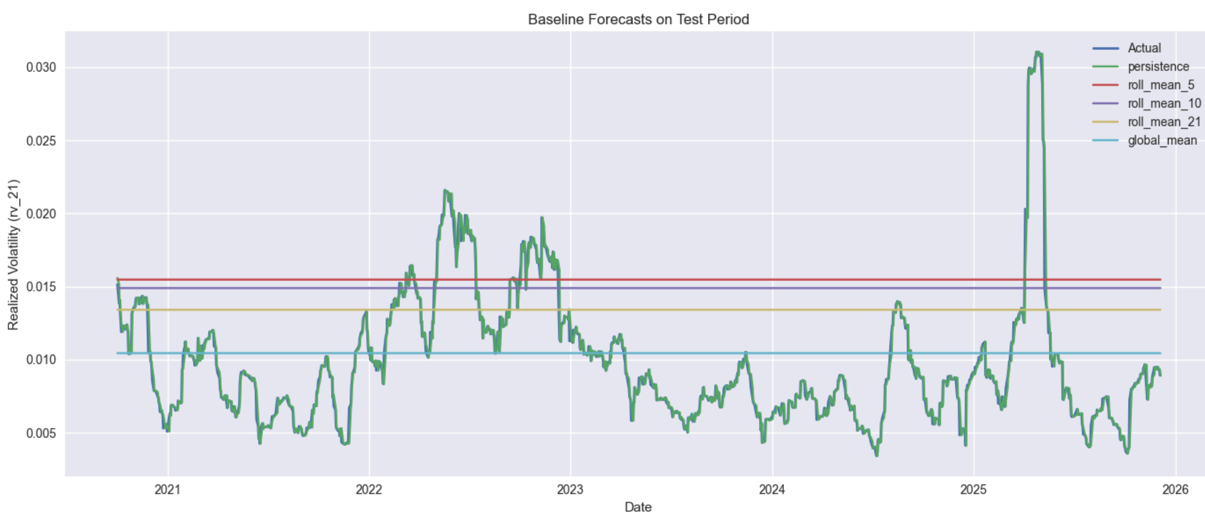
A visual comparison is useful to understand how each baseline behaves across the test period.

In [9]:
```
plt.figure(figsize=(14, 6))

plt.plot(test["Date"], y_test, label="Actual", linewidth=2)

for col in baseline_cols:
    plt.plot(test["Date"], test[col], label=col)

plt.title("Baseline Forecasts on Test Period")
plt.xlabel("Date")
plt.ylabel("Realized Volatility (rv_21)")
plt.legend()
plt.tight_layout()
plt.savefig(FIG_DIR / "baseline_forecasts.png", dpi=200)
plt.show()
```



The rolling mean forecasts appear as flat horizontal lines. This is expected, since we use the final training rolling mean as a constant forecast across the entire test period for a leak-free approach.

Forecast Errors Over Time

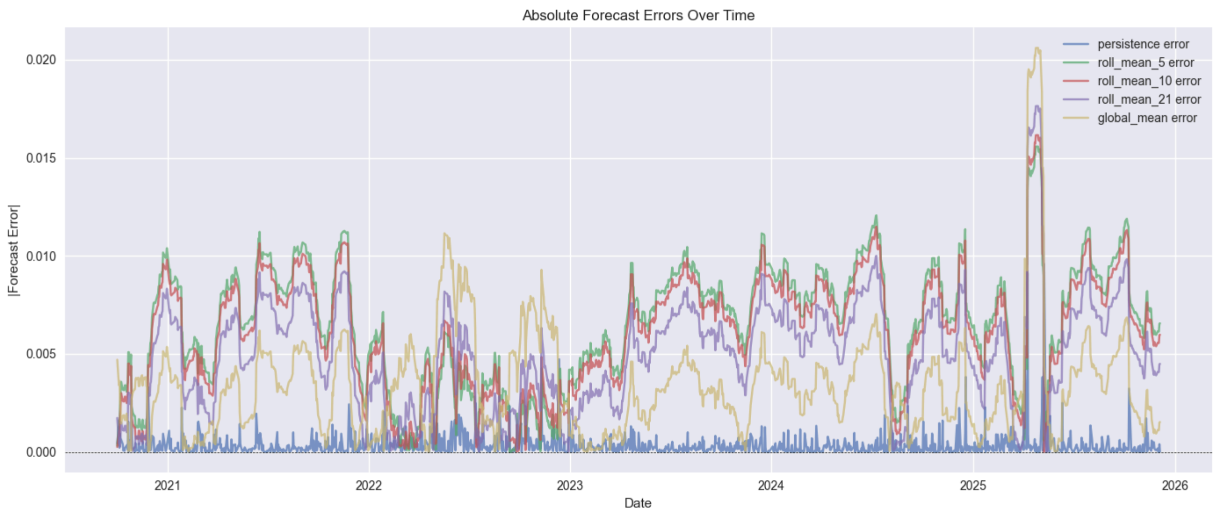
Since rolling means are constant, plotting forecasts directly isn't informative. Plotting forecast errors might give more insights.

In [10]:
```
plt.figure(figsize=(14, 6))

# Plot absolute errors
```

```
for col in baseline_cols:
    errors = np.abs(test[col] - y_test)
    plt.plot(test["Date"], errors, label=f"{col} error", alpha=0.7)

plt.title("Absolute Forecast Errors Over Time")
plt.xlabel("Date")
plt.ylabel("|Forecast Error|")
plt.legend()
plt.axhline(y=0, color='black', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig(FIG_DIR / "baseline_errors.png", dpi=200)
plt.show()
```



Visual observations:

- Persistence errors are small and stable (tracks volatility well)
- Rolling mean errors spike during volatility regime changes (static forecasts can't adapt)
- Global mean errors moderate (right on average, wrong in detail)

Save Outputs

We save both the forecasts and the evaluation metrics for downstream comparison in later notebooks.

In [11]:
```
# Save predictions
test_out = test[["Date", target_col] + baseline_cols]
test_out.to_csv(RESULTS_DIR / "baseline_forecasts.csv", index=False)

# Save metrics
metrics_df.to_csv(RESULTS_DIR / "baseline_metrics.csv", index=False)

test_out.head(), metrics_df
```

Out[11]:
```
(           Date     rv_21  persistence  roll_mean_5  roll_mean_10  \
 5200 2020-10-02  0.015151     0.015589     0.015475      0.014895
 5201 2020-10-05  0.013848     0.015151     0.015475      0.014895
 5202 2020-10-06  0.014067     0.013848     0.015475      0.014895
 5203 2020-10-07  0.013131     0.014067     0.015475      0.014895
 5204 2020-10-08  0.012524     0.013131     0.015475      0.014895

       roll_mean_21  global_mean
 5200      0.013412     0.010445
 5201      0.013412     0.010445
 5202      0.013412     0.010445
 5203      0.013412     0.010445
 5204      0.013412     0.010445  ,
          model      rmse       mae
 0   persistence  0.000698  0.000351
 1   roll_mean_5  0.007216  0.006536
 2  roll_mean_10  0.006772  0.006086
 3  roll_mean_21  0.005747  0.005011
 4   global_mean  0.004536  0.003477)
```

Summary

Best baseline: Persistence (RMSE = 0.000698)

Worst baseline: 5-day rolling mean (RMSE = 0.007216)

Performance range: approximately 10× difference between best and worst

Key Insight

Simple persistence leverages `rv_21` 's strong autocorrelation (ACF = 0.31) to achieve remarkably low error. This creates a high bar for sophisticated models.

Other Insights

Autocorrelation matters more than complexity

- Persistence (zero parameters) beats all averaging methods
- Confirms EDA finding: volatility changes slowly

Smoothing can worsen performance

- Rolling means lag reality
- Global mean is relatively competitive (right average, wrong timing)

The modeling challenge ahead

- GARCH/LSTM/Transformer must beat RMSE = 0.000698
- Given strong persistence, marginal improvements may be the best possible