In [73]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, KFold, GridSearchCV, T
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncode
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.linear_model import LinearRegression, Ridge, Lasso, LogisticReg
from sklearn.metrics import mean_squared_error, r2_score
RANDOM_STATE = 42
np.random.seed(RANDOM_STATE)
```

In [74]:
```
df = pd.read_csv('/Users/leopoldhuang/Desktop/data1030-fall2025/data/psd_cof
print("\nINITIAL DATA INSPECTION")
print(f"Dataset shape: {df.shape}")
print(f"Number of rows: {df.shape[0]}")
print(f"Number of features: {df.shape[1]}")
print("\nFIRST 5 ROWS")
print(df.head())
print("\nDATA TYPES")
print(df.dtypes)
print("\nSTATISTICAL SUMMARY")
print(df.describe())
```

```
INITIAL DATA INSPECTION
Dataset shape: (85937, 12)
Number of rows: 85937
Number of features: 12

FIRST 5 ROWS
   Commodity_Code Commodity_Description Country_Code Country_Name  \
0          711100         Coffee, Green           AL      Albania
1          711100         Coffee, Green           AL      Albania
2          711100         Coffee, Green           AL      Albania
3          711100         Coffee, Green           AL      Albania
4          711100         Coffee, Green           AL      Albania

   Market_Year  Calendar_Year  Month  Attribute_ID Attribute_Description  \
0         2005           2023      6            29    Arabica Production
1         2005           2023      6            90          Bean Exports
2         2005           2023      6            58          Bean Imports
3         2005           2023      6            20      Beginning Stocks
4         2005           2023      6           125  Domestic Consumption

   Unit_ID   Unit_Description  Value
0        2  (1000 60 KG BAGS)    0.0
1        2  (1000 60 KG BAGS)    0.0
2        2  (1000 60 KG BAGS)   80.0
3        2  (1000 60 KG BAGS)    0.0
4        2  (1000 60 KG BAGS)   80.0

DATA TYPES
Commodity_Code             int64
Commodity_Description     object
Country_Code              object
Country_Name              object
Market_Year                int64
Calendar_Year              int64
Month                      int64
Attribute_ID               int64
Attribute_Description     object
Unit_ID                    int64
Unit_Description          object
Value                    float64
dtype: object

STATISTICAL SUMMARY
       Commodity_Code   Market_Year  Calendar_Year         Month  \
count         85937.0  85937.000000   85937.000000  85937.000000
mean         711100.0   1996.409463    1998.252929      3.865576
std               0.0     19.353087      20.795698      4.484462
min          711100.0   1960.000000    1960.000000      0.000000
25%          711100.0   1980.000000    1980.000000      0.000000
50%          711100.0   2000.000000    2000.000000      0.000000
75%          711100.0   2013.000000    2016.000000      6.000000
max          711100.0   2025.000000    2025.000000     12.000000

       Attribute_ID  Unit_ID         Value
count  85937.000000  85937.0  85937.000000
mean      90.368421      2.0    829.702899
```

```
std       46.643611     0.0   4118.713029
min       20.000000     2.0      0.000000
25%       56.000000     2.0      0.000000
50%       86.000000     2.0      2.000000
75%      125.000000     2.0    220.000000
max      178.000000     2.0  97806.000000
```

In [75]:
```
print("MISSING VALUE ANALYSIS")
missing_values = df.isnull().sum()
print("\nMissing values per column:")
print(missing_values[missing_values > 0])
total_cells = np.prod(df.shape)
total_missing = missing_values.sum()
print(f"\nTotal missing cells: {total_missing}")
print(f"Fraction of dataset that is missing: {total_missing/total_cells:.4f}
```

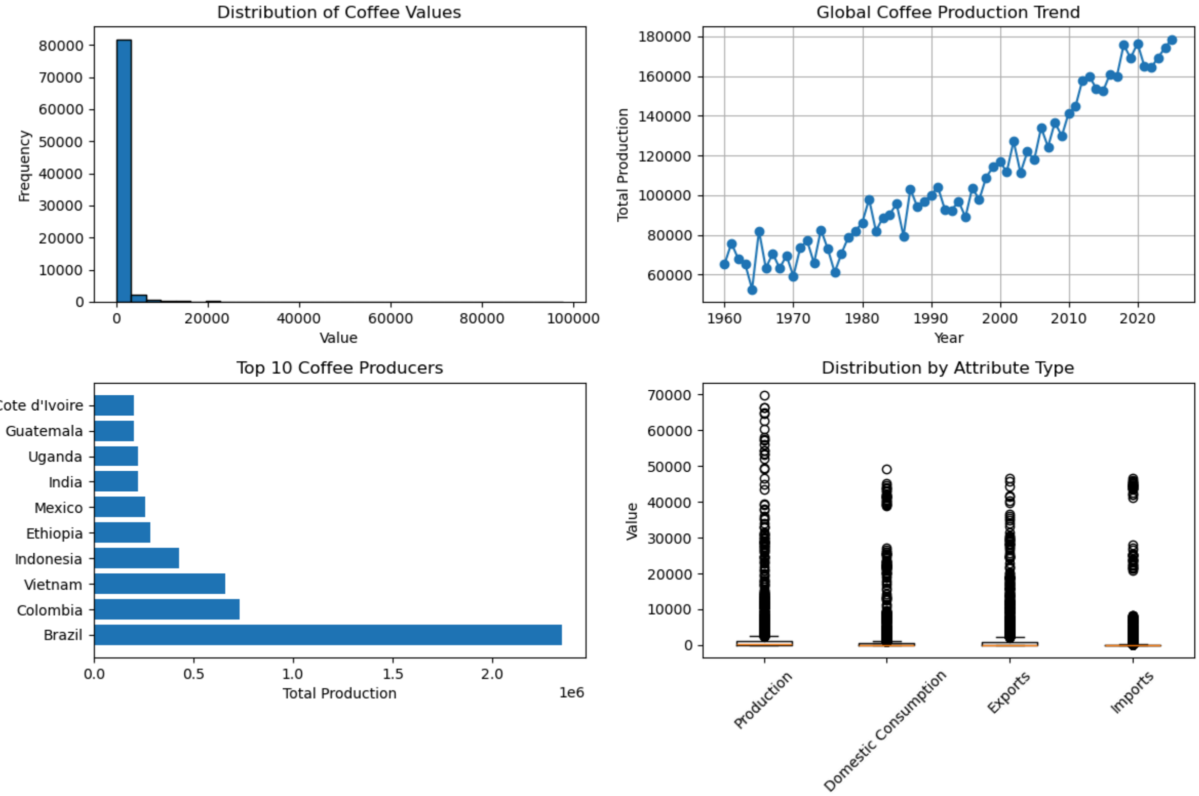
```
MISSING VALUE ANALYSIS

Missing values per column:
Series([], dtype: int64)

Total missing cells: 0
Fraction of dataset that is missing: 0.0000
```

In [76]:
```
print("FEATURE ENGINEERING")
def calculate_stu(df, year):
    year_data = df[df['Market_Year'] == year]
    production = year_data[year_data['Attribute_Description'] == 'Production
    consumption = year_data[year_data['Attribute_Description'] == 'Domestic
    ending_stocks = year_data[year_data['Attribute_Description'] == 'Ending
    exports = year_data[year_data['Attribute_Description'] == 'Exports']['Va
    total_use = consumption + exports
    stu = ending_stocks / total_use if total_use > 0 else 0
    return stu, production, consumption, ending_stocks
years = df['Market_Year'].unique()
recent_years = sorted(years)[-6:]
print("Stock to Use Analysis:")
for year in recent_years:
    stu, prod, cons, stocks = calculate_stu(df, year)
    print(f"Year {year}: STU={stu:.3f}, Production={prod:.0f}, Consumption={
    if stu < 0.20:
        print(f"Low STU - Price risk")
```

```
FEATURE ENGINEERING
Stock to Use Analysis:
Year 2020: STU=0.122, Production=176549, Consumption=162093
Low STU - Price risk
Year 2021: STU=0.103, Production=165044, Consumption=167868
Low STU - Price risk
Year 2022: STU=0.089, Production=164389, Consumption=168789
Low STU - Price risk
Year 2023: STU=0.075, Production=169345, Consumption=163921
Low STU - Price risk
Year 2024: STU=0.069, Production=174395, Consumption=166515
Low STU - Price risk
Year 2025: STU=0.072, Production=178680, Consumption=169363
Low STU - Price risk
```

In [77]:
```
print("EXPLORATORY DATA ANALYSIS - VISUALIZATIONS")
fig, axes = plt.subplots(2, 2, figsize=(12, 8))
# Plot 1: Distribution of Values
ax1 = axes[0, 0]
ax1.hist(df['Value'], bins=30, edgecolor='black')
ax1.set_xlabel('Value')
ax1.set_ylabel('Frequency')
ax1.set_title('Distribution of Coffee Values')
# Plot 2: Production over time
ax2 = axes[0, 1]
prod_by_year = df[df['Attribute_Description'] == 'Production'].groupby('Mark
ax2.plot(prod_by_year.index, prod_by_year.values, marker='o')
ax2.set_xlabel('Year')
ax2.set_ylabel('Total Production')
ax2.set_title('Global Coffee Production Trend')
ax2.grid(True)
# Plot 3: Top producing countries
ax3 = axes[1, 0]
top_countries = df[df['Attribute_Description'] == 'Production'].groupby('Cou
ax3.barh(range(len(top_countries)), top_countries.values)
ax3.set_yticks(range(len(top_countries)))
ax3.set_yticklabels(top_countries.index)
ax3.set_xlabel('Total Production')
ax3.set_title('Top 10 Coffee Producers')
# Plot 4: Box plot of values by attribute type
ax4 = axes[1, 1]
main_attributes = ['Production', 'Domestic Consumption', 'Exports', 'Imports
data_for_box = [df[df['Attribute_Description'] == attr]['Value'].values
                for attr in main_attributes]
ax4.boxplot(data_for_box, tick_labels=main_attributes)
ax4.set_ylabel('Value')
ax4.set_title('Distribution by Attribute Type')
ax4.set_xticklabels(main_attributes, rotation=45)
plt.tight_layout()
plt.show()
```

```
EXPLORATORY DATA ANALYSIS - VISUALIZATIONS
```



In [96]:
```
print("DATA PREPARATION FOR MODELING")
numerical_features = ['Market_Year', 'Calendar_Year', 'Month', 'Attribute_ID
categorical_features = ['Country_Name', 'Country_Code', 'Attribute_Descripti
all_feature_cols = numerical_features + categorical_features
X = df[all_feature_cols].copy()
y = df['Value'].copy()
print(f"Feature matrix shape: {X.shape}")
print(f"Target shape: {y.shape}")

print("\nData types verification:")
for col in all_feature_cols:
    dtype = X[col].dtype
    sample_value = X[col].iloc[0]
    print(f"{col}: {dtype} (sample: {sample_value})")

print("\nExample of feature ranges (showing why different scalers are needec
print(f"Month: {X['Month'].min()}-{X['Month'].max()}")
print(f"Market_Year: {X['Market_Year'].min()}-{X['Market_Year'].max()}")
print(f"Country_Code: {X['Country_Code'].nunique()} unique values")
print(f"Country_Name: {X['Country_Name'].nunique()} unique values")
```

```
DATA PREPARATION FOR MODELING
Feature matrix shape: (85937, 8)
Target shape: (85937,)

Data types verification:
Market_Year: int64 (sample: 2005)
Calendar_Year: int64 (sample: 2023)
Month: int64 (sample: 6)
Attribute_ID: int64 (sample: 29)
Unit_ID: int64 (sample: 2)
Country_Name: object (sample: Albania)
Country_Code: object (sample: AL)
Attribute_Description: object (sample: Arabica Production)

Example of feature ranges (showing why different scalers are needed):
Month: 0-12
Market_Year: 1960-2025
Country_Code: 94 unique values
Country_Name: 94 unique values
```

In [97]:

```
print("Checking for Group Structure:")
country_counts = df.groupby(['Country_Name', 'Market_Year']).size()
print(f"Unique countries: {df['Country_Name'].nunique()}")
print(f"Rows per country-year: {country_counts.mean():.1f} (average)")
print(f"Example: Brazil 2023 has {len(df[(df['Country_Name']=='Brazil') & (c
print(f"WARNING: This has GROUP structure - same country measured multiple t
print("\nChecking for Panel Data Structure:")
countries_with_multiple_years = df.groupby('Country_Name')['Market_Year'].nu
print(f"Countries tracked over multiple years: {(countries_with_multiple_yea
print(f"Average years per country: {countries_with_multiple_years.mean():.1f
print(f"WARNING:This is PANEL data - same entities tracked over time")

#Time Series Split
# Sort by time first
df_sorted = df.sort_values(['Market_Year', 'Month', 'Country_Name'])
X_sorted = df_sorted[all_feature_cols]
y_sorted = df_sorted['Value']
cutoff_year_1 = 2020
cutoff_year_2 = 2022
X_train = X_sorted[X_sorted['Market_Year'] < cutoff_year_1]
y_train = y_sorted[X_sorted['Market_Year'] < cutoff_year_1]
X_val = X_sorted[(X_sorted['Market_Year'] >= cutoff_year_1) & (X_sorted['Mar
y_val = y_sorted[(X_sorted['Market_Year'] >= cutoff_year_1) & (X_sorted['Mar
X_test = X_sorted[X_sorted['Market_Year'] >= cutoff_year_2]
y_test = y_sorted[X_sorted['Market_Year'] >= cutoff_year_2]
print(f"Time-based split results:")
print(f"Train: Years < {cutoff_year_1}, {len(X_train)} samples")
print(f"Val: Years {cutoff_year_1}-{cutoff_year_2-1}, {len(X_val)} samples")
print(f"Test: Years >= {cutoff_year_2}, {len(X_test)} samples")
print(f"No temporal leakage - always predicting future from past!")

# Using TimeSeriesSplit for cross-validation
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=5)
X_for_cv = X_sorted.head(10000)
y_for_cv = y_sorted.head(10000)
```

```
print(f"\nTimeSeriesSplit Cross-Validation:")
for i, (train_idx, val_idx) in enumerate(tscv.split(X_for_cv)):
    train_years = X_for_cv.iloc[train_idx]['Market_Year']
    val_years = X_for_cv.iloc[val_idx]['Market_Year']
    print(f"Fold {i+1}: Train years {train_years.min()}-{train_years.max()}, 
          f"Val years {val_years.min()}-{val_years.max()}")

#Group-Based Split
from sklearn.model_selection import GroupKFold
groups = X['Country_Name']
gkf = GroupKFold(n_splits=5)
print(f"GroupKFold Cross-Validation:")
X_subset = X.head(10000)
y_subset = y.head(10000)
groups_subset = X_subset['Country_Name']
for i, (train_idx, val_idx) in enumerate(gkf.split(X_subset, y_subset, group
    train_countries = X_subset.iloc[train_idx]['Country_Name'].unique()
    val_countries = X_subset.iloc[val_idx]['Country_Name'].unique()
    print(f"Fold {i+1}: Train {len(train_countries)} countries, Val {len(val
          f"Overlap: {len(set(train_countries) & set(val_countries))}")
    if i >= 2:
        break

#Combined Time-Group Split
test_years = [2023, 2024]
val_years = [2021, 2022]
train_years = df[~df['Market_Year'].isin(test_years + val_years)]['Market_Ye
X_train = X[X['Market_Year'].isin(train_years)]
y_train = y[X['Market_Year'].isin(train_years)]
X_val = X[X['Market_Year'].isin(val_years)]
y_val = y[X['Market_Year'].isin(val_years)]

X_test = X[X['Market_Year'].isin(test_years)]
y_test = y[X['Market_Year'].isin(test_years)]
print(f"Final Time-Based Split Results:")
print(f"Train: Years {min(train_years)}-{max(train_years)}, {len(X_train)} s
print(f"Val: Years {val_years}, {len(X_val)} samples")
print(f"Test: Years {test_years}, {len(X_test)} samples")
```

```
Checking for Group Structure:
Unique countries: 94
Rows per country-year: 19.0 (average)
Example: Brazil 2023 has 19 rows
WARNING: This has GROUP structure - same country measured multiple times

Checking for Panel Data Structure:
Countries tracked over multiple years: 94
Average years per country: 48.1
WARNING:This is PANEL data - same entities tracked over time
Time-based split results:
Train: Years < 2020, 75335 samples
Val: Years 2020-2021, 3534 samples
Test: Years >= 2022, 7068 samples
No temporal leakage - always predicting future from past!

TimeSeriesSplit Cross-Validation:
Fold 1: Train years 1960-1961, Val years 1961-1963
Fold 2: Train years 1960-1963, Val years 1963-1964
Fold 3: Train years 1960-1964, Val years 1964-1966
Fold 4: Train years 1960-1966, Val years 1966-1967
Fold 5: Train years 1960-1967, Val years 1967-1969
GroupKFold Cross-Validation:
Fold 1: Train 11 countries, Val 2 countries, Overlap: 0
Fold 2: Train 10 countries, Val 3 countries, Overlap: 0
Fold 3: Train 10 countries, Val 3 countries, Overlap: 0
Final Time-Based Split Results:
Train: Years 1960-2025, 78869 samples
Val: Years [2021, 2022], 3534 samples
Test: Years [2023, 2024], 3534 samples
```

In [80]:

```python
ordinal_features = []
onehot_features = ['Country_Name', 'Attribute_Description', 'Country_Code']
minmax_features = ['Month', 'Attribute_ID', 'Unit_ID']
standard_features = ['Market_Year', 'Calendar_Year']

print("Feature categorization")
print(f"Ordinal features: {ordinal_features if ordinal_features else 'None'}
print(f"OneHot features: {onehot_features}")
print(f"MinMax features: {minmax_features}")
print(f"Standard features: {standard_features}")

transformers = []
if ordinal_features:
    transformers.append(('ord', OrdinalEncoder(), ordinal_features))
if onehot_features:
    transformers.append(('onehot', OneHotEncoder(sparse_output=False, handle
if minmax_features:
    transformers.append(('minmax', MinMaxScaler(), minmax_features))
if standard_features:
    transformers.append(('std', StandardScaler(), standard_features))

preprocessor = ColumnTransformer(transformers=transformers)
preprocessor.fit(X_train)
X_train_prep = preprocessor.transform(X_train)
X_val_prep = preprocessor.transform(X_val)
```

```
X_test_prep = preprocessor.transform(X_test)
print(f"\nShape after preprocessing:")
print(f"X_train: {X_train.shape} -> {X_train_prep.shape}")
print(f"X_val: {X_val.shape} -> {X_val_prep.shape}")
print(f"X_test: {X_test.shape} -> {X_test_prep.shape}")

n_features_original = X_train.shape[1]
n_features_preprocessed = X_train_prep.shape[1]
print(f"\nFeature expansion: {n_features_original} -> {n_features_preprocess
print(f"Original: {n_features_original} features")
print(f"After preprocessing: {n_features_preprocessed} features")
print(f"Expansion due to OneHotEncoder: {n_features_preprocessed - n_feature
```

```
Feature categorization
Ordinal features: None
OneHot features: ['Country_Name', 'Attribute_Description', 'Country_Code']
MinMax features: ['Month', 'Attribute_ID', 'Unit_ID']
Standard features: ['Market_Year', 'Calendar_Year']

Shape after preprocessing:
X_train: (78869, 8) -> (78869, 212)
X_val: (3534, 8) -> (3534, 212)
X_test: (3534, 8) -> (3534, 212)

Feature expansion: 8 -> 212
Original: 8 features
After preprocessing: 212 features
Expansion due to OneHotEncoder: 204 new features
```

In [90]:

```
print("MODEL TRAINING")
models = {
    'Linear Regression': LinearRegression(),
    'Ridge (alpha=1.0)': Ridge(alpha=1.0, random_state=RANDOM_STATE),
    'Ridge (alpha=10.0)': Ridge(alpha=10.0, random_state=RANDOM_STATE),
    'Lasso (alpha=1.0)': Lasso(alpha=1.0, random_state=RANDOM_STATE),
    'Lasso (alpha=10.0)': Lasso(alpha=10.0, random_state=RANDOM_STATE)
}
results = {}
for name, model in models.items():
    model.fit(X_train_prep, y_train)
    y_train_pred = model.predict(X_train_prep)
    y_val_pred = model.predict(X_val_prep)
    train_mse = mean_squared_error(y_train, y_train_pred)
    val_mse = mean_squared_error(y_val, y_val_pred)
    train_r2 = r2_score(y_train, y_train_pred)
    val_r2 = r2_score(y_val, y_val_pred)
    results[name] = {
        'train_mse': train_mse,
        'val_mse': val_mse,
        'train_r2': train_r2,
        'val_r2': val_r2
    }
    print(f"\n{name}:")
    print(f"Train:MSE={train_mse:.2f}, R_squared={train_r2:.4f}")
    print(f"Val:MSE={val_mse:.2f}, R_squared={val_r2:.4f}")
```

```
MODEL TRAINING

Linear Regression:
Train:MSE=10532517.40, R_squared=0.3500
Val:MSE=16376594.20, R_squared=0.3521

Ridge (alpha=1.0):
Train:MSE=10532520.39, R_squared=0.3500
Val:MSE=16377869.72, R_squared=0.3521

Ridge (alpha=10.0):
Train:MSE=10532810.49, R_squared=0.3499
Val:MSE=16389796.89, R_squared=0.3516

Lasso (alpha=1.0):
Train:MSE=10544501.43, R_squared=0.3492
Val:MSE=16448009.32, R_squared=0.3493

Lasso (alpha=10.0):
Train:MSE=10757201.67, R_squared=0.3361
Val:MSE=17101611.18, R_squared=0.3234
```

In [95]:

```python
# Best model for cross-validation
best_model_name = min(results, key=lambda x: results[x]['val_mse'])
print(f"Best model based on validation MSE: {best_model_name}")

#k-fold cross-validation
kf = KFold(n_splits=5, shuffle=True, random_state=RANDOM_STATE)

# Use the best model type for cross-validation
if 'Ridge' in best_model_name:
    if 'alpha=10.0' in best_model_name:
        model_for_cv = Ridge(alpha=10.0, random_state=RANDOM_STATE)
    else:
        model_for_cv = Ridge(alpha=1.0, random_state=RANDOM_STATE)
    param_grid = {'model__alpha': [0.1, 1.0, 10.0, 100.0]}
elif 'Lasso' in best_model_name:
    if 'alpha=10.0' in best_model_name:
        model_for_cv = Lasso(alpha=10.0, random_state=RANDOM_STATE)
    else:
        model_for_cv = Lasso(alpha=1.0, random_state=RANDOM_STATE)
    param_grid = {'model__alpha': [0.1, 1.0, 10.0, 100.0]}
else:
    model_for_cv = LinearRegression()
    param_grid = {}

# Create pipeline
pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('model', model_for_cv)
])
if param_grid:
    grid_search = GridSearchCV(pipeline, param_grid, cv=kf,
                               scoring='neg_mean_squared_error')
    grid_search.fit(X_train, y_train)
    print(f"GridSearchCV Results:")
```

```
    print(f"  Best alpha: {grid_search.best_params_['model__alpha']}")
    print(f"  Best CV MSE: {-grid_search.best_score_:.2f}")
else:
# cross-validation for LinearRegression
    cv_scores = []
    for train_idx, val_idx in kf.split(X, y):
        X_cv_train = X.iloc[train_idx]
        X_cv_val = X.iloc[val_idx]
        y_cv_train = y.iloc[train_idx]
        y_cv_val = y.iloc[val_idx]
        pipeline.fit(X_cv_train, y_cv_train)
        y_cv_pred = pipeline.predict(X_cv_val)
        cv_mse = mean_squared_error(y_cv_val, y_cv_pred)
        cv_scores.append(cv_mse)
    print(f"Cross-validation MSE scores: {[f'{s:.2f}' for s in cv_scores]}")
    print(f"Mean CV MSE: {np.mean(cv_scores):.2f} ± {np.std(cv_scores):.2f}"
```

```
Best model based on validation MSE: Linear Regression
Cross-validation MSE scores: ['11311407.89', '10643910.29', '11104755.15',
'9715102.98', '12466057.93']
Mean CV MSE: 11048246.85 ± 897039.11
```

In [94]:

```
print("COMPARING SPLITTING STRATEGIES")
preprocessor_comparison = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), ['Market_Year', 'Attribute_ID']),
        ('cat', OneHotEncoder(sparse_output=False, handle_unknown='ignore'),
         ['Country_Name', 'Country_Code'])
    ])
print("Training with time-aware split")
X_train_time = X[(X['Market_Year'] < 2021)][['Market_Year', 'Attribute_ID',
y_train_time = y[X['Market_Year'] < 2021]
X_test_time = X[(X['Market_Year'] >= 2023)][['Market_Year', 'Attribute_ID',
y_test_time = y[X['Market_Year'] >= 2023]
preprocessor_time = preprocessor_comparison.fit(X_train_time)
X_train_prep_time = preprocessor_time.transform(X_train_time)
X_test_prep_time = preprocessor_time.transform(X_test_time)
model_time = Ridge(alpha=1.0, random_state=RANDOM_STATE)
model_time.fit(X_train_prep_time, y_train_time)
y_pred_time = model_time.predict(X_test_prep_time)
mse_time = mean_squared_error(y_test_time, y_pred_time)
r2_time = r2_score(y_test_time, y_pred_time)
print(f"\nTime Aware Split Results:")
print(f"MSE: {mse_time:.2f}")
print(f"R_squared: {r2_time:.4f}")
print("This is the realistic performance for future predictions in time seri
```

```
COMPARING SPLITTING STRATEGIES
Training with time-aware split

Time Aware Split Results:
MSE: 17544943.02
R_squared: 0.3114
This is the realistic performance for future predictions in time series data
```

In [93]:

```
print("TIME SERIES FEATURE ENGINEERING")
# Create lagged features
```

```python
prod_data = df[df['Attribute_Description'] == 'Production'].copy()
prod_data = prod_data.sort_values(['Country_Name', 'Market_Year'])
lagged_features = []
for country in prod_data['Country_Name'].unique()[:5]:
    country_data = prod_data[prod_data['Country_Name'] == country].copy()
    for lag in [1, 2, 3]:
        country_data[f'Value_lag_{lag}'] = country_data['Value'].shift(lag)
    lagged_features.append(country_data)
ts_features = pd.concat(lagged_features).dropna()
print(f"Original features: {prod_data.shape[1]}")
print(f"After time series engineering: {ts_features.shape[1]}")
print(f"New features added: {ts_features.shape[1] - prod_data.shape[1]}")
```

```
TIME SERIES FEATURE ENGINEERING
Original features: 12
After time series engineering: 15
New features added: 3
```