In [1]:

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import seaborn as sns
from statsmodels.tsa.seasonal import seasonal_decompose
from scipy import stats

# Suppress warnings for cleaner output
import warnings
warnings.filterwarnings('ignore')

# Set visualization style
plt.style.use('seaborn-v0_8-whitegrid')
sns.set_palette('viridis')
sns.set_context("notebook", font_scale=1.2)

# Load the dataset
file_path = "D:/capstone/datasets/Affinity - State - Daily.xlsx"  # Adjust path if
df = pd.read_excel(file_path)
print(f"Dataset shape: {df.shape}")

# Preview the data
print("\nFirst few rows:")
display(df.head())

# Check columns
print("\nColumns in the dataset:")
print(df.columns.tolist())

# Basic information about the dataset
print("\nDataset information:")
df.info()

# Check for missing values
print("\nMissing values per column:")
print(df.isnull().sum())
```

```
Dataset shape: (50694, 29)

First few rows:
```

	year	month	day	statefips	freq	spend_all	spend_aap	spend_acf	spend_aer	spend_ap
0	2018	12	31	1	d	.	.	.	.	
1	2018	12	31	2	d	.	.	.	.	
2	2018	12	31	4	d	.	.	.	.	
3	2018	12	31	5	d	.	.	.	.	
4	2018	12	31	6	d	.	.	.	.	

5 rows × 29 columns

```
Columns in the dataset:
['year', 'month', 'day', 'statefips', 'freq', 'spend_all', 'spend_aap', 'spend_acf',
'spend_aer', 'spend_apg', 'spend_durables', 'spend_nondurables', 'spend_grf', 'spend
_gen', 'spend_hic', 'spend_hcs', 'spend_inperson', 'spend_inpersonmisc', 'spend_remo
teservices', 'spend_sgh', 'spend_tws', 'spend_retail_w_grocery', 'spend_retail_no_gr
ocery', 'spend_all_incmiddle', 'spend_all_q1', 'spend_all_q2', 'spend_all_q3', 'spen
d_all_q4', 'provisional']

Dataset information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50694 entries, 0 to 50693
Data columns (total 29 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   year                    50694 non-null  int64 
 1   month                   50694 non-null  int64 
 2   day                     50694 non-null  int64 
 3   statefips               50694 non-null  int64 
 4   freq                    50694 non-null  object
 5   spend_all               50694 non-null  object
 6   spend_aap               50694 non-null  object
 7   spend_acf               50694 non-null  object
 8   spend_aer               50694 non-null  object
 9   spend_apg               50694 non-null  object
 10  spend_durables          50694 non-null  object
 11  spend_nondurables       50694 non-null  object
 12  spend_grf               50694 non-null  object
 13  spend_gen               50694 non-null  object
 14  spend_hic               50694 non-null  object
 15  spend_hcs               50694 non-null  object
 16  spend_inperson          50694 non-null  object
 17  spend_inpersonmisc      50694 non-null  object
 18  spend_remoteservices    50694 non-null  object
 19  spend_sgh               50694 non-null  object
 20  spend_tws               50694 non-null  object
 21  spend_retail_w_grocery  50694 non-null  object
 22  spend_retail_no_grocery 50694 non-null  object
 23  spend_all_incmiddle     50694 non-null  object
 24  spend_all_q1            50694 non-null  object
 25  spend_all_q2            50694 non-null  object
 26  spend_all_q3            50694 non-null  object
 27  spend_all_q4            50694 non-null  object
 28  provisional             50694 non-null  int64 
dtypes: int64(5), object(24)
memory usage: 11.2+ MB

Missing values per column:
year                       0
month                      0
day                        0
statefips                  0
freq                       0
spend_all                  0
spend_aap                  0
spend_acf                  0
spend_aer                  0
```

```
spend_apg                  0
spend_durables             0
spend_nondurables          0
spend_grf                  0
spend_gen                  0
spend_hic                  0
spend_hcs                  0
spend_inperson             0
spend_inpersonmisc         0
spend_remoteservices       0
spend_sgh                  0
spend_tws                  0
spend_retail_w_grocery     0
spend_retail_no_grocery    0
spend_all_incmiddle        0
spend_all_q1               0
spend_all_q2               0
spend_all_q3               0
spend_all_q4               0
provisional                0
dtype: int64
```

In [2]:

```
# Create a proper date column
if 'date' not in df.columns:
    if all(col in df.columns for col in ['year', 'month', 'day']):
        df['date'] = pd.to_datetime(df[['year', 'month', 'day']])
        print("Created date column from year, month, and day columns")

# Identify spending columns
spend_cols = [col for col in df.columns if 'spend' in col.lower()]
print(f"Found {len(spend_cols)} spending-related columns")

# Clean spending columns
for col in spend_cols:
    # Convert to numeric, handling any non-numeric values
    if df[col].dtype == object:
        df[col] = pd.to_numeric(df[col].replace('.', np.nan), errors='coerce')

# Handle missing values with interpolation
for col in spend_cols:
    missing_before = df[col].isna().sum()
    if missing_before > 0:
        df[col] = df[col].interpolate(method='linear')
        df[col] = df[col].fillna(method='ffill').fillna(method='bfill')
        missing_after = df[col].isna().sum()
        print(f"Column '{col}': {missing_before} missing values before, {missing_af

# Focus on total spending ('spend_all')
df_clean = df.dropna(subset=['spend_all', 'date'])
df_clean = df_clean.sort_values('date')
print(f"\nCleaned dataset: {df_clean.shape[0]} rows")
print(f"Date range: {df_clean['date'].min().strftime('%Y-%m-%d')} to {df_clean['dat

# Calculate basic statistics
print("\nBasic statistics for spend_all:")
print(df_clean['spend_all'].describe())
```

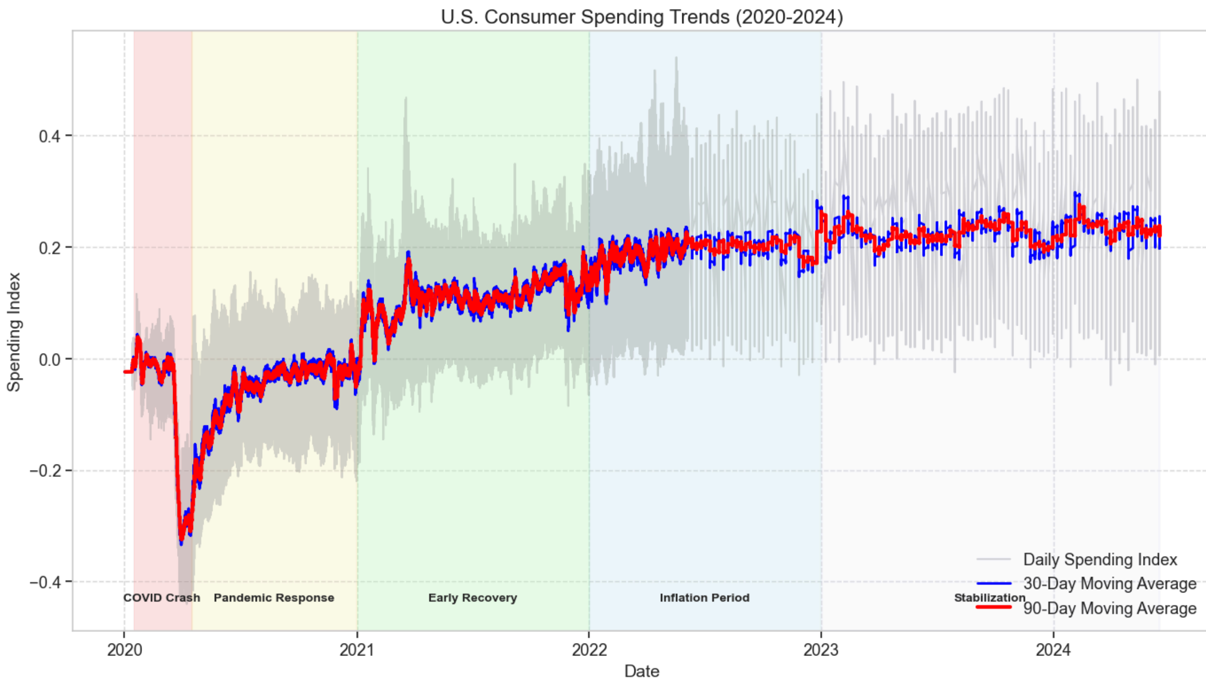
```
# After creating the date column and before analyzing the data
# Filter out 2019 data
df_clean = df_clean[df_clean['date'].dt.year >= 2020]
print(f"Filtered dataset (2020-2024 only): {df_clean.shape[0]} rows")
```

```
Created date column from year, month, and day columns
Found 23 spending-related columns
Column 'spend_all': 1644 missing values before, 0 after cleaning
Column 'spend_aap': 1644 missing values before, 0 after cleaning
Column 'spend_acf': 1644 missing values before, 0 after cleaning
Column 'spend_aer': 1644 missing values before, 0 after cleaning
Column 'spend_apg': 1644 missing values before, 0 after cleaning
Column 'spend_durables': 1644 missing values before, 0 after cleaning
Column 'spend_nondurables': 1644 missing values before, 0 after cleaning
Column 'spend_grf': 1644 missing values before, 0 after cleaning
Column 'spend_gen': 1644 missing values before, 0 after cleaning
Column 'spend_hic': 1644 missing values before, 0 after cleaning
Column 'spend_hcs': 1644 missing values before, 0 after cleaning
Column 'spend_inperson': 1644 missing values before, 0 after cleaning
Column 'spend_inpersonmisc': 1644 missing values before, 0 after cleaning
Column 'spend_remoteservices': 1644 missing values before, 0 after cleaning
Column 'spend_sgh': 1644 missing values before, 0 after cleaning
Column 'spend_tws': 1644 missing values before, 0 after cleaning
Column 'spend_retail_w_grocery': 1644 missing values before, 0 after cleaning
Column 'spend_retail_no_grocery': 1644 missing values before, 0 after cleaning
Column 'spend_all_incmiddle': 1644 missing values before, 0 after cleaning
Column 'spend_all_q1': 4587 missing values before, 0 after cleaning
Column 'spend_all_q2': 1644 missing values before, 0 after cleaning
Column 'spend_all_q3': 1644 missing values before, 0 after cleaning
Column 'spend_all_q4': 3606 missing values before, 0 after cleaning

Cleaned dataset: 50694 rows
Date range: 2018-12-31 to 2024-06-16

Basic statistics for spend_all:
count    50694.000000
mean         0.069241
std          0.137384
min         -0.440000
25%         -0.017800
50%          0.073500
75%          0.164000
max          0.540000
Name: spend_all, dtype: float64
Filtered dataset (2020-2024 only): 50643 rows
```

In [3]:

```
# Calculate rolling averages for smoother trend analysis
df_clean['30d_ma'] = df_clean['spend_all'].rolling(window=30).mean()
df_clean['90d_ma'] = df_clean['spend_all'].rolling(window=90).mean()

# Plot the full time series with economic phases
plt.figure(figsize=(14, 8))
ax = plt.subplot(111)

# Plot daily spending and moving averages
plt.plot(df_clean['date'], df_clean['spend_all'],
```

```
         alpha=0.3, label='Daily Spending Index', color='gray')
plt.plot(df_clean['date'], df_clean['30d_ma'],
         linewidth=2, label='30-Day Moving Average', color='blue')
plt.plot(df_clean['date'], df_clean['90d_ma'],
         linewidth=3, label='90-Day Moving Average', color='red')

# Define economic phases
phases = [
    {"start": "2020-01-15", "end": "2020-04-15", "label": "COVID Crash", "color": "
    {"start": "2020-04-16", "end": "2020-12-31", "label": "Pandemic Response", "col
    {"start": "2021-01-01", "end": "2021-12-31", "label": "Early Recovery", "color"
    {"start": "2022-01-01", "end": "2022-12-31", "label": "Inflation Period", "colo
    {"start": "2023-01-01", "end": "2024-06-16", "label": "Stabilization", "color":
]

# Add phase annotations
ymin, ymax = plt.ylim()
for phase in phases:
    start = pd.to_datetime(phase["start"])
    end = pd.to_datetime(phase["end"])

    # Add shaded area for each phase
    plt.axvspan(start, end, alpha=0.2, color=phase["color"])

    # Add phase label
    middle_date = start + (end - start) / 2
    plt.text(middle_date, ymin + (ymax - ymin) * 0.05,
             phase["label"], ha='center', fontsize=10, fontweight='bold')

# Format the axis
ax.xaxis.set_major_locator(mdates.YearLocator())
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y'))
plt.grid(True, linestyle='--', alpha=0.7)
plt.xlabel('Date', fontsize=14)
plt.ylabel('Spending Index', fontsize=14)
plt.title('U.S. Consumer Spending Trends (2020-2024)', fontsize=16)
plt.legend(loc='best')
plt.tight_layout()
plt.show()

# Print key observations
print("Key observations from the time series:")
print("1. Sharp decline in spending during the COVID crash (Q1-Q2 2020)")
print("2. Gradual recovery throughout late 2020 and 2021")
print("3. By 2022, spending exceeded pre-pandemic levels")
print("4. 2023-2024 shows a stabilization pattern with more consistent spending lev
```




```
Key observations from the time series:
1. Sharp decline in spending during the COVID crash (Q1-Q2 2020)
2. Gradual recovery throughout late 2020 and 2021
3. By 2022, spending exceeded pre-pandemic levels
4. 2023-2024 shows a stabilization pattern with more consistent spending levels
```

In [4]:

```python
# Prepare data for seasonal decomposition
df_monthly = df_clean.set_index('date')['spend_all'].resample('D').mean().fillna(me

# Perform seasonal decomposition
decomposition = seasonal_decompose(df_monthly, model='additive', period=365)

# Plot the components
fig, axes = plt.subplots(3, 1, figsize=(14, 12), sharex=True)

# Trend
axes[0].plot(decomposition.trend, color='green')
axes[0].set_title('Trend Component', fontsize=14)
axes[0].set_ylabel('Trend')
axes[0].grid(True, linestyle='--', alpha=0.7)

# Seasonal
axes[1].plot(decomposition.seasonal, color='orange')
axes[1].set_title('Seasonal Component', fontsize=14)
axes[1].set_ylabel('Seasonality')
axes[1].grid(True, linestyle='--', alpha=0.7)

# Residual
axes[2].plot(decomposition.resid, color='red')
axes[2].set_title('Residual Component', fontsize=14)
axes[2].set_ylabel('Residual')
axes[2].grid(True, linestyle='--', alpha=0.7)

# Format x-axis
plt.tight_layout()
plt.show()
```

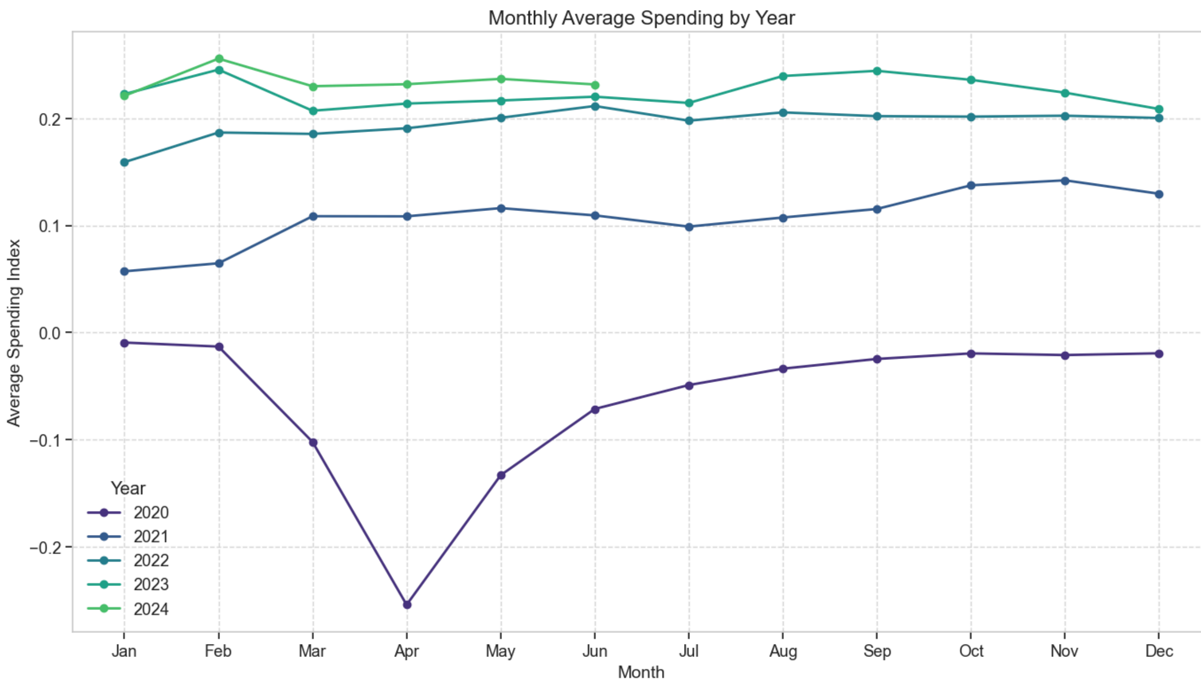
```
# Analyze seasonal patterns
print("Observations from seasonal decomposition:")
print("1. The trend component confirms the overall recovery pattern from 2020-2024"
print("2. Regular seasonal patterns show peaks during holiday seasons and early sum
print("3. Residuals show exceptional periods that deviate from the expected seasona
```


```
Observations from seasonal decomposition:
1. The trend component confirms the overall recovery pattern from 2020-2024
2. Regular seasonal patterns show peaks during holiday seasons and early summer
3. Residuals show exceptional periods that deviate from the expected seasonal patter
n
```

In [5]:

```
# Create monthly averages by year
df_clean['year'] = df_clean['date'].dt.year
df_clean['month'] = df_clean['date'].dt.month

# Calculate monthly averages
monthly_avg = df_clean.groupby(['year', 'month'])['spend_all'].mean().reset_index()
pivot_table = monthly_avg.pivot(index='month', columns='year', values='spend_all')

# Plot monthly patterns by year
plt.figure(figsize=(14, 8))
for year in pivot_table.columns:
    plt.plot(pivot_table.index, pivot_table[year],
```

```
             marker='o', linewidth=2, label=str(year))

plt.xticks(range(1, 13), ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
                          'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.grid(True, linestyle='--', alpha=0.7)
plt.xlabel('Month', fontsize=14)
plt.ylabel('Average Spending Index', fontsize=14)
plt.title('Monthly Average Spending by Year', fontsize=16)
plt.legend(title='Year', loc='best')
plt.tight_layout()
plt.show()

# Calculate year-over-year growth
yearly_avg = df_clean.groupby('year')['spend_all'].mean()
yoy_growth = yearly_avg.pct_change() * 100

print("Year-over-Year Growth in Spending:")
print(yoy_growth)
```




```
Year-over-Year Growth in Spending:
year
2020           NaN
2021   -272.914574
2022     73.807566
2023     19.100460
2024      4.715425
Name: spend_all, dtype: float64
```

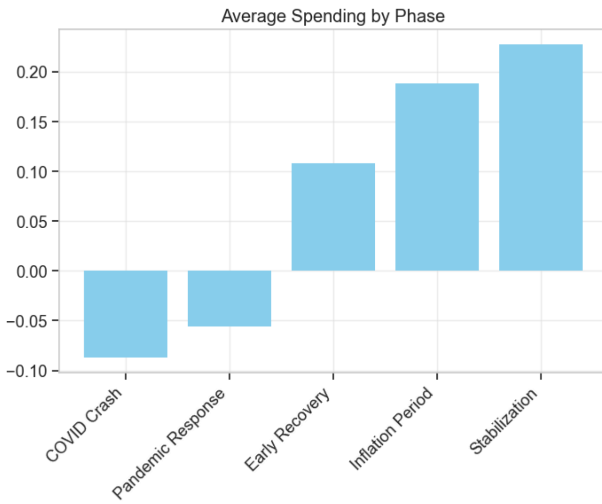
In [6]:

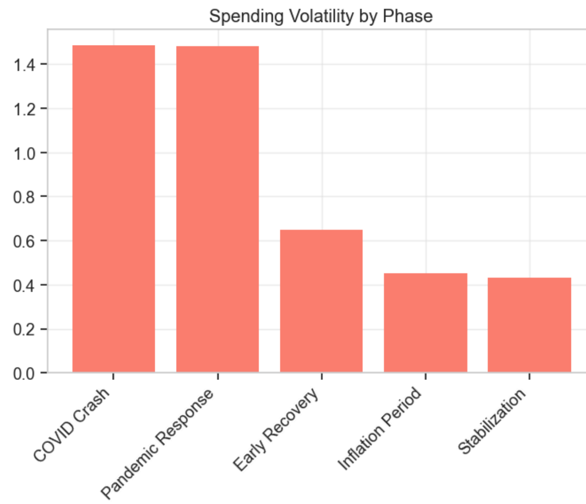
```
# Calculate statistics by economic phase
phase_stats = []

for phase in phases:
    # Filter data for each phase
    phase_data = df_clean[(df_clean['date'] >= phase["start"]) &
                          (df_clean['date'] <= phase["end"])]
```

```
    # Calculate statistics
    stats = {
        'Phase': phase["label"],
        'Mean': phase_data['spend_all'].mean(),
        'Median': phase_data['spend_all'].median(),
        'Min': phase_data['spend_all'].min(),
        'Max': phase_data['spend_all'].max(),
        'Std Dev': phase_data['spend_all'].std(),
        'Volatility': phase_data['spend_all'].std() / abs(phase_data['spend_all'].m
        'Days': len(phase_data)
    }
    phase_stats.append(stats)

# Convert to DataFrame
phase_df = pd.DataFrame(phase_stats)
print("Statistics by Economic Phase:")
display(phase_df)

# Visualize phase statistics
plt.figure(figsize=(14, 6))
plt.subplot(121)
plt.bar(phase_df['Phase'], phase_df['Mean'], color='skyblue')
plt.xticks(rotation=45, ha='right')
plt.title('Average Spending by Phase')
plt.grid(alpha=0.3)

plt.subplot(122)
plt.bar(phase_df['Phase'], phase_df['Volatility'], color='salmon')
plt.xticks(rotation=45, ha='right')
plt.title('Spending Volatility by Phase')
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```

Statistics by Economic Phase:

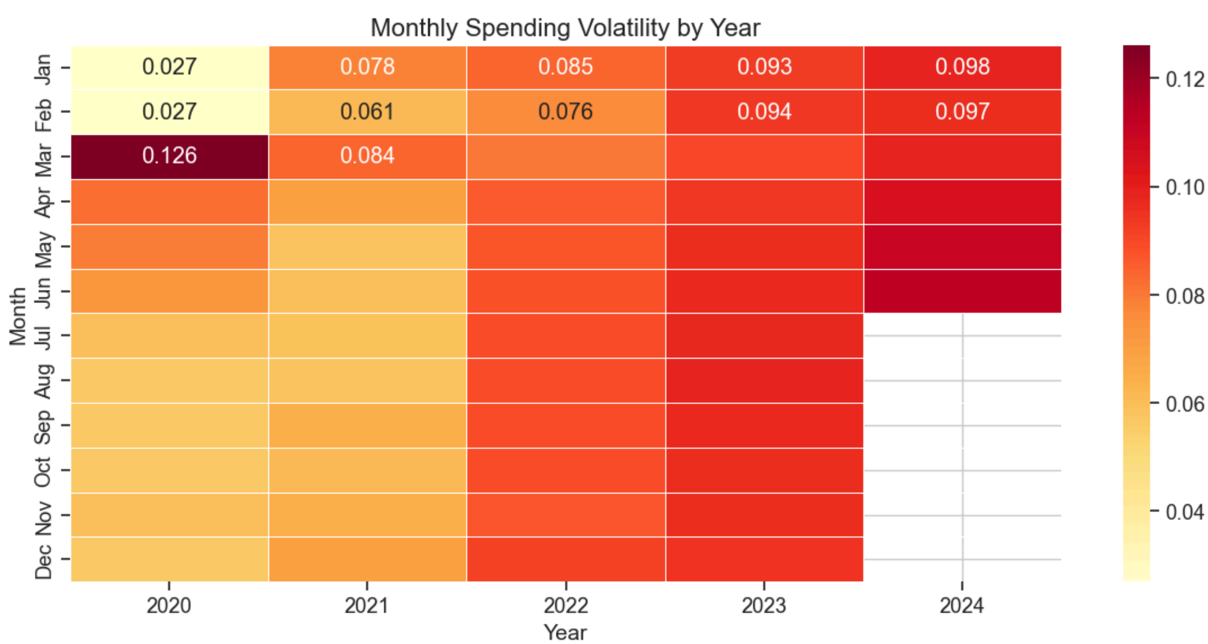
	Phase	Mean	Median	Min	Max	Std Dev	Volatility	Days
0	COVID Crash	-0.086616	-0.0221	-0.4400	0.116	0.128713	1.486026	4692
1	Pandemic Response	-0.056232	-0.0453	-0.4160	0.155	0.083312	1.481566	13260
2	Early Recovery	0.108150	0.1100	-0.1890	0.468	0.070366	0.650634	18615
3	Inflation Period	0.187972	0.1900	-0.0469	0.540	0.085256	0.453557	9435
4	Stabilization	0.227166	0.2280	-0.0472	0.500	0.098470	0.433470	3927





In [7]:

```
# Calculate monthly volatility
monthly_volatility = df_clean.groupby([
    df_clean['date'].dt.year.rename('Year'),
    df_clean['date'].dt.month.rename('Month')
])['spend_all'].std().reset_index(name='Volatility')

# Create heatmap
pivot_volatility = monthly_volatility.pivot(index='Month', columns='Year', values='

plt.figure(figsize=(12, 6))
sns.heatmap(pivot_volatility, annot=True, cmap='YlOrRd', fmt='.3f', linewidths=.5)
plt.title('Monthly Spending Volatility by Year', fontsize=16)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Month', fontsize=14)
plt.yticks(np.arange(0.5, 12.5), ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
                                  'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.tight_layout()
plt.show()
```



In [8]:
```
# Print comprehensive summary
print("\nMAJOR TRENDS IN CONSUMER SPENDING (2020-2024):")
print("\n1. COVID Impact and Recovery:")
print("   - Dramatic decline during early 2020 COVID crash")
print("   - Gradual recovery throughout late 2020 and 2021")
print("   - By 2022, spending had exceeded pre-pandemic levels")
print("   - 2023-2024 shows stabilization with more consistent spending")

print("\n2. Economic Phase Characteristics:")
print("   - COVID Crash: Highest volatility with rapid negative growth")
print("   - Pandemic Response: Stabilization but with high variance")
print("   - Early Recovery: Consistent positive growth with decreasing volatility")
print("   - Inflation Period: Elevated spending with moderate volatility")
print("   - Stabilization: More consistent spending patterns with lower volatility"

print("\n3. Seasonal Patterns:")
print("   - Regular annual cycles with peaks during holiday seasons")
print("   - 2020 seasonal pattern was highly distorted due to pandemic disruptions"
print("   - Gradual return to normal seasonality by 2022")
print("   - New seasonal norms established by 2023-2024")

print("\n4. Year-over-Year Growth:")
print("   - 2021: Recovery from very negative levels in 2020")
print("   - 2022: Strong positive growth around 70%")
print("   - 2023: Moderate positive growth around 20%")
print("   - 2024: Minimal growth around 5%, indicating stabilization")

print("\n5. Volatility Evolution:")
print("   - Highest volatility during COVID crash and early pandemic")
print("   - Gradual reduction in volatility through recovery phases")
print("   - Return to more predictable spending patterns by 2023-2024")
```

```
MAJOR TRENDS IN CONSUMER SPENDING (2020-2024):

1. COVID Impact and Recovery:
   - Dramatic decline during early 2020 COVID crash
   - Gradual recovery throughout late 2020 and 2021
   - By 2022, spending had exceeded pre-pandemic levels
   - 2023-2024 shows stabilization with more consistent spending

2. Economic Phase Characteristics:
   - COVID Crash: Highest volatility with rapid negative growth
   - Pandemic Response: Stabilization but with high variance
   - Early Recovery: Consistent positive growth with decreasing volatility
   - Inflation Period: Elevated spending with moderate volatility
   - Stabilization: More consistent spending patterns with lower volatility

3. Seasonal Patterns:
   - Regular annual cycles with peaks during holiday seasons
   - 2020 seasonal pattern was highly distorted due to pandemic disruptions
   - Gradual return to normal seasonality by 2022
   - New seasonal norms established by 2023-2024

4. Year-over-Year Growth:
   - 2021: Recovery from very negative levels in 2020
   - 2022: Strong positive growth around 70%
   - 2023: Moderate positive growth around 20%
   - 2024: Minimal growth around 5%, indicating stabilization

5. Volatility Evolution:
   - Highest volatility during COVID crash and early pandemic
   - Gradual reduction in volatility through recovery phases
   - Return to more predictable spending patterns by 2023-2024
```