In [7]:

```
import pandas as pd
import numpy as np
```

In [8]:

```
df=pd.read_csv('creditcard.csv')
```

In [6]:

```
df.shape
```

Out[6]:

```
(284807, 31)
```

In [7]:

```
df.head()
```

Out[7]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798

5 rows × 31 columns

In [9]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

In [14]:

```
df['Time'].max()
```

```
Out[14]: np.float64(172792.0)
```

```
In [9]: #helps to know hour of transaction
        df['Hour'] = (df['Time'] // 3600) % 24
```

```
In [23]: df['Amount'].value_counts()
```

```
Out[23]: Amount
         1.00      13688
         1.98       6044
         0.89       4872
         9.99       4747
         15.00      3280
                   ...
         202.24        1
         252.85        1
         615.52        1
         180.93        1
         807.48        1
         Name: count, Length: 32767, dtype: int64
```

```
In [10]: df['AmountBin'] = pd.cut(df['Amount'],
                                  bins=[0, 10, 100, 500, 1000, df['Amount'].max()],
                                  labels=['Very Low', 'Low', 'Medium', 'High', 'Very High'],include_lowest=True) #inculde lo
```

```
In [25]: df.head()
```

Out[25]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V23	V
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.110474	0.066
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	0.101288	-0.339
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.909412	-0.689
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.190321	-1.175
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.137458	0.141

5 rows × 33 columns

In [26]:

```
df.isnull().sum()
```

Out[26]:
```
Time         0
V1           0
V2           0
V3           0
V4           0
V5           0
V6           0
V7           0
V8           0
V9           0
V10          0
V11          0
V12          0
V13          0
V14          0
V15          0
V16          0
V17          0
V18          0
V19          0
V20          0
V21          0
V22          0
V23          0
V24          0
V25          0
V26          0
V27          0
V28          0
Amount       0
Class        0
Hour         0
AmountBin    0
dtype: int64
```

EDA

In [11]:

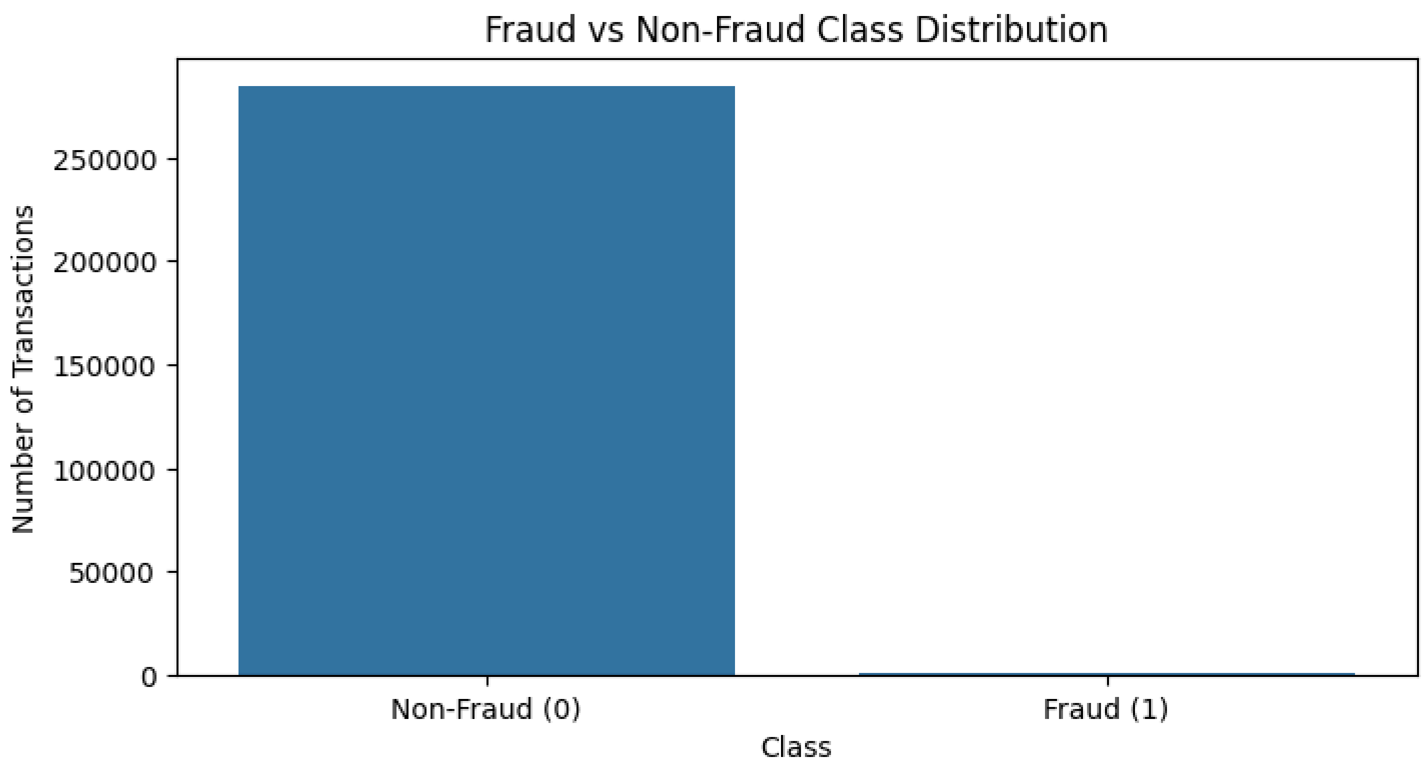
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Count of fraud and non-fraud
class_counts = df['Class'].value_counts()

print("Class distribution:\n", class_counts)

# Plot
plt.figure(figsize=(8,4))
sns.barplot(x=class_counts.index, y=class_counts.values)
plt.xticks([0, 1], ['Non-Fraud (0)', 'Fraud (1)'])
plt.ylabel('Number of Transactions')
plt.title('Fraud vs Non-Fraud Class Distribution')
plt.show()
```

```
Class distribution:
 Class
0    284315
1       492
Name: count, dtype: int64
```



-The dataset is extremely imbalanced.

-Only about 0.17% of all transactions are fraudulent.

-This makes it challenging to detect fraud, which is why fraud detection is so valuable in real life

In [13]:
```
fraud_rate = (df['Class'].value_counts(normalize=True)[1]) * 100
print(f"Fraudulent transactions: {fraud_rate:.4f}% of all data")
```

```
Fraudulent transactions: 0.1727% of all data
```

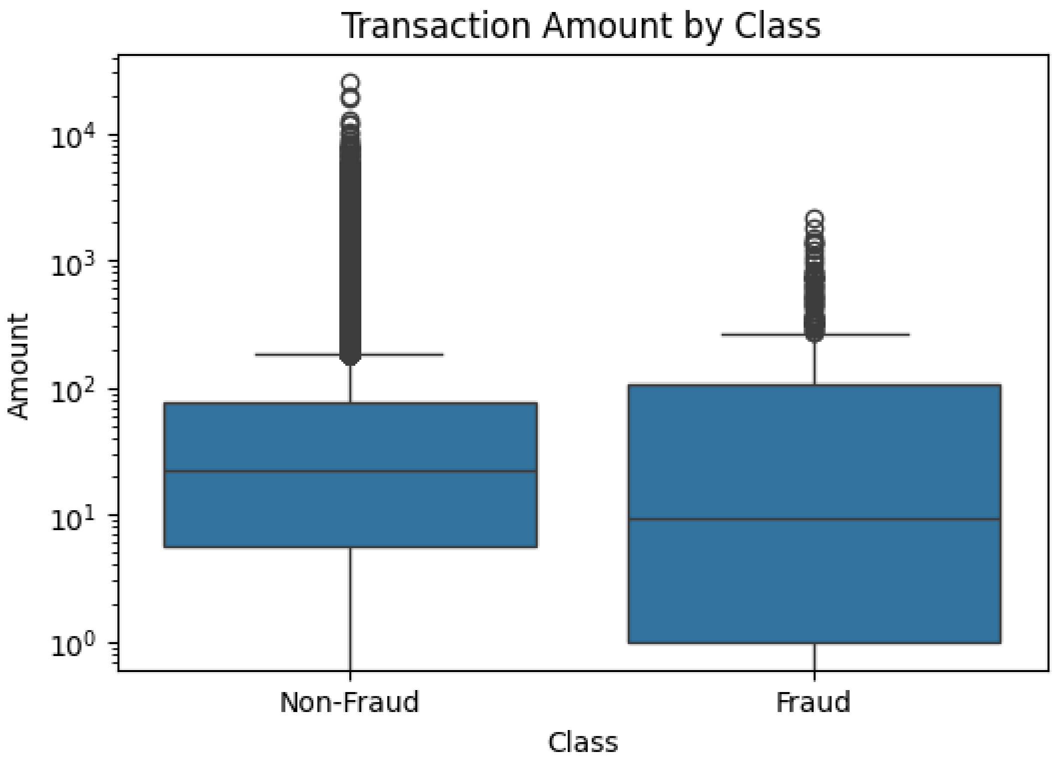
Only 0.17% of transactions are fraudulent. This extreme imbalance highlights the difficulty of fraud detection and the need for strong data analysis and visual storytelling to surface potential patterns.

In [14]:
```
df.groupby('Class')['Amount'].describe()
```

Out[14]:

Class	count	mean	std	min	25%	50%	75%	max
0	284315.0	88.291022	250.105092	0.0	5.65	22.00	77.05	25691.16
1	492.0	122.211321	256.683288	0.0	1.00	9.25	105.89	2125.87

In [36]:
```
#amount-fraud
plt.figure(figsize=(6, 4))
sns.boxplot(x='Class', y='Amount', data=df)
plt.xticks([0, 1], ['Non-Fraud', 'Fraud'])
plt.title('Transaction Amount by Class')
plt.yscale('log')  # log scale helps if there are extreme outliers
plt.show()
```

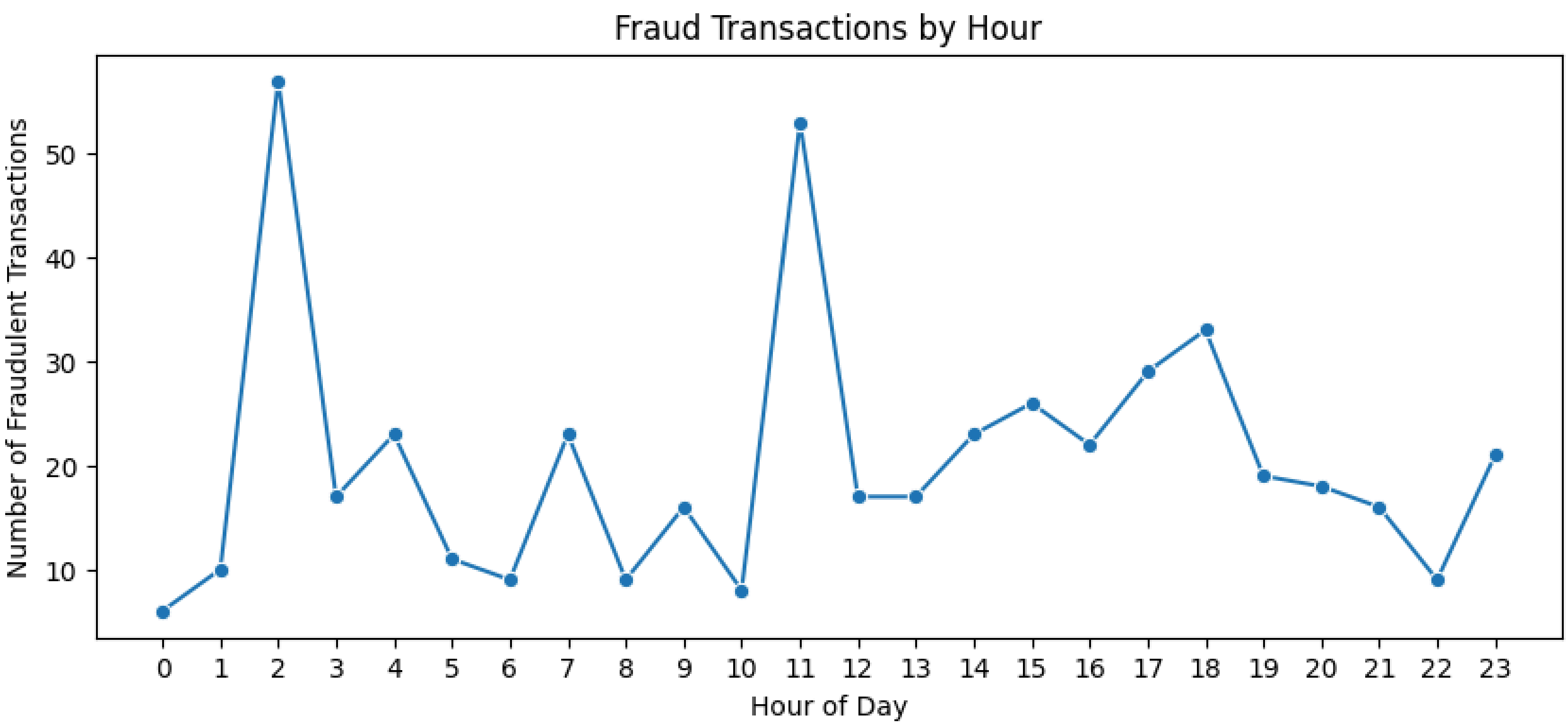


While both fraudulent and non-fraudulent transactions span a wide range of amounts, the median amount for fraud is notably lower than for non-fraud. This suggests that fraudulent activity often involves smaller transactions, potentially to avoid detection. However, a few high-value fraud outliers exist highlighting occasional large-scale fraud attempts

In [44]:
```
# hour-fraud

# Count of frauds per hour
fraud_by_hour = df[df['Class'] == 1]['Hour'].value_counts().sort_index()

plt.figure(figsize=(10, 4))
sns.lineplot(x=fraud_by_hour.index, y=fraud_by_hour.values, marker='o')
plt.xticks(range(24))
plt.xlabel('Hour of Day')
plt.ylabel('Number of Fraudulent Transactions')
plt.title('Fraud Transactions by Hour')
plt.show()
```

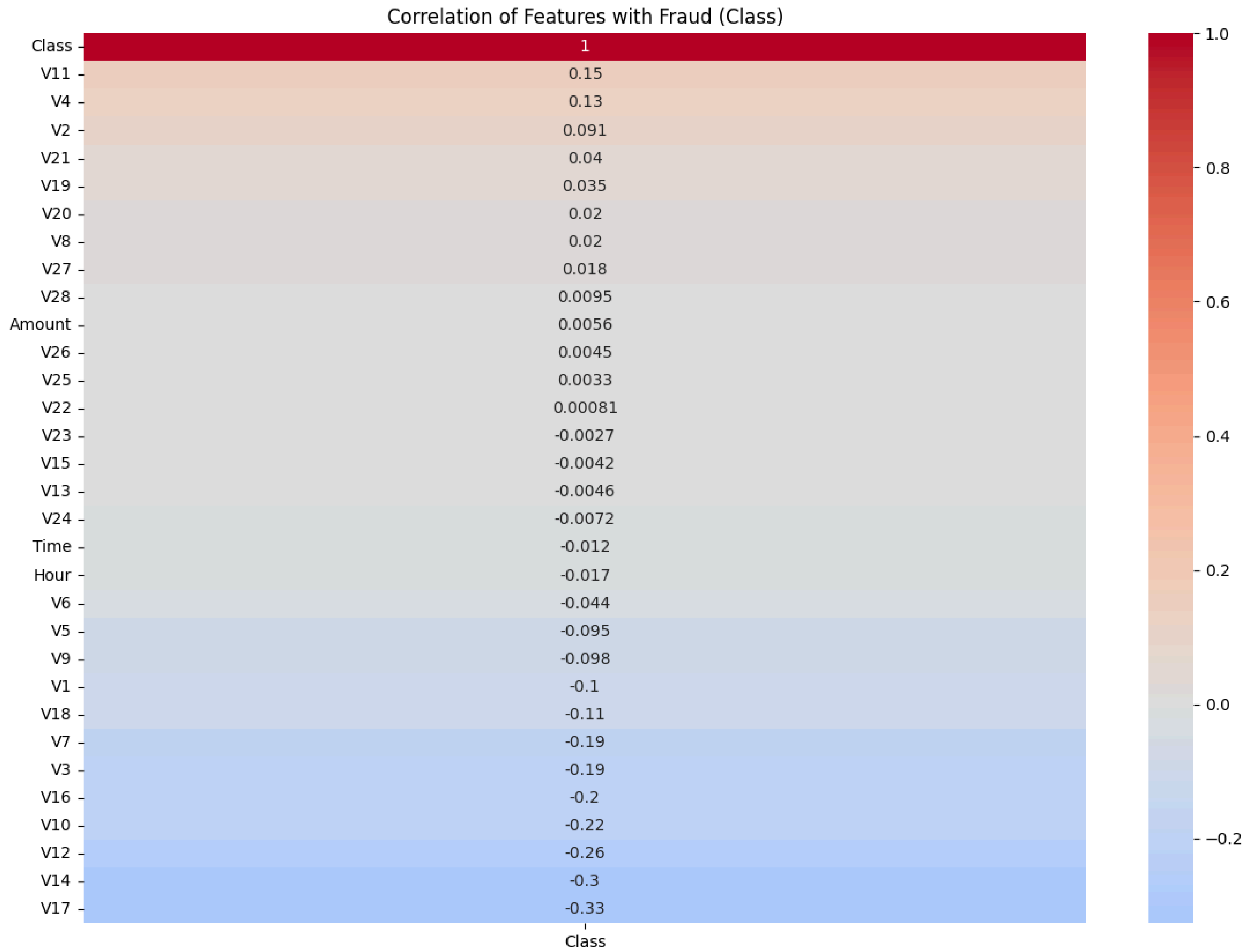


Fraudulent transactions show clear time-based patterns, with noticeable spikes around 2 AM and 11 AM. This suggests that fraudsters may be targeting off-peak hours, potentially to avoid detection when human or system monitoring is reduced. Evening hours also show moderate fraud activity, possibly designed to blend in with legitimate user behavior. Such insights are valuable for optimizing fraud detection systems to monitor more aggressively during vulnerable time windows.

In [15]:

```
# Correlation matrix
corr = df.select_dtypes(include='number').corr()


plt.figure(figsize=(14, 10))
sns.heatmap(corr[['Class']].sort_values(by='Class', ascending=False),
            annot=True, cmap='coolwarm', center=0)
plt.title('Correlation of Features with Fraud (Class)')
plt.show()
```


Correlation of Features with Fraud (Class)
Class 1
V11 0.15
V4 0.13
V2 0.091
V21 0.04
V19 0.035
V20 0.02
V8 0.02
V27 0.018
V28 0.0095
Amount 0.0056
V26 0.0045
V25 0.0033
V22 0.00081
V23 -0.0027
V15 -0.0042
V13 -0.0046
V24 -0.0072
Time -0.012
Hour -0.017
V6 -0.044
V5 -0.095
V9 -0.098
V1 -0.1
V18 -0.11
V7 -0.19
V3 -0.19
V16 -0.2
V10 -0.22
V12 -0.26
V14 -0.3
V17 -0.33
Class
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

So a positive correlation (e.g., 0.15) means As the value of V11 increases, the likelihood of the transaction being fraud also increases

In [19]:

```
#saving correlation output csv to use it in tableau
# ✅ Keep only numeric columns (important!)
numeric_df = df.select_dtypes(include='number')

# ✅ Extract correlations directly with 'Class'
class_corr = numeric_df.corrwith(df['Class']).sort_values(ascending=False)

# Convert to DataFrame
class_corr = class_corr.reset_index()
class_corr.columns = ['Feature', 'Correlation_with_Class']

# Drop the 'Class' row itself (self-correlation = 1.0)
class_corr = class_corr[class_corr['Feature'] != 'Class']

# Save to CSV
class_corr.to_csv("feature_correlations.csv", index=False)
```

In [53]:

```
df.to_csv('cleaned_fraud_data.csv', index=False)
```

In [ ]:

```

```