In [143…

```python
# Importing all the libraries and the csv for analysis

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from scipy.stats import chi2_contingency
d1 = pd.read_csv('loan.csv',low_memory=False)
```

In [5]:

```python
# head for verification
d1.head()
```

Out[5]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	insta
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	

5 rows × 111 columns

In [31]:

```python
print(d1.columns.tolist())
```

```
['id', 'member_id', 'loan_amnt', 'funded_amnt', 'funded_amnt_inv', 'term',
'int_rate', 'installment', 'grade', 'sub_grade', 'emp_title', 'emp_length',
'home_ownership', 'annual_inc', 'verification_status', 'issue_d', 'loan_stat
us', 'pymnt_plan', 'url', 'desc', 'purpose', 'title', 'zip_code', 'addr_stat
e', 'dti', 'delinq_2yrs', 'earliest_cr_line', 'inq_last_6mths', 'mths_since_
last_delinq', 'mths_since_last_record', 'open_acc', 'pub_rec', 'revol_bal',
'revol_util', 'total_acc', 'initial_list_status', 'out_prncp', 'out_prncp_in
v', 'total_pymnt', 'total_pymnt_inv', 'total_rec_prncp', 'total_rec_int', 't
otal_rec_late_fee', 'recoveries', 'collection_recovery_fee', 'last_pymnt_d',
'last_pymnt_amnt', 'next_pymnt_d', 'last_credit_pull_d', 'collections_12_mth
s_ex_med', 'mths_since_last_major_derog', 'policy_code', 'application_type',
'annual_inc_joint', 'dti_joint', 'verification_status_joint', 'acc_now_delin
q', 'tot_coll_amt', 'tot_cur_bal', 'open_acc_6m', 'open_il_6m', 'open_il_12
m', 'open_il_24m', 'mths_since_rcnt_il', 'total_bal_il', 'il_util', 'open_rv
_12m', 'open_rv_24m', 'max_bal_bc', 'all_util', 'total_rev_hi_lim', 'inq_f
i', 'total_cu_tl', 'inq_last_12m', 'acc_open_past_24mths', 'avg_cur_bal', 'b
c_open_to_buy', 'bc_util', 'chargeoff_within_12_mths', 'delinq_amnt', 'mo_si
n_old_il_acct', 'mo_sin_old_rev_tl_op', 'mo_sin_rcnt_rev_tl_op', 'mo_sin_rcn
t_tl', 'mort_acc', 'mths_since_recent_bc', 'mths_since_recent_bc_dlq', 'mths
_since_recent_inq', 'mths_since_recent_revol_delinq', 'num_accts_ever_120_p
d', 'num_actv_bc_tl', 'num_actv_rev_tl', 'num_bc_sats', 'num_bc_tl', 'num_il
_tl', 'num_op_rev_tl', 'num_rev_accts', 'num_rev_tl_bal_gt_0', 'num_sats',
'num_tl_120dpd_2m', 'num_tl_30dpd', 'num_tl_90g_dpd_24m', 'num_tl_op_past_12
m', 'pct_tl_nvr_dlq', 'percent_bc_gt_75', 'pub_rec_bankruptcies', 'tax_lien
s', 'tot_hi_cred_lim', 'total_bal_ex_mort', 'total_bc_limit', 'total_il_high
_credit_limit']
```

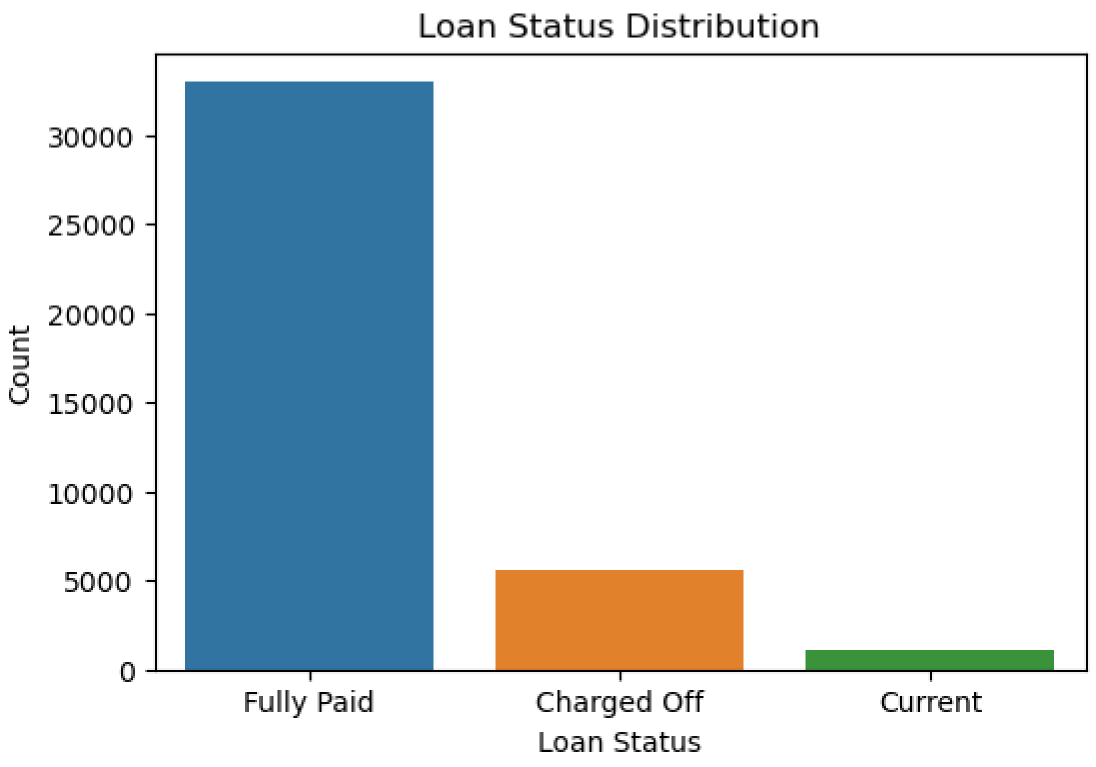
The list of selected columns from the given ones which seems important for this analysis:

1. **loan_status**: This is the target variable, indicating whether the loan was fully paid or charged off (defaulted). It's essential for understanding loan outcomes.
2. **annual_inc**: The borrower's self-reported annual income provides insights into their ability to make loan payments and manage their finances.
3. **dti**: The debt-to-income ratio helps assess the borrower's financial health by comparing their monthly debt payments to their income.
4. **emp_length**: Employment length is crucial for evaluating the borrower's stability and income source, which impacts their repayment capability.
5. **int_rate**: The interest rate on the loan affects the borrower's monthly payment and overall affordability.
6. **purpose**: The purpose of the loan can provide insights into the borrower's financial goals and intentions.
7. **term**: The loan term affects the monthly payment and can influence the borrower's ability to repay.
8. **open_acc** and **total_acc**: These two variables give an overview of the borrower's credit history and current credit lines.
9. **revol_util**: The revolving line utilization rate reflects the borrower's credit utilization, impacting their credit score and risk.
10. **pub_rec** and **pub_rec_bankruptcies**: These variables indicate derogatory public records and bankruptcies, highlighting potential credit risk.
11. **addr_state** and **zip_code**: Location might influence economic conditions and repayment capability.
12. **avg_cur_bal**: The average current balance of all accounts can provide insights into the borrower's financial stability.
13. **delinq_2yrs**: The number of past-due incidences of delinquency over the past 2 years reflects credit behavior history.

In [53]:
```
selected_columns = [
    'id','loan_status', 'annual_inc', 'dti', 'emp_length',
    'int_rate', 'purpose', 'term', 'open_acc', 'total_acc',
    'revol_util', 'pub_rec', 'pub_rec_bankruptcies', 'addr_state',
    'zip_code', 'avg_cur_bal', 'delinq_2yrs','loan_amnt'
]

d2 = d1[selected_columns].copy()
```

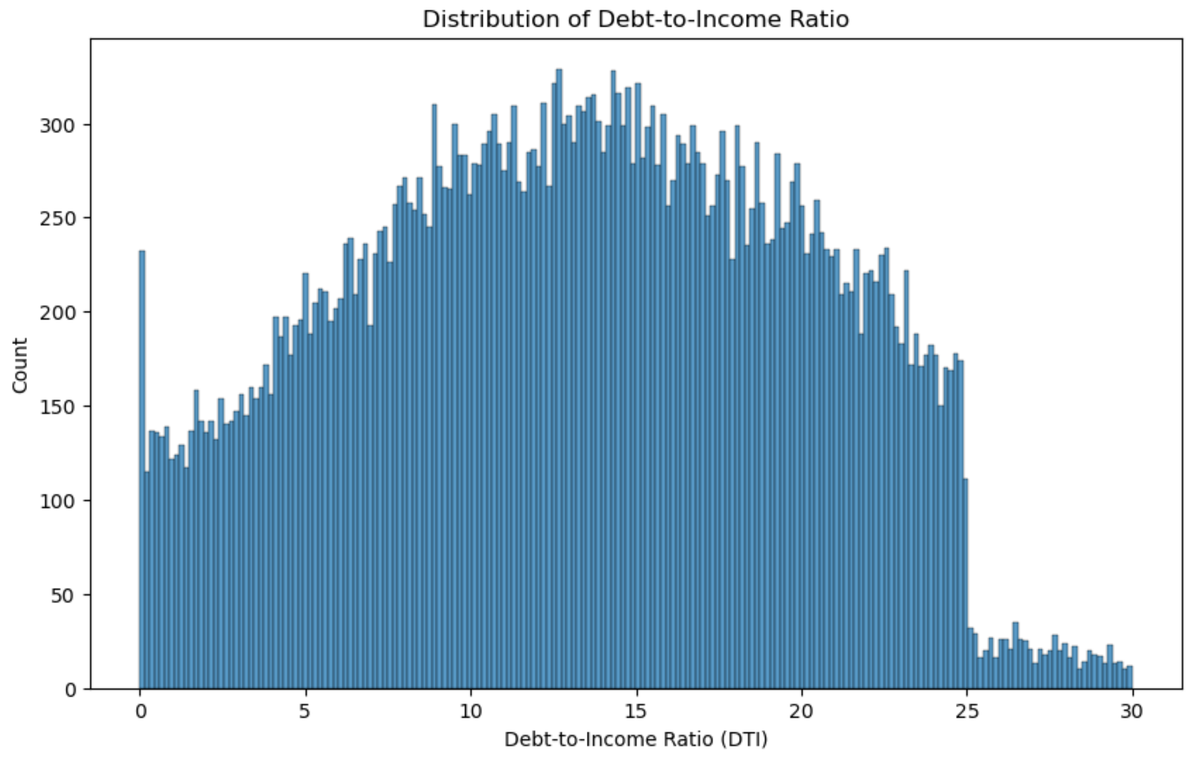
Univariate Exploration

In [27]:
```
# Explore loan status distribution
plt.figure(figsize=(6, 4))
sns.countplot(x='loan_status', data=d2)
plt.title('Loan Status Distribution')
plt.xlabel('Loan Status')
plt.ylabel('Count')
plt.show()
```



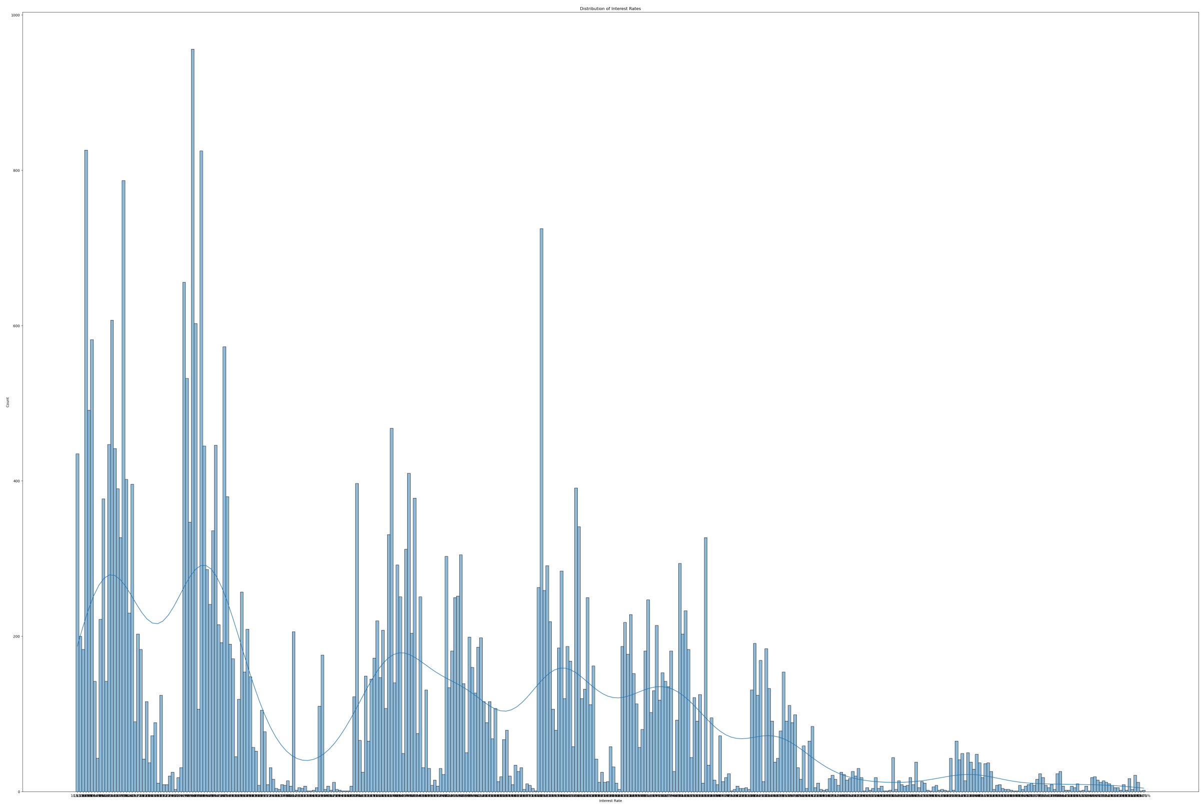
This initial visualization provides you with a quick overview of the proportion of loan statuses in the dataset. We can further investigate how other variables influence these statuses through bivariate analysis, correlation analysis, and more visualizations.

In [29]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data=d2, x='dti', bins=200)
plt.xlabel('Debt-to-Income Ratio (DTI)')
plt.ylabel('Count')
plt.title('Distribution of Debt-to-Income Ratio')
plt.show()
```



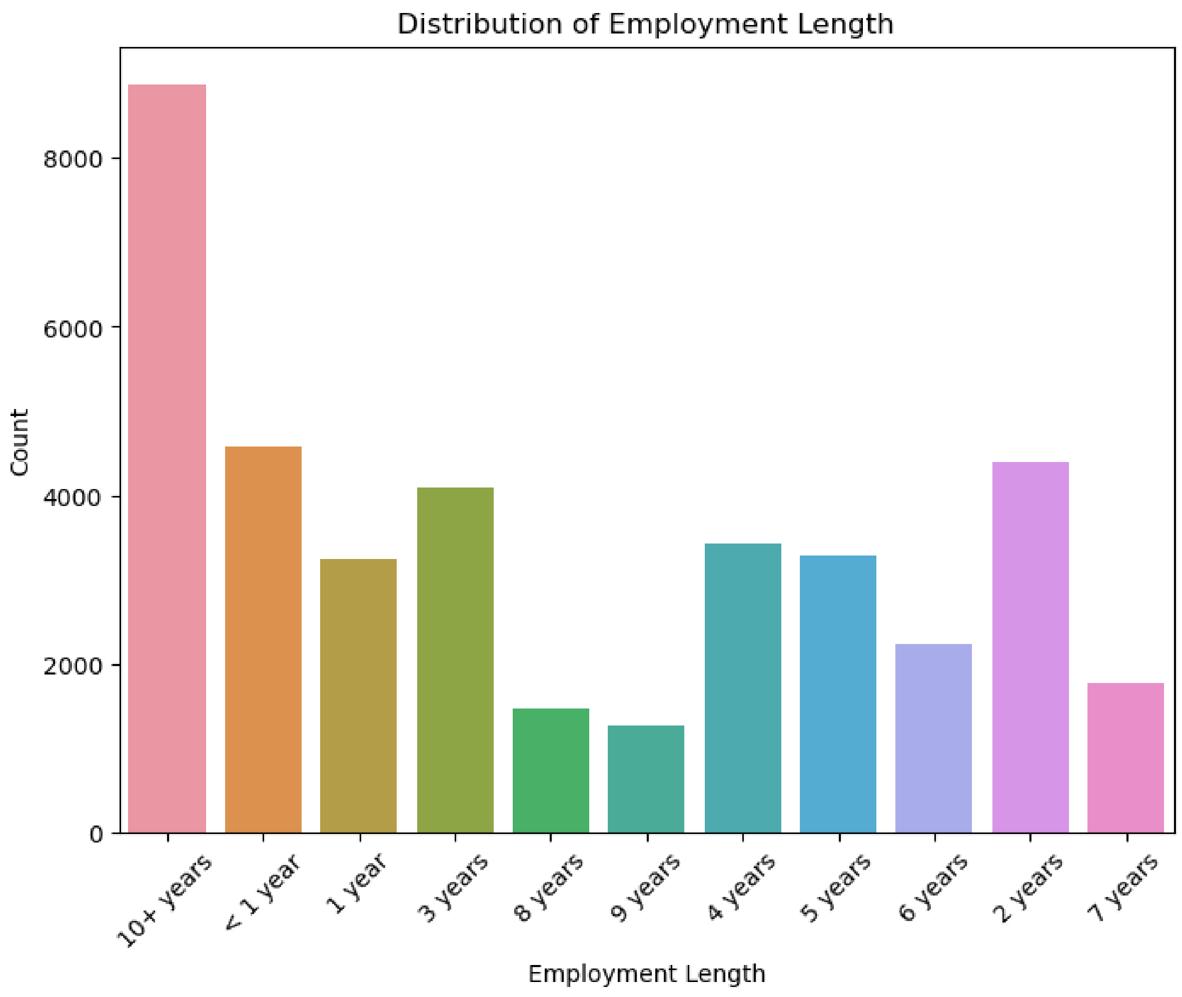
The Debt-to-Income Ratio (DTI) represents the ratio of a borrower's monthly debt payments to their monthly income. The histogram shows how many loans fall into different ranges of DTI values. You can observe whether there are any specific ranges of DTI that have higher or lower loan counts, which could indicate how this variable might influence loan default.

In [41]:
```
plt.figure(figsize=(60, 40))
sns.histplot(data=d2, x='int_rate', bins=10, kde=True)
plt.xlabel('Interest Rate')
plt.ylabel('Count')
plt.title('Distribution of Interest Rates')
plt.show()
```



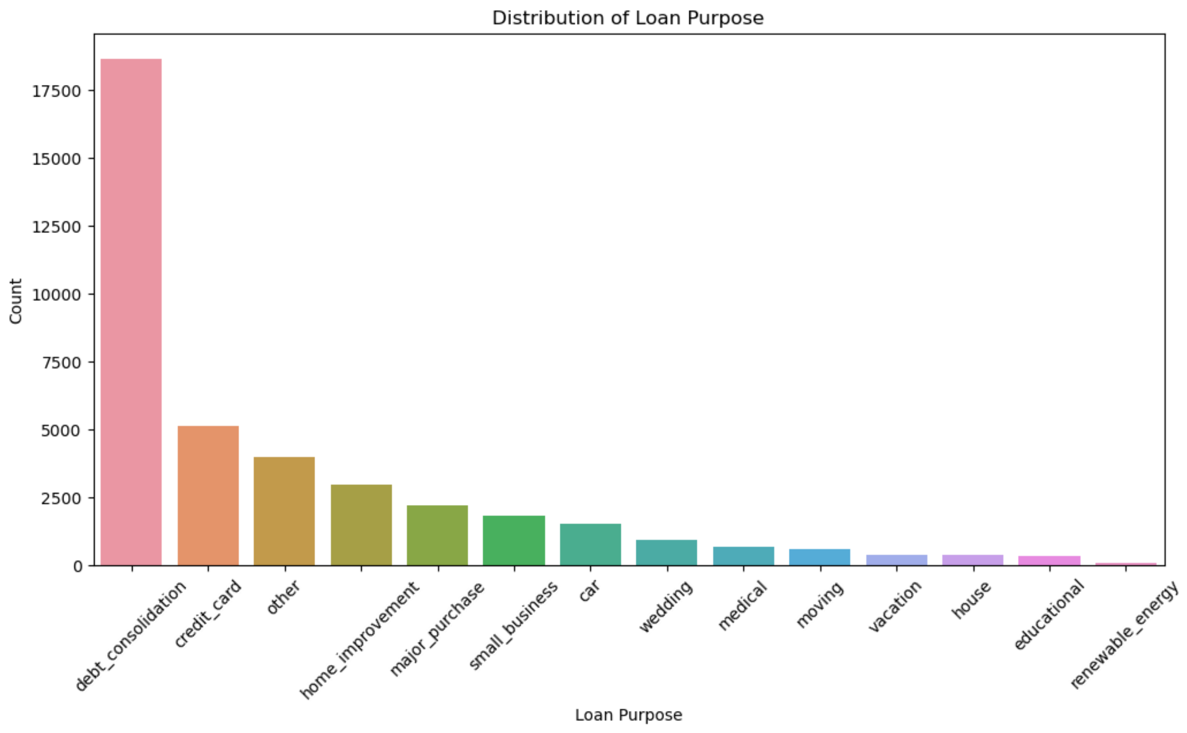
Interest rate is the percentage charged on the loan amount as interest. The histogram displays the frequency of loans with different interest rate ranges. This analysis helps you understand the spread of interest rates and whether higher interest rates are associated with different loan statuses.

In [43]:
```
plt.figure(figsize=(8, 6))
sns.countplot(data=d2, x='emp_length')
plt.xlabel('Employment Length')
plt.ylabel('Count')
plt.title('Distribution of Employment Length')
plt.xticks(rotation=45)
plt.show()
```



This analysis provides the count of loans based on the length of employment of the borrowers. You can identify the distribution of borrowers across different employment lengths, such as '1 year', '2 years', '3 years', and so on. This variable could potentially provide insights into whether borrowers with longer employment lengths are less likely to default.

In [46]:
```
plt.figure(figsize=(12, 6))
sns.countplot(data=d2, x='purpose', order=d2['purpose'].value_counts().index
plt.xlabel('Loan Purpose')
plt.ylabel('Count')
plt.title('Distribution of Loan Purpose')
plt.xticks(rotation=45)
plt.show()
```



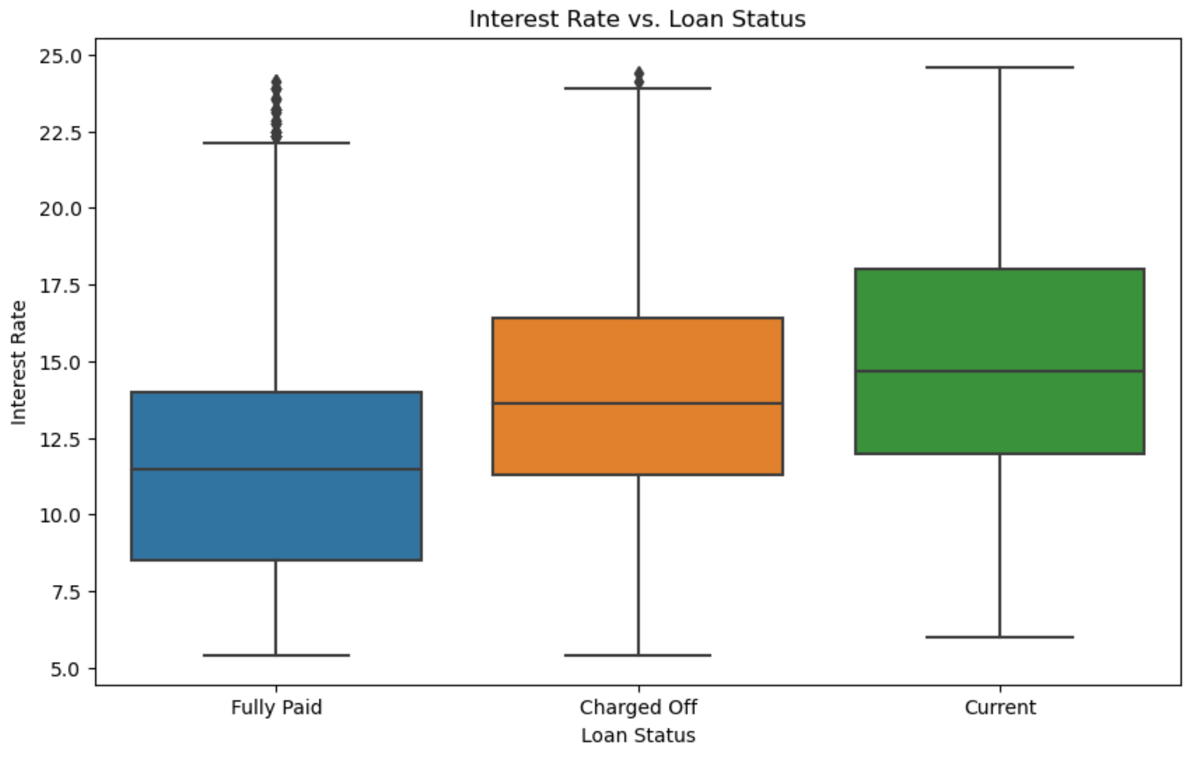
This analysis shows the count of loans based on their stated purpose. The x-axis lists various loan purposes, such as 'debt_consolidation', 'credit_card', 'home_improvement', etc. By examining the distribution, you can understand the most common reasons borrowers are seeking loans, and whether certain purposes have different default rates.

Bivariate exploration

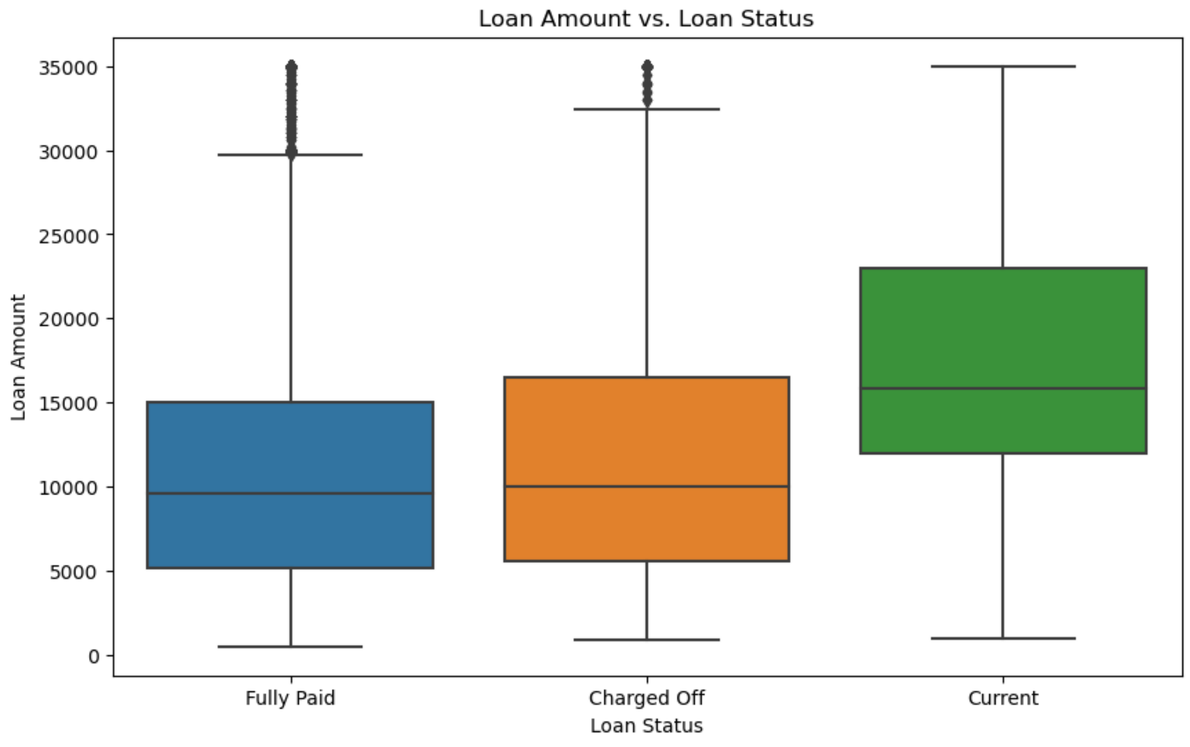
In [49]:
```
intrt = d2.copy()
```

Creating a new copy of the dataset for ploting intrest rate and loan status relation

In [50]:
```
# Convert 'int_rate' column to numeric
intrt['int_rate'] = pd.to_numeric(intrt['int_rate'].str.replace('%', ''), er

# Create the box plot
plt.figure(figsize=(10, 6))
sns.boxplot(data=intrt, x='loan_status', y='int_rate')
plt.xlabel('Loan Status')
plt.ylabel('Interest Rate')
plt.title('Interest Rate vs. Loan Status')
plt.show()
```

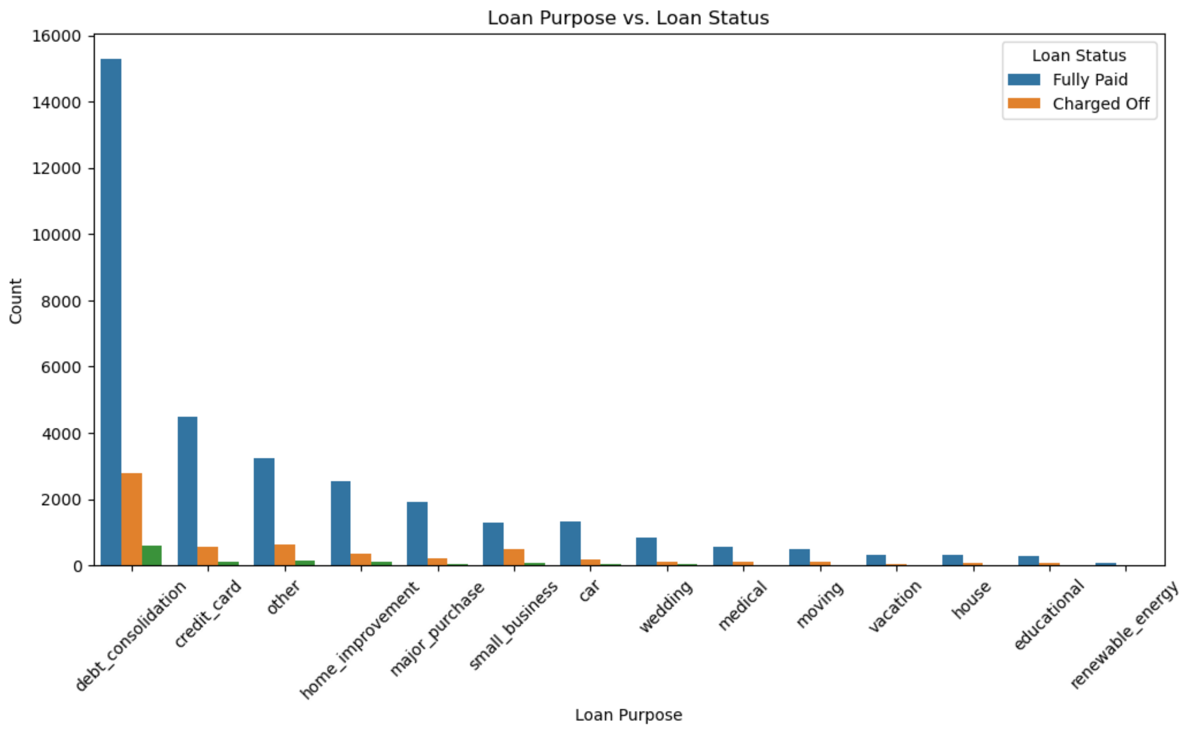


In [54]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=d2, x='loan_status', y='loan_amnt')
plt.xlabel('Loan Status')
plt.ylabel('Loan Amount')
plt.title('Loan Amount vs. Loan Status')
plt.show()
```



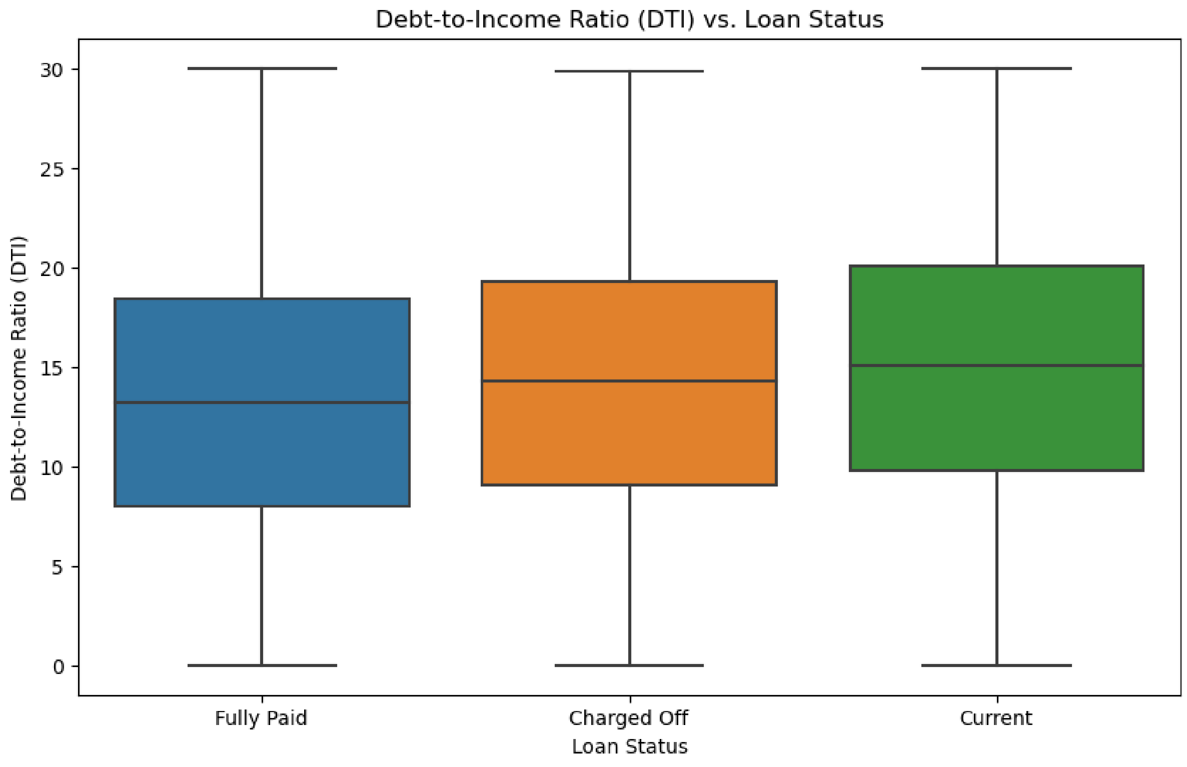
This box plot compares the distribution of loan amounts for fully paid loans and defaulted loans. It helps us identify any differences in loan amounts between the two groups.

In [61]:
```
plt.figure(figsize=(12, 6))
sns.countplot(data=d2, x='purpose', hue='loan_status', order=d2['purpose'].v
plt.xlabel('Loan Purpose')
plt.ylabel('Count')
plt.title('Loan Purpose vs. Loan Status')
plt.xticks(rotation=45)
plt.legend(title='Loan Status', labels=['Fully Paid', 'Charged Off'])
plt.show()
```



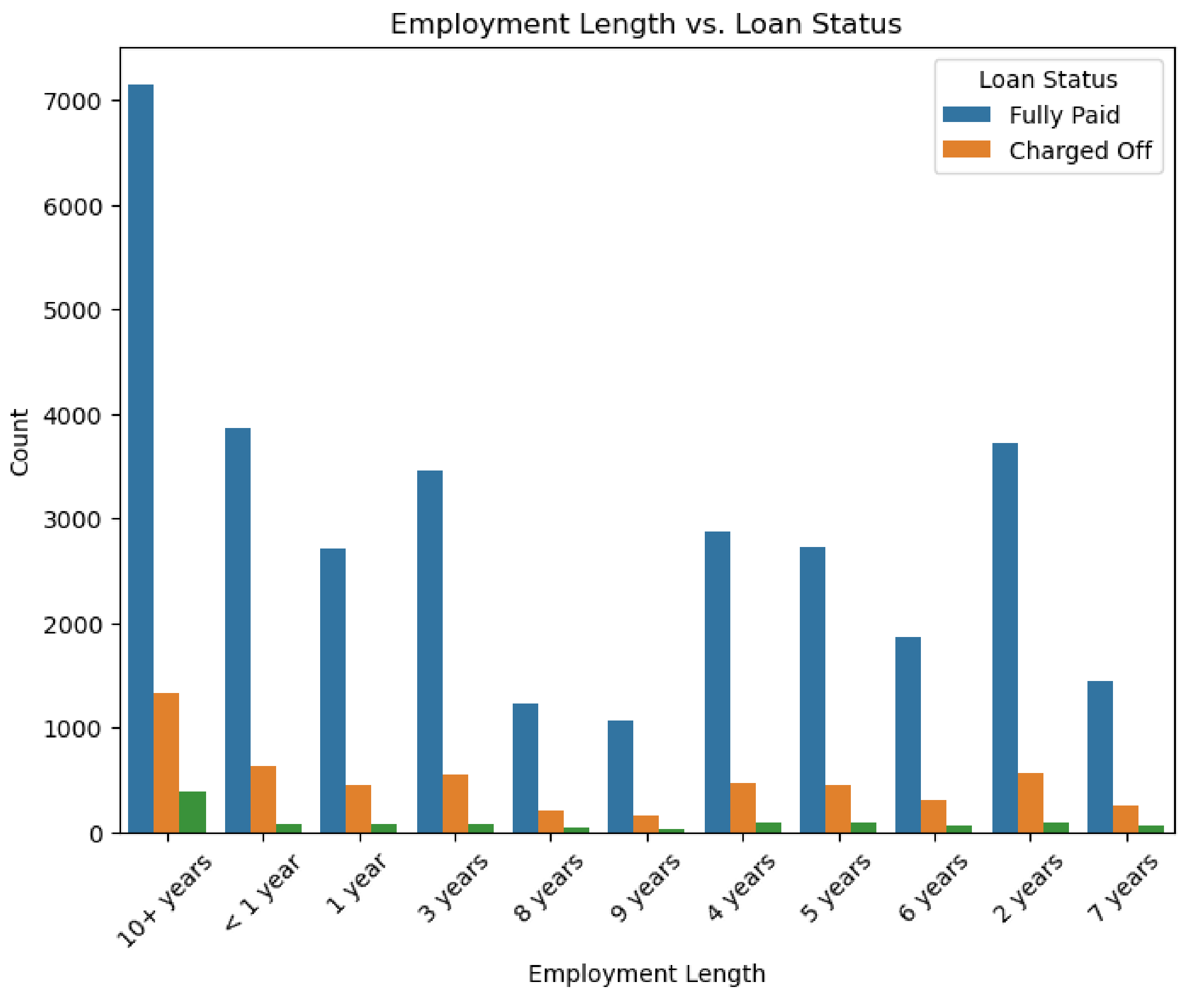
This count plot shows the distribution of loan purposes based on loan status. It helps us understand how different loan purposes relate to loan default, whether certain purposes have higher default rates, and how they compare to fully paid loans.

```
In [64]: plt.figure(figsize=(10, 6))
         sns.boxplot(data=d2, x='loan_status', y='dti')
         plt.xlabel('Loan Status')
         plt.ylabel('Debt-to-Income Ratio (DTI)')
         plt.title('Debt-to-Income Ratio (DTI) vs. Loan Status')
         plt.show()
```



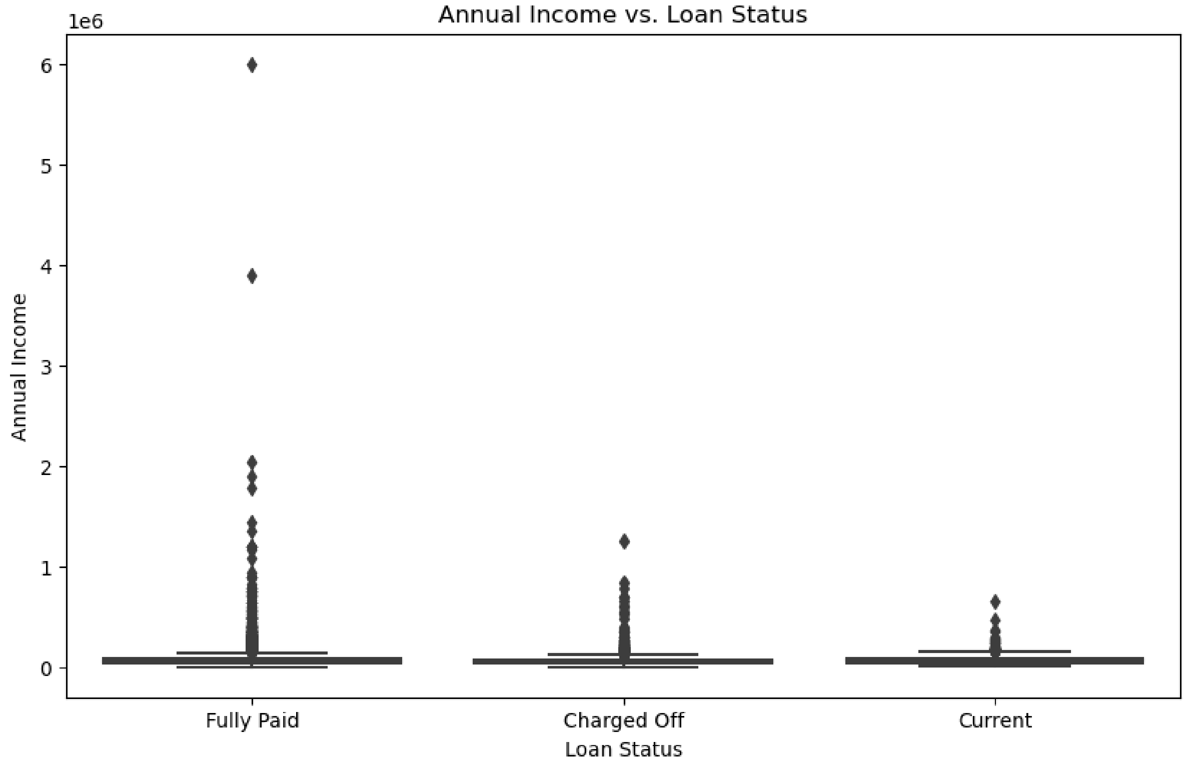
This box plot compares the distribution of debt-to-income ratios (DTI) for fully paid loans and defaulted loans. It helps us understand if borrowers with higher DTI ratios are more likely to default.

In [65]:
```
plt.figure(figsize=(8, 6))
sns.countplot(data=d1, x='emp_length', hue='loan_status')
plt.xlabel('Employment Length')
plt.ylabel('Count')
plt.title('Employment Length vs. Loan Status')
plt.xticks(rotation=45)
plt.legend(title='Loan Status', labels=['Fully Paid', 'Charged Off'])
plt.show()
```



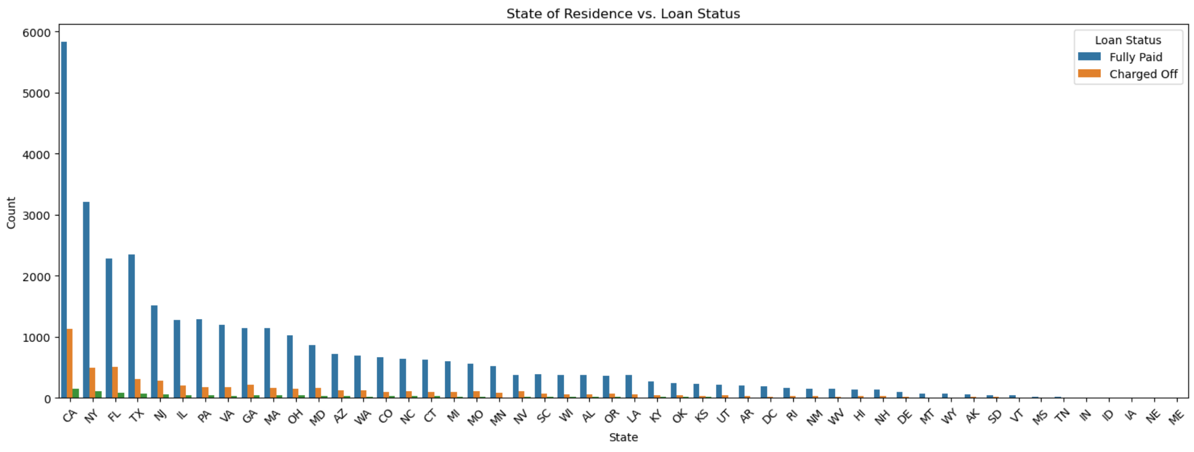
This count plot shows the distribution of loan statuses based on different employment lengths. It helps us understand how the length of employment relates to loan default.

In [67]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=d1, x='loan_status', y='annual_inc')
plt.xlabel('Loan Status')
plt.ylabel('Annual Income')
plt.title('Annual Income vs. Loan Status')
plt.show()
```



This box plot compares the distribution of annual incomes for fully paid loans and defaulted loans. It helps us understand if borrowers' annual income influences the likelihood of loan default.

In [68]:
```
plt.figure(figsize=(18, 6))
sns.countplot(data=d2, x='addr_state', hue='loan_status', order=d2['addr_sta
plt.xlabel('State')
plt.ylabel('Count')
plt.title('State of Residence vs. Loan Status')
plt.xticks(rotation=45)
plt.legend(title='Loan Status', labels=['Fully Paid', 'Charged Off'])
plt.show()
```



This count plot shows the distribution of loan statuses based on the state of residence. It helps us understand if loan default rates vary by state.

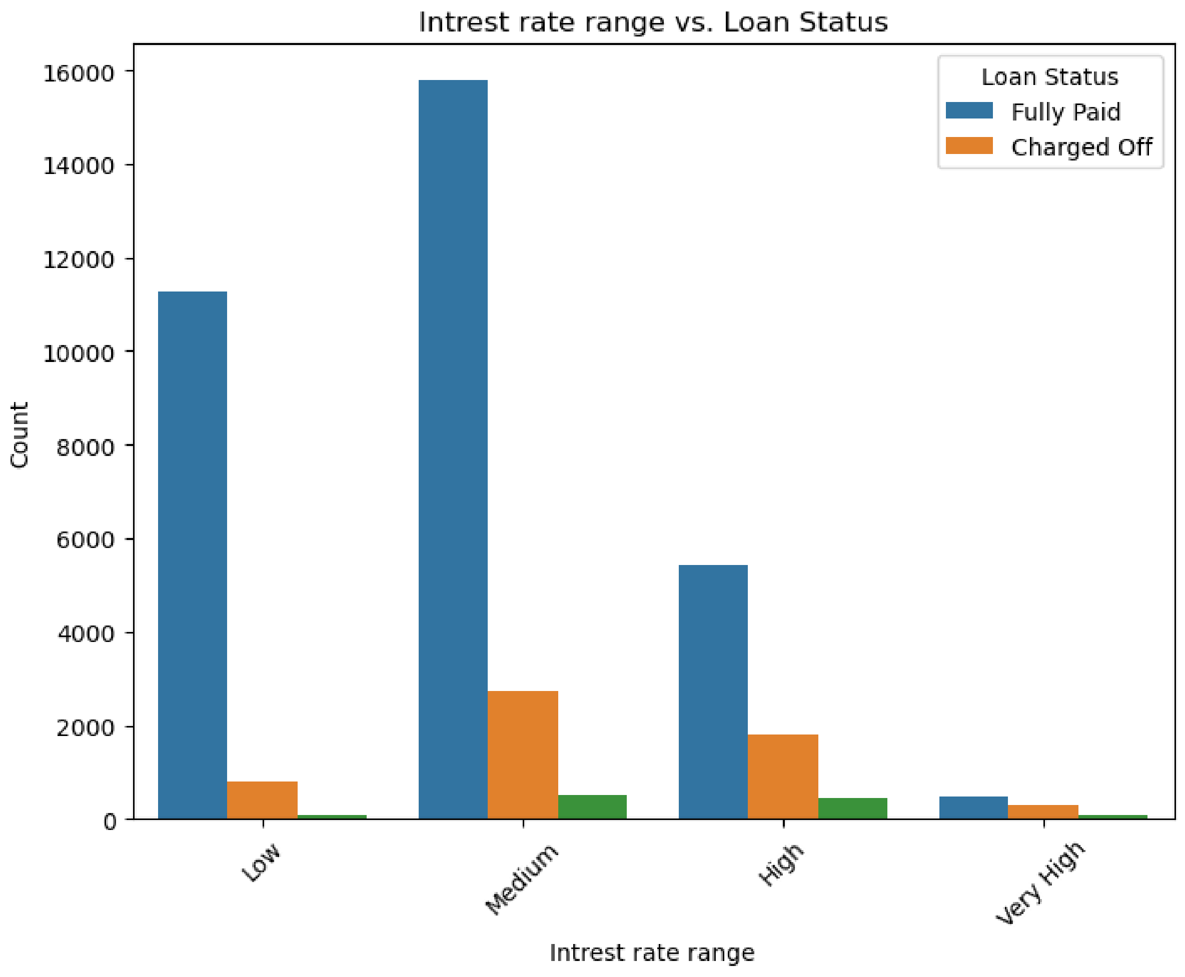
In [ ]:
```
# d3 = d2.copy()
# d3 for derived variables creation
```

In [70]:
```
d3['int_rate'] = pd.to_numeric(d3['int_rate'].str.replace('%', ''), errors='

# Define interest rate ranges and labels
```

```
interest_rate_ranges = [(0, 10), (10, 15), (15, 20), (20, 100)]
interest_rate_labels = ['Low', 'Medium', 'High', 'Very High']

# Create a new column 'int_rate_range' with the interest rate ranges
d3['int_rate_range'] = pd.cut(d3['int_rate'], bins=[r[0] for r in interest_r
                                              labels=interest_rate_labels, right=
```

In [74]:

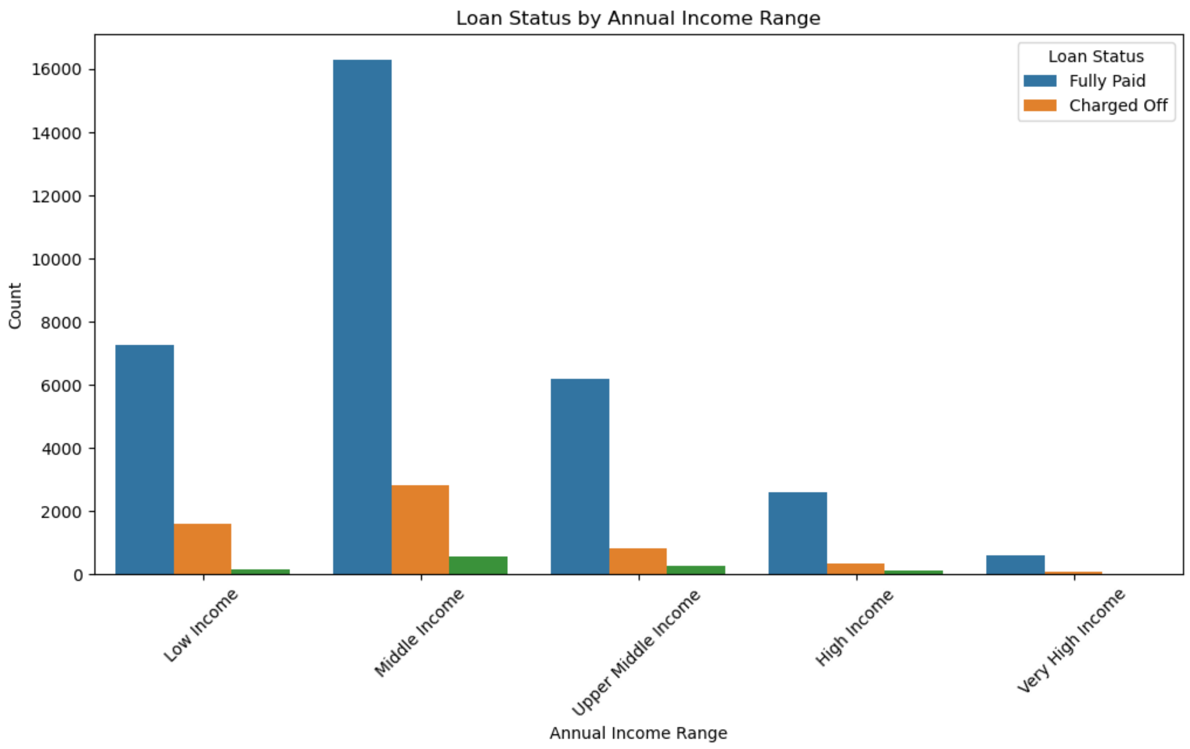
```
plt.figure(figsize=(8, 6))
sns.countplot(data=d3, x='int_rate_range', hue='loan_status')
plt.xlabel('Intrest rate range')
plt.ylabel('Count')
plt.title('Intrest rate range vs. Loan Status')
plt.xticks(rotation=45)
plt.legend(title='Loan Status', labels=['Fully Paid', 'Charged Off'])
plt.show()
```



Creating categorical bins for interest rates, such as 'low', 'medium', 'high', and 'very high'. This can provide a more understanding of how different interest rate ranges impact loan default.

In [75]:

```
income_ranges = [(0, 40000), (40000, 80000), (80000, 120000), (120000, 20000
income_labels = ['Low Income', 'Middle Income', 'Upper Middle Income', 'High
d3['income_range'] = pd.cut(d3['annual_inc'], bins=[r[0] for r in income_ran
                                       labels=income_labels, right=False)
plt.figure(figsize=(12, 6))
sns.countplot(data=d3, x='income_range', hue='loan_status', order=income_lab
plt.xlabel('Annual Income Range')
plt.ylabel('Count')
plt.title('Loan Status by Annual Income Range')
plt.xticks(rotation=45)
plt.legend(title='Loan Status', labels=['Fully Paid', 'Charged Off'])
plt.show()
```



Creating income brackets, such as 'low income', 'middle income', and 'high income'. This can show whether borrowers in certain income ranges are more likely to default.

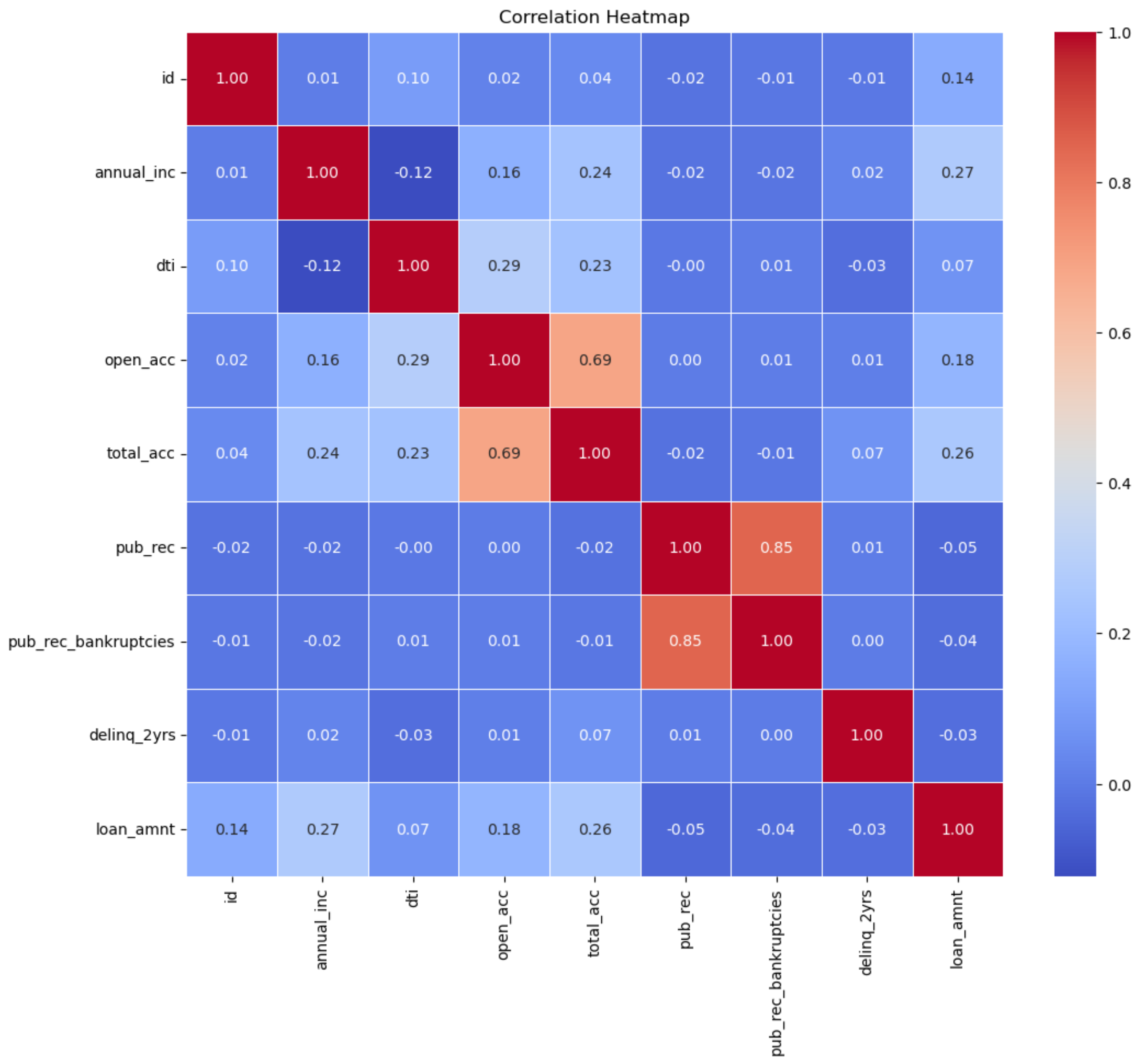
Corelation matrix

In [79]:
```
# d4 = d2.drop(columns=['avg_cur_bal'])
#removing the avg_cur_bal column cause its creating issues in the corelation
```

Out[79]:
```
Index(['id', 'loan_status', 'annual_inc', 'dti', 'emp_length', 'int_rate',
       'purpose', 'term', 'open_acc', 'total_acc', 'revol_util', 'pub_rec',
       'pub_rec_bankruptcies', 'addr_state', 'zip_code', 'delinq_2yrs',
       'loan_amnt'],
      dtype='object')
```

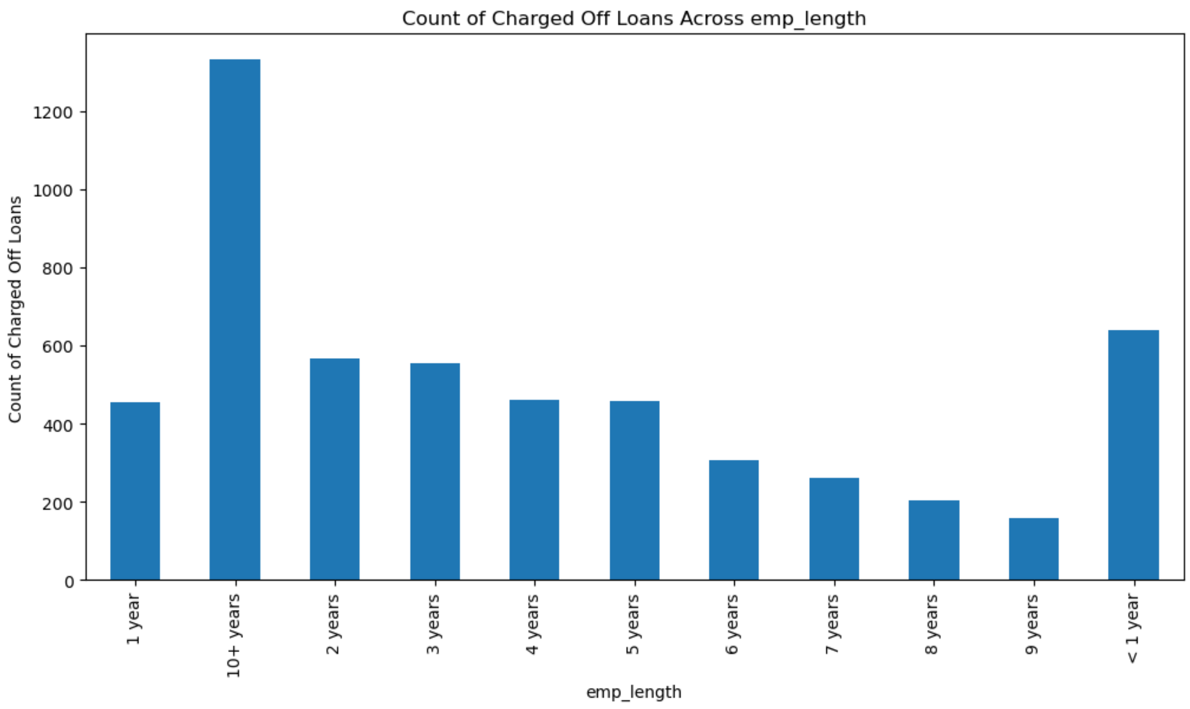
In [78]:
```
correlation_matrix = d4.corr()
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, cmap='coolwarm', annot=True, fmt=".2f", line
plt.title('Correlation Heatmap')
plt.show()
```

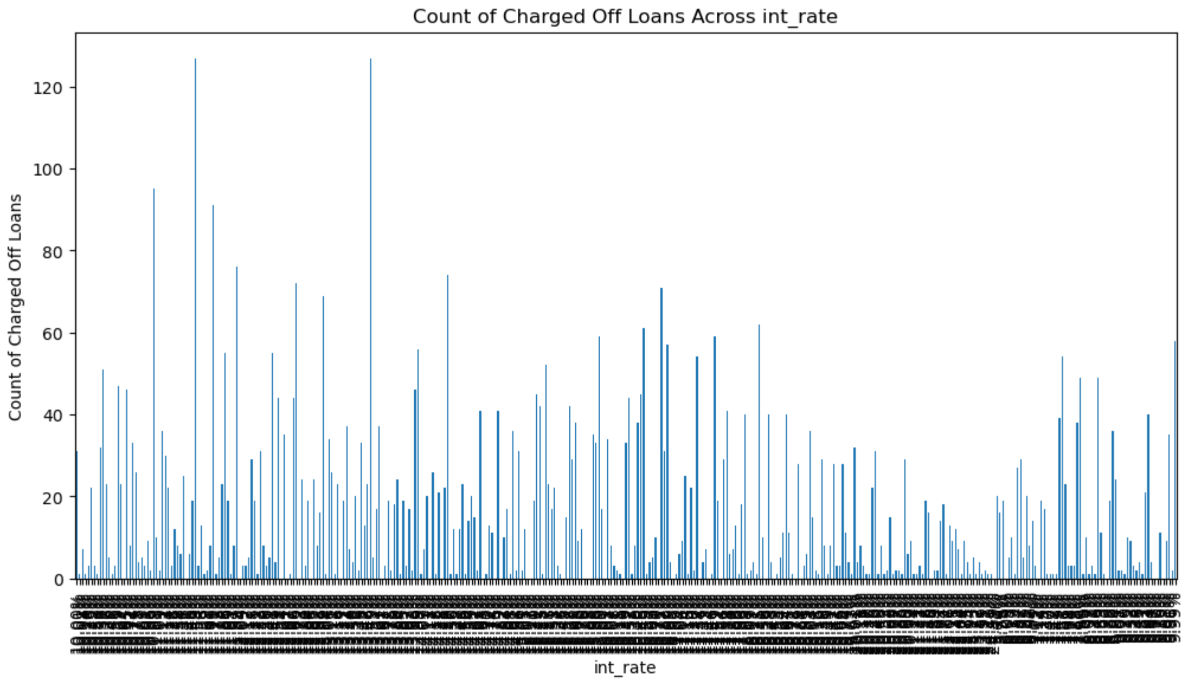
```
/var/folders/8j/l5qhmn695n3cctcl4h0dzkqr0000gp/T/ipykernel_81762/2316707516.
py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  correlation_matrix = d4.corr()
```

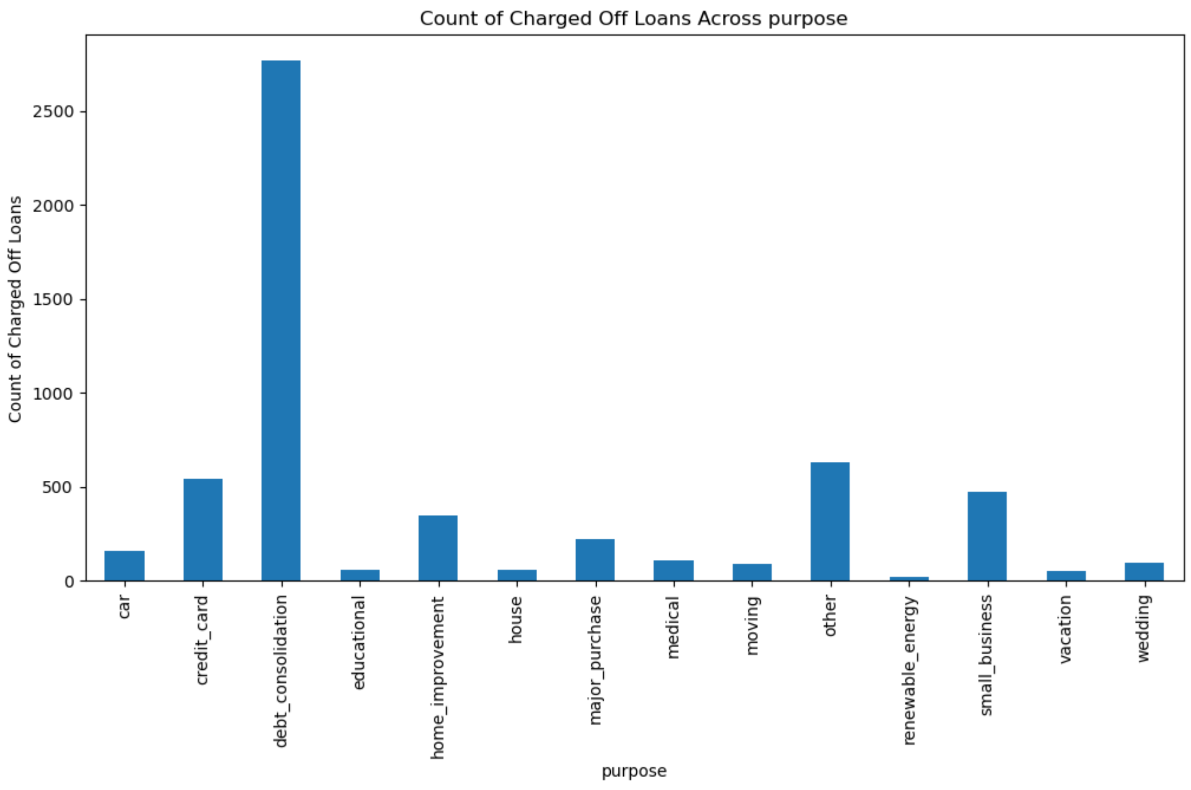


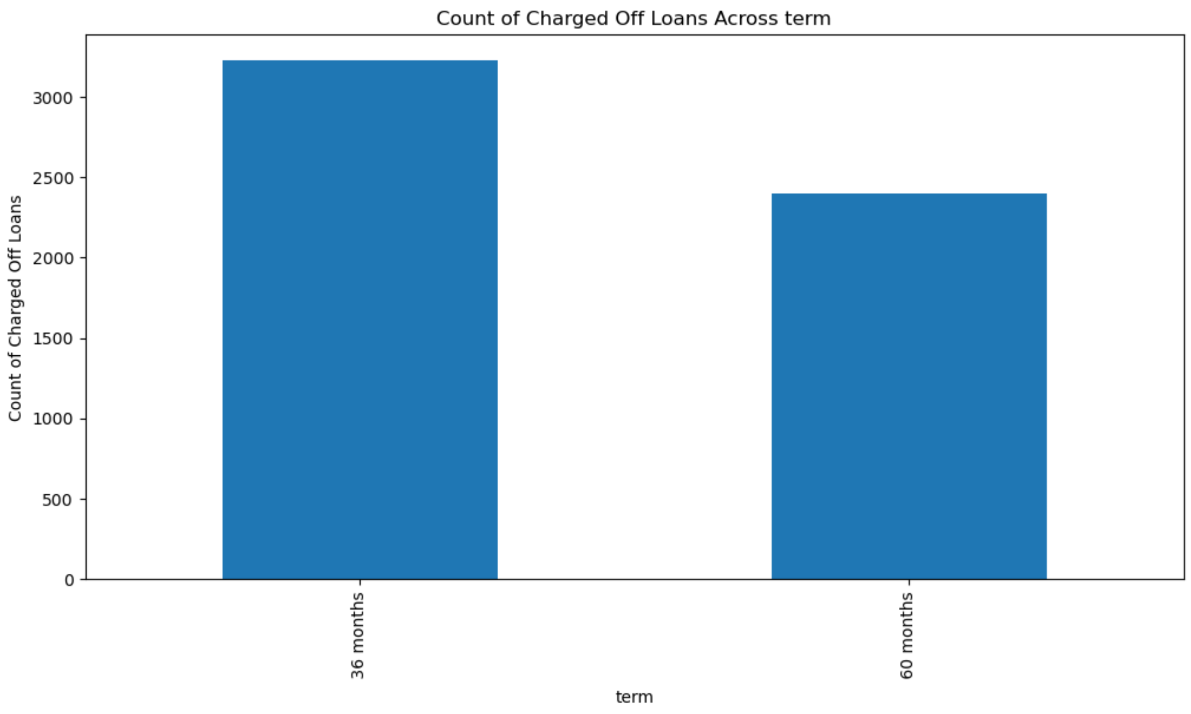
unable to find much relations here which are usefull

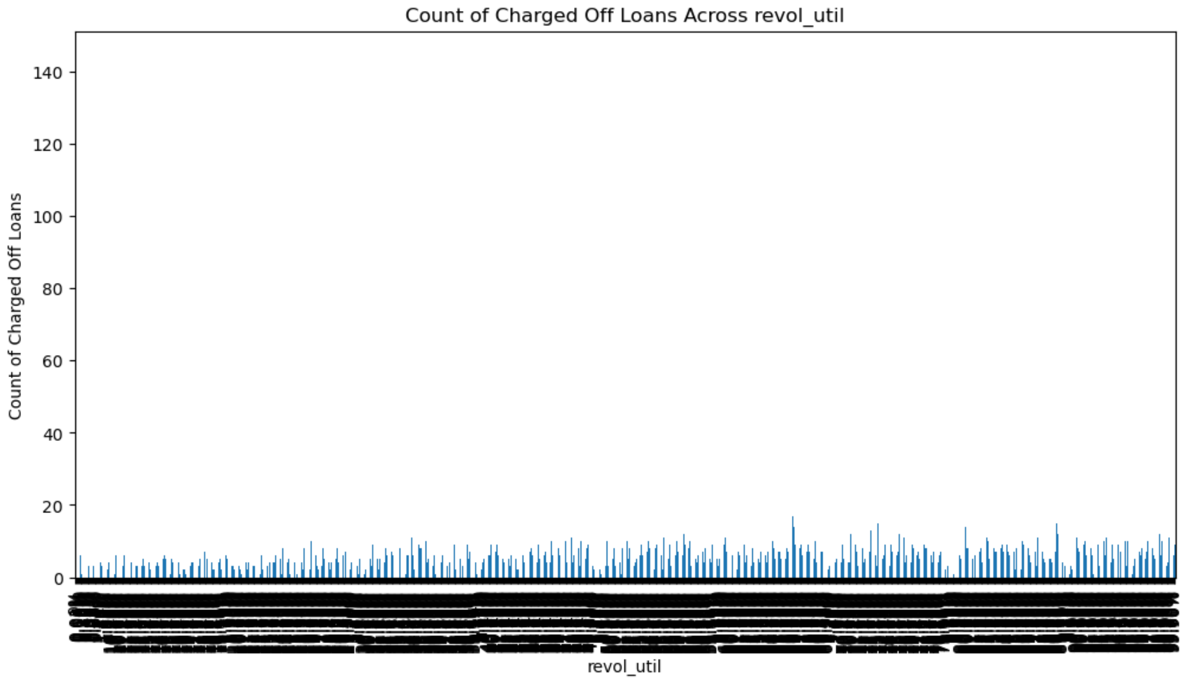
In [126…
```
d2.columns
```
Out[126]:
```
Index(['id', 'loan_status', 'annual_inc', 'dti', 'emp_length', 'int_rate',
       'purpose', 'term', 'open_acc', 'total_acc', 'revol_util', 'pub_rec',
       'pub_rec_bankruptcies', 'addr_state', 'zip_code', 'avg_cur_bal',
       'delinq_2yrs', 'loan_amnt'],
      dtype='object')
```
In [129…
```
categorical_columns = d2.select_dtypes(include='object').columns
strong_categorical = []
for column in categorical_columns:
    if column != 'loan_status':
        cross_tab = pd.crosstab(d2[column], d2['loan_status'])
        charged_off_counts = cross_tab['Charged Off']
        charged_off_counts.plot(kind='bar', figsize=(12, 6))
        plt.xticks(rotation=90)
        plt.title(f'Count of Charged Off Loans Across {column}')
        plt.xlabel(column)
        plt.ylabel('Count of Charged Off Loans')
        plt.show()
```

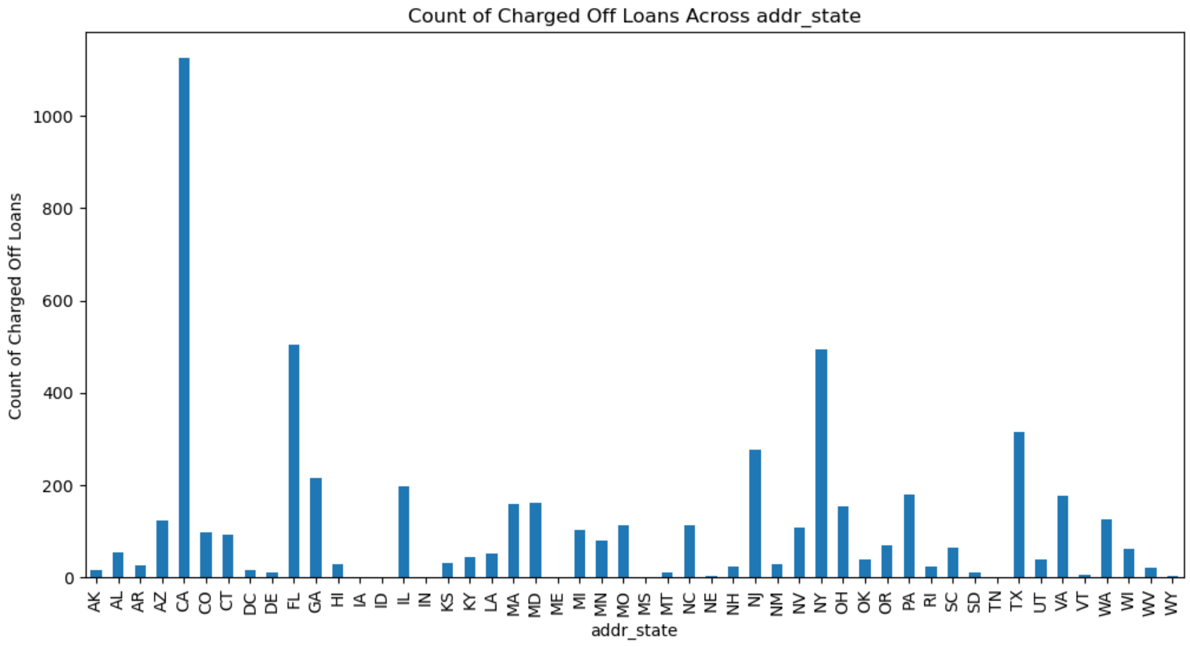

Count of Charged Off Loans Across emp_length
Count of Charged Off Loans
0
200
400
600
800
1000
1200
1 year
10+ years
2 years
3 years
4 years
5 years
6 years
7 years
8 years
9 years
< 1 year
emp_length

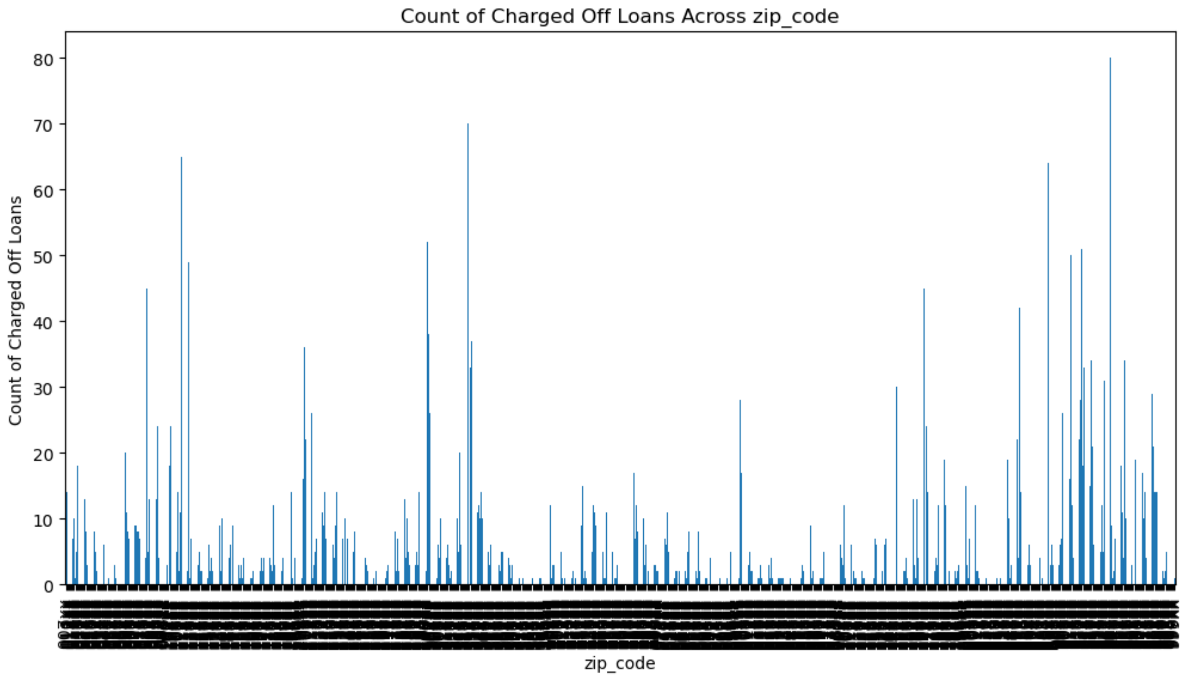

Count of Charged Off Loans Across int_rate
Count of Charged Off Loans
0
20
40
60
80
100
120
int_rate


Count of Charged Off Loans Across purpose
Count of Charged Off Loans
0
500
1000
1500
2000
2500
car
credit_card
debt_consolidation
educational
home_improvement
house
major_purchase
medical
moving
other
renewable_energy
small_business
vacation
wedding
purpose


Count of Charged Off Loans Across term
Count of Charged Off Loans
0
500
1000
1500
2000
2500
3000
36 months
60 months
term


Count of Charged Off Loans Across revol_util
Count of Charged Off Loans
revol_util
0
20
40
60
80
100
120
140


Count of Charged Off Loans Across addr_state
Count of Charged Off Loans
addr_state
0
200
400
600
800
1000
AK AL AR AZ CA CO CT DC DE FL GA HI IA ID IL IN KS KY LA MA MD ME MI MN MO MS MT NC NE NH NJ NM NV NY OH OK OR PA RI SC SD TN TX UT VA VT WA WI WV WY


Count of Charged Off Loans Across zip_code
Count of Charged Off Loans
zip_code
0
10
20
30
40
50
60
70
80

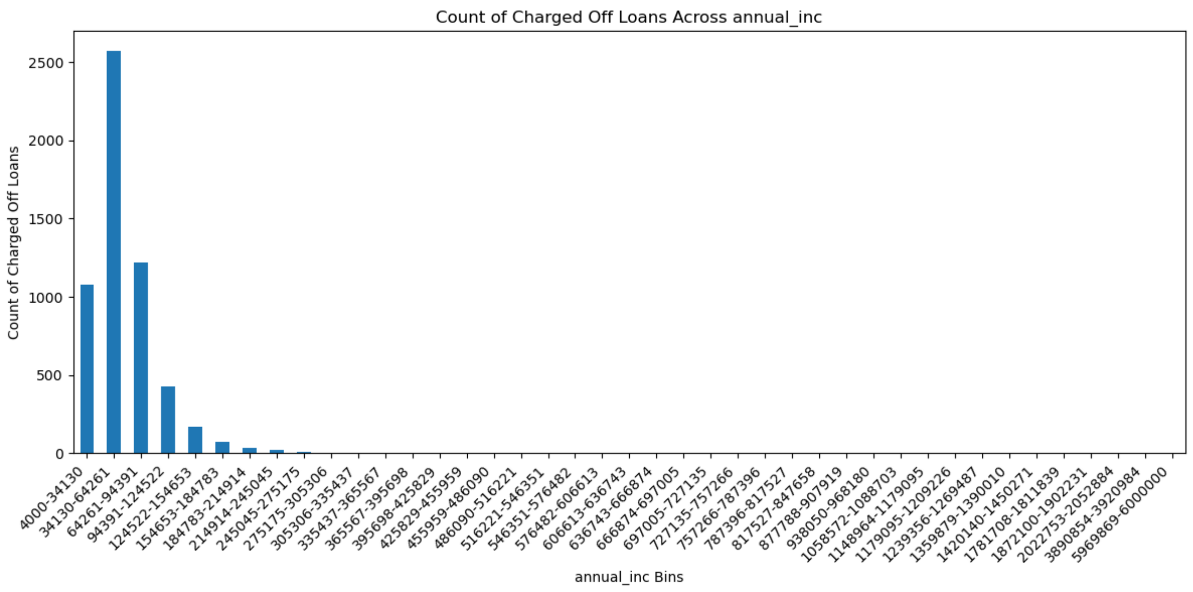
In [140…
```
categorical_columns = d2.select_dtypes(include='number').columns
categorical_columns
```

Out[140]:
```
Index(['id', 'annual_inc', 'dti', 'open_acc', 'total_acc', 'pub_rec',
       'pub_rec_bankruptcies', 'avg_cur_bal', 'delinq_2yrs', 'loan_amnt'],
      dtype='object')
```

validating thedefaulters accross diferent numerical variables.

Annual Income

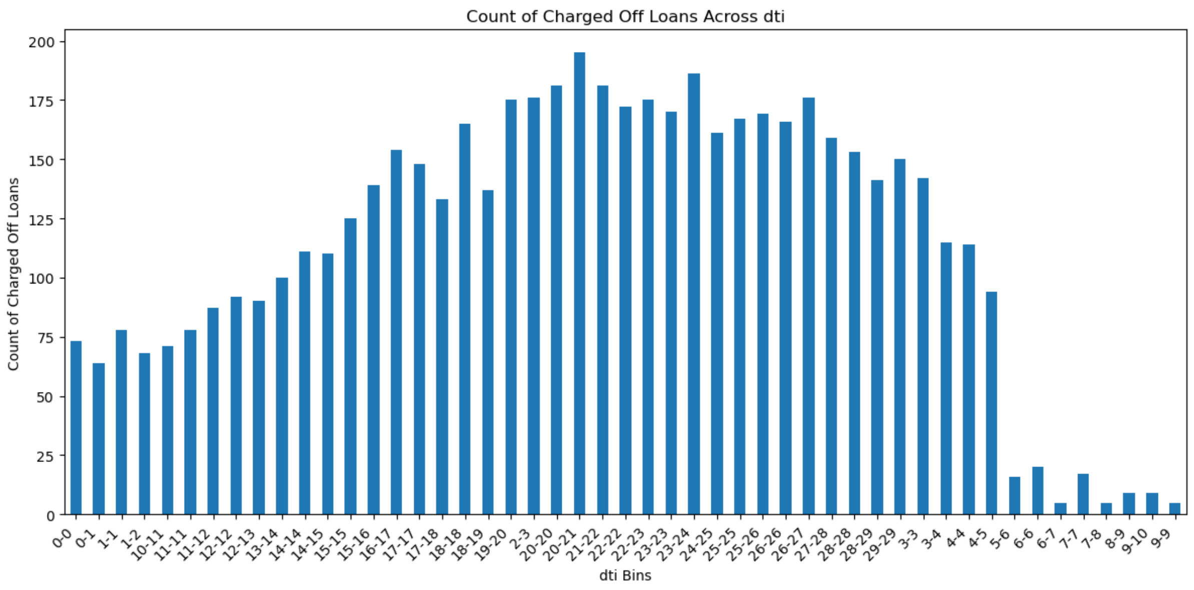
In [146…
```
column='annual_inc'



# Define bin edges
bin_edges = np.linspace(d2[column].min(), d2[column].max(), num=200)

# Create bins and labels
bin_labels = [f'{int(bin_edges[i])}-{int(bin_edges[i+1])}' for i in range(le

# Assign each value to a bin
d2['income_bin'] = pd.cut(d2[column], bins=bin_edges, labels=bin_labels, inc

# Create cross-tabulation
cross_tab = pd.crosstab(d2['income_bin'], d2['loan_status'])
charged_off_counts = cross_tab['Charged Off']

# Plot the bar chart
charged_off_counts.plot(kind='bar', figsize=(12, 6))
plt.xticks(rotation=45, ha='right')
plt.title(f'Count of Charged Off Loans Across {column}')
plt.xlabel(f'{column} Bins')
plt.ylabel('Count of Charged Off Loans')
plt.tight_layout()
plt.show()
```



DTI

In [152…
```
column='dti'

# Define bin edges
bin_edges = np.linspace(d2[column].min(), d2[column].max(), num=50)
```

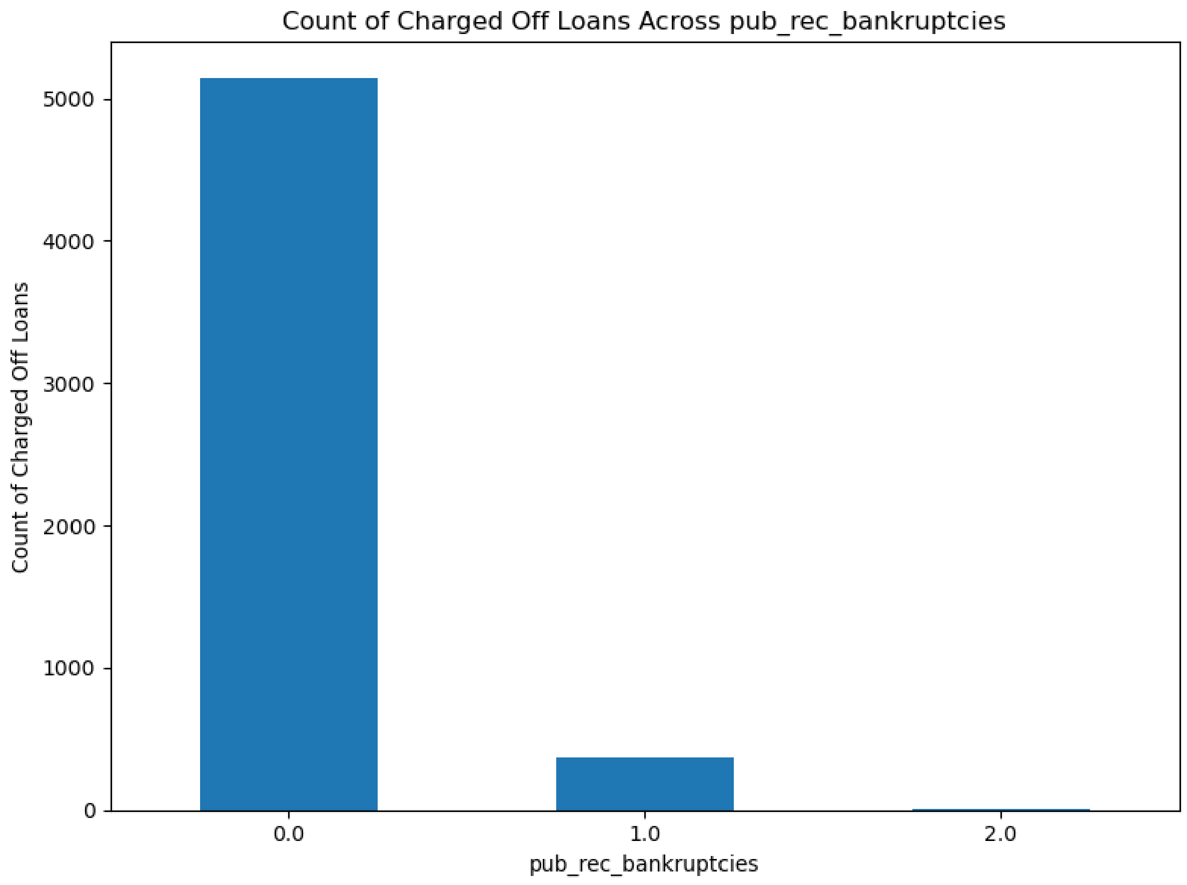
```
# Create bins and labels
bin_labels = [f'{int(bin_edges[i])}-{int(bin_edges[i+1])}' for i in range(le
unique_bin_labels = np.unique(bin_labels)  # Get unique labels

# Assign each value to a bin
d2[f'{column}_bins'] = pd.cut(d2[column], bins=bin_edges, labels=unique_bin_

# Create cross-tabulation
cross_tab = pd.crosstab(d2[f'{column}_bins'], d2['loan_status'])
charged_off_counts = cross_tab['Charged Off']

# Plot the bar chart
charged_off_counts.plot(kind='bar', figsize=(12, 6))
plt.xticks(rotation=45, ha='right')
plt.title(f'Count of Charged Off Loans Across {column}')
plt.xlabel(f'{column} Bins')
plt.ylabel('Count of Charged Off Loans')
plt.tight_layout()
plt.show()
```



Bankruptcy

In [163…

```
column='pub_rec_bankruptcies'

cross_tab = pd.crosstab(d2[column], d2['loan_status'])
charged_off_counts = cross_tab['Charged Off']

# Plot the bar chart
charged_off_counts.plot(kind='bar', figsize=(8, 6))
plt.title(f'Count of Charged Off Loans Across {column}')
plt.xlabel(column)
plt.ylabel('Count of Charged Off Loans')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



In [164…

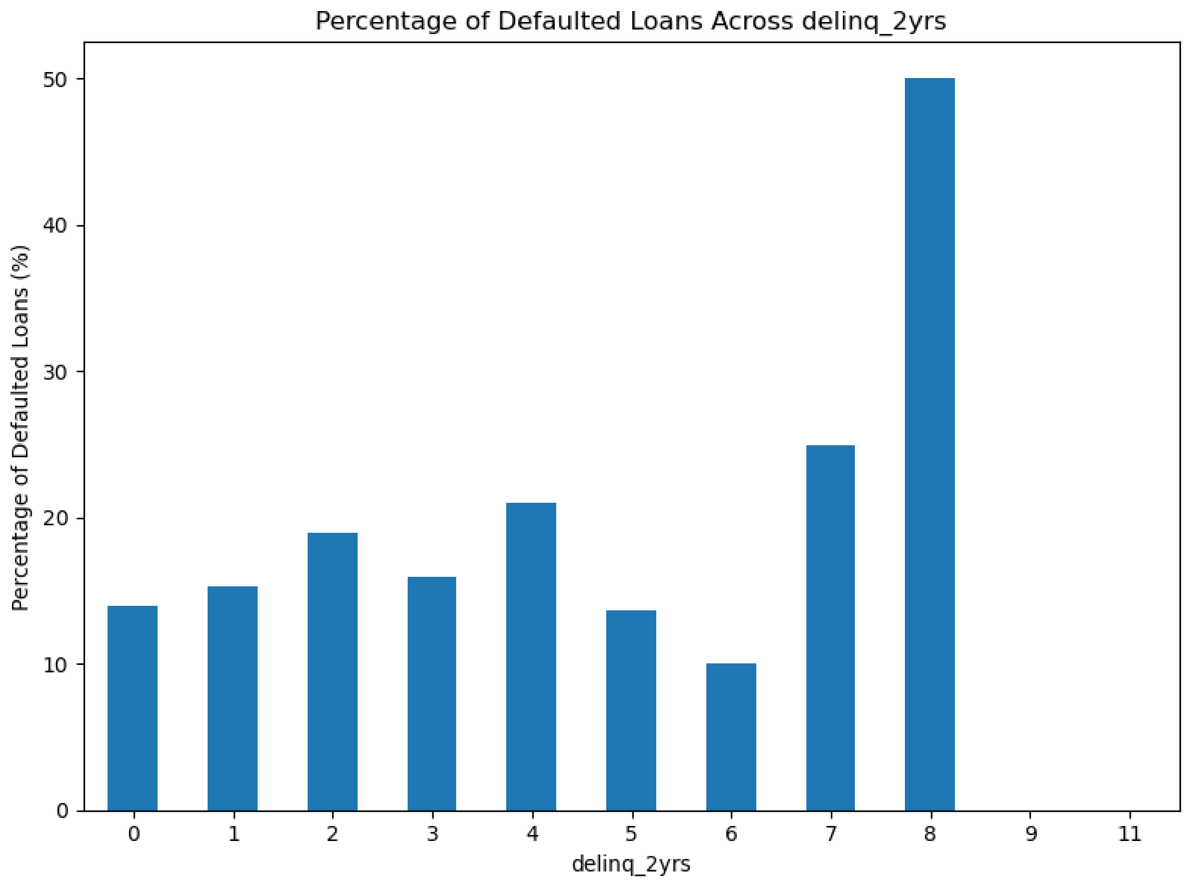
```
d2.delinq_2yrs.value_counts()
```

Out[164]:

```
0     35405
1      3303
2       687
3       220
4        62
5        22
6        10
7         4
8         2
9         1
11        1
Name: delinq_2yrs, dtype: int64
```

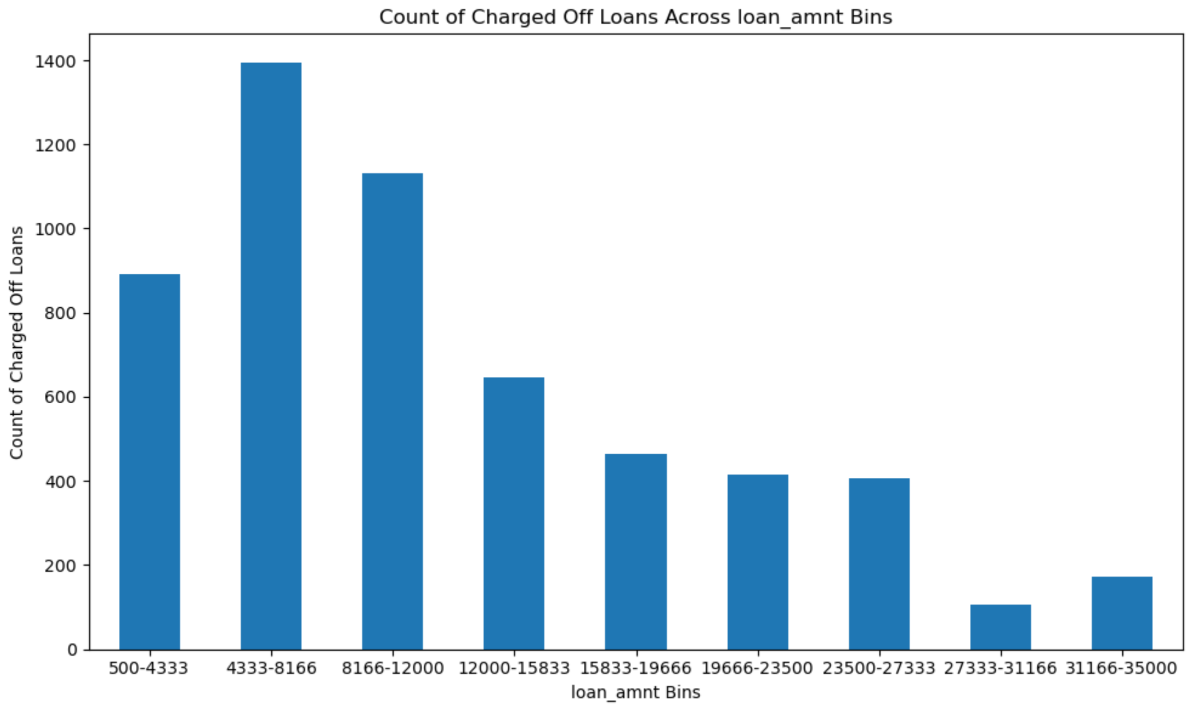
In [169…

```
column = 'delinq_2yrs'

# Create cross-tabulation
cross_tab = pd.crosstab(d2[column], d2['loan_status'])
percentage_defaulted = (cross_tab['Charged Off'] / cross_tab.sum(axis=1)) *

# Plot the bar chart
percentage_defaulted.plot(kind='bar', figsize=(8, 6))
plt.title(f'Percentage of Defaulted Loans Across {column}')
plt.xlabel(column)
plt.ylabel('Percentage of Defaulted Loans (%)')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



In [171…

```
column = 'loan_amnt'

# Define bin edges
bin_edges = np.linspace(d2[column].min(), d2[column].max(), num=10)

# Create bins and labels
bin_labels = [f'{int(bin_edges[i])}-{int(bin_edges[i+1])}' for i in range(le

# Assign each value to a bin
d2[f'{column}_bins'] = pd.cut(d2[column], bins=bin_edges, labels=bin_labels,

# Create cross-tabulation
cross_tab = pd.crosstab(d2[f'{column}_bins'], d2['loan_status'])
charged_off_counts = cross_tab['Charged Off']

# Plot the bar chart
charged_off_counts.plot(kind='bar', figsize=(10, 6))
plt.title(f'Count of Charged Off Loans Across {column} Bins')
plt.xlabel(f'{column} Bins')
plt.ylabel('Count of Charged Off Loans')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```


Count of Charged Off Loans Across loan_amnt Bins
Count of Charged Off Loans
0
200
400
600
800
1000
1200
1400
500-4333
4333-8166
8166-12000
12000-15833
15833-19666
19666-23500
23500-27333
27333-31166
31166-35000
loan_amnt Bins

```
In [ ]:
```