LOAN ANALYSIS

In [4]:

```
# Load the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
loan = pd.read_csv(r"C:\Users\hp\Desktop\SQL Projects\New folder\loan.csv")

# Display the first few rows of the dataframe
#print(loan_df.head())
loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Columns: 111 entries, id to total_il_high_credit_limit
dtypes: float64(74), int64(13), object(24)
memory usage: 33.6+ MB

C:\Users\hp\AppData\Local\Temp\ipykernel_11208\1448332866.py:8: DtypeWarning: Columns (47) have mixed ty
pes. Specify dtype option on import or set low_memory=False.
  loan = pd.read_csv(r"C:\Users\hp\Desktop\SQL Projects\New folder\loan.csv")
```

Data Understanding

In [5]:
```
# Let's look at the first few rows of the df
loan.head()
```

Out[5]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	num_tl_90g
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	B	B2	...	
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	C	C4	...	
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	C	C5	...	
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	C	C1	...	
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	B	B5	...	

5 rows × 111 columns

In [6]:
```
# Looking at all the column names
loan.columns
```

Out[6]:
```
Index(['id', 'member_id', 'loan_amnt', 'funded_amnt', 'funded_amnt_inv',
       'term', 'int_rate', 'installment', 'grade', 'sub_grade',
       ...
       'num_tl_90g_dpd_24m', 'num_tl_op_past_12m', 'pct_tl_nvr_dlq',
       'percent_bc_gt_75', 'pub_rec_bankruptcies', 'tax_liens',
       'tot_hi_cred_lim', 'total_bal_ex_mort', 'total_bc_limit',
       'total_il_high_credit_limit'],
      dtype='object', length=111)
```

Some of the important columns in the dataset are loan_amount, term, interest rate, grade, sub grade, annual income, purpose of the loan etc.

The **target variable**, which we want to compare across the independent variables, is loan status. The strategy is to figure out compare

Data Cleaning

Some columns have a large number of missing values, let's first fix the missing values and then check for other types of data quality problems.

In [7]:
```
# summarising number of missing values in each column
loan.isnull().sum()
```

Out[7]:
```
id                                0
member_id                         0
loan_amnt                         0
funded_amnt                       0
funded_amnt_inv                   0
                              ...
tax_liens                        39
tot_hi_cred_lim               39717
total_bal_ex_mort             39717
total_bc_limit                39717
total_il_high_credit_limit    39717
Length: 111, dtype: int64
```

In [8]:
```
# percentage of missing values in each column
round(loan.isnull().sum()/len(loan.index), 2)*100
```

Out[8]:
```
id                              0.0
member_id                       0.0
loan_amnt                       0.0
funded_amnt                     0.0
funded_amnt_inv                 0.0
                              ...
tax_liens                       0.0
tot_hi_cred_lim               100.0
total_bal_ex_mort             100.0
total_bc_limit                100.0
total_il_high_credit_limit    100.0
Length: 111, dtype: float64
```

You can see that many columns have 100% missing values, some have 65%, 33% etc. First, let's get rid of the columns having 100% missing values.

In [9]:

```
# removing the columns having more than 90% missing values
missing_columns = loan.columns[100*(loan.isnull().sum()/len(loan.index)) > 90]
print(missing_columns)
```

```
Index(['mths_since_last_record', 'next_pymnt_d', 'mths_since_last_major_derog',
       'annual_inc_joint', 'dti_joint', 'verification_status_joint',
       'tot_coll_amt', 'tot_cur_bal', 'open_acc_6m', 'open_il_6m',
       'open_il_12m', '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_fi', 'total_cu_tl', 'inq_last_12m',
       'acc_open_past_24mths', 'avg_cur_bal', 'bc_open_to_buy', 'bc_util',
       'mo_sin_old_il_acct', 'mo_sin_old_rev_tl_op', 'mo_sin_rcnt_rev_tl_op',
       'mo_sin_rcnt_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_pd',
       '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_12m', 'pct_tl_nvr_dlq', 'percent_bc_gt_75',
       'tot_hi_cred_lim', 'total_bal_ex_mort', 'total_bc_limit',
       'total_il_high_credit_limit'],
      dtype='object')
```

In [10]:

```
loan = loan.drop(missing_columns, axis=1)
print(loan.shape)
```

```
(39717, 55)
```

In [11]:
```
# summarise number of missing values again
100*(loan.isnull().sum()/len(loan.index))
```

Out[11]:
```
id                          0.000000
member_id                   0.000000
loan_amnt                   0.000000
funded_amnt                 0.000000
funded_amnt_inv             0.000000
term                        0.000000
int_rate                    0.000000
installment                 0.000000
grade                       0.000000
sub_grade                   0.000000
emp_title                   6.191303
emp_length                  2.706650
home_ownership              0.000000
annual_inc                  0.000000
verification_status         0.000000
issue_d                     0.000000
loan_status                 0.000000
pymnt_plan                  0.000000
url                         0.000000
desc                       32.580507
purpose                     0.000000
title                       0.027696
zip_code                    0.000000
addr_state                  0.000000
dti                         0.000000
delinq_2yrs                 0.000000
earliest_cr_line            0.000000
inq_last_6mths              0.000000
mths_since_last_delinq     64.662487
open_acc                    0.000000
pub_rec                     0.000000
revol_bal                   0.000000
revol_util                  0.125891
total_acc                   0.000000
initial_list_status         0.000000
out_prncp                   0.000000
out_prncp_inv               0.000000
total_pymnt                 0.000000
total_pymnt_inv             0.000000
total_rec_prncp             0.000000
total_rec_int               0.000000
total_rec_late_fee          0.000000
recoveries                  0.000000
```

```
collection_recovery_fee       0.000000
last_pymnt_d                  0.178765
last_pymnt_amnt               0.000000
last_credit_pull_d            0.005036
collections_12_mths_ex_med    0.140998
policy_code                   0.000000
application_type              0.000000
acc_now_delinq                0.000000
chargeoff_within_12_mths      0.140998
delinq_amnt                   0.000000
pub_rec_bankruptcies          1.754916
tax_liens                     0.098195
dtype: float64
```

In [12]:

```
# There are now 2 columns having approx 32 and 64% missing values -
# description and months since last delinquent

# let's have a look at a few entries in the columns
loan.loc[:, ['desc', 'mths_since_last_delinq']].head()
```

Out[12]:

	desc	mths_since_last_delinq
0	Borrower added on 12/22/11 > I need to upgra...	NaN
1	Borrower added on 12/22/11 > I plan to use t...	NaN
2	NaN	NaN
3	Borrower added on 12/21/11 > to pay for prop...	35.0
4	Borrower added on 12/21/11 > I plan on combi...	38.0

The column description contains the comments the applicant had written while applying for the loan. Although one can use some text analysis techniques to derive new features from this column (such as sentiment, number of positive/negative words etc.), we will not use this column in this analysis.

Secondly, months since last delinquent represents the number months passed since the person last fell into the 90 DPD group. There is an important reason we shouldn't use this column in analysis - since at the time of loan application, we will not have this data (it gets generated months after the loan has been approved), it cannot be used as a predictor of default at the time of loan approval.

Thus let's drop the two columns.

In [13]:

```
# dropping the two columns
loan = loan.drop(['desc', 'mths_since_last_delinq'], axis=1)
```

In [14]:
```
# summarise number of missing values again
100*(loan.isnull().sum()/len(loan.index))
```

Out[14]:
```
id                            0.000000
member_id                     0.000000
loan_amnt                     0.000000
funded_amnt                   0.000000
funded_amnt_inv               0.000000
term                          0.000000
int_rate                      0.000000
installment                   0.000000
grade                         0.000000
sub_grade                     0.000000
emp_title                     6.191303
emp_length                    2.706650
home_ownership                0.000000
annual_inc                    0.000000
verification_status           0.000000
issue_d                       0.000000
loan_status                   0.000000
pymnt_plan                    0.000000
url                           0.000000
purpose                       0.000000
title                         0.027696
zip_code                      0.000000
addr_state                    0.000000
dti                           0.000000
delinq_2yrs                   0.000000
earliest_cr_line              0.000000
inq_last_6mths                0.000000
open_acc                      0.000000
pub_rec                       0.000000
revol_bal                     0.000000
revol_util                    0.125891
total_acc                     0.000000
initial_list_status           0.000000
out_prncp                     0.000000
out_prncp_inv                 0.000000
total_pymnt                   0.000000
total_pymnt_inv               0.000000
total_rec_prncp               0.000000
total_rec_int                 0.000000
total_rec_late_fee            0.000000
recoveries                    0.000000
collection_recovery_fee       0.000000
last_pymnt_d                  0.178765
```

```
last_pymnt_amnt               0.000000
last_credit_pull_d            0.005036
collections_12_mths_ex_med    0.140998
policy_code                   0.000000
application_type              0.000000
acc_now_delinq                0.000000
chargeoff_within_12_mths      0.140998
delinq_amnt                   0.000000
pub_rec_bankruptcies          1.754916
tax_liens                     0.098195
dtype: float64
```

There are some more columns with missing values, but let's ignore them for now (since we are ntot doing any modeling, we don't need to impute all missing values anyway).

But let's check whether some rows have a large number of missing values.

In [15]:

```
# missing values in rows
loan.isnull().sum(axis=1)
```

Out[15]:

```
0        1
1        0
2        1
3        0
4        0
        ..
39712    4
39713    4
39714    5
39715    5
39716    4
Length: 39717, dtype: int64
```

In [16]:

```
# checking whether some rows have more than 5 missing values
len(loan[loan.isnull().sum(axis=1) > 5].index)
```

Out[16]:

```
0
```

The data looks clean by and large. Let's also check whether all columns are in the correct format.

In [17]:
```
loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 53 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   id                          39717 non-null  int64  
 1   member_id                   39717 non-null  int64  
 2   loan_amnt                   39717 non-null  int64  
 3   funded_amnt                 39717 non-null  int64  
 4   funded_amnt_inv             39717 non-null  float64
 5   term                        39717 non-null  object 
 6   int_rate                    39717 non-null  object 
 7   installment                 39717 non-null  float64
 8   grade                       39717 non-null  object 
 9   sub_grade                   39717 non-null  object 
 10  emp_title                   37258 non-null  object 
 11  emp_length                  38642 non-null  object 
 12  home_ownership              39717 non-null  object 
 13  annual_inc                  39717 non-null  float64
 14  verification_status         39717 non-null  object 
 15  issue_d                     39717 non-null  object 
 16  loan_status                 39717 non-null  object 
 17  pymnt_plan                  39717 non-null  object 
 18  url                         39717 non-null  object 
 19  purpose                     39717 non-null  object 
 20  title                       39706 non-null  object 
 21  zip_code                    39717 non-null  object 
 22  addr_state                  39717 non-null  object 
 23  dti                         39717 non-null  float64
 24  delinq_2yrs                 39717 non-null  int64  
 25  earliest_cr_line            39717 non-null  object 
 26  inq_last_6mths              39717 non-null  int64  
 27  open_acc                    39717 non-null  int64  
 28  pub_rec                     39717 non-null  int64  
 29  revol_bal                   39717 non-null  int64  
 30  revol_util                  39667 non-null  object 
 31  total_acc                   39717 non-null  int64  
 32  initial_list_status         39717 non-null  object 
 33  out_prncp                   39717 non-null  float64
 34  out_prncp_inv               39717 non-null  float64
 35  total_pymnt                 39717 non-null  float64
 36  total_pymnt_inv             39717 non-null  float64
 37  total_rec_prncp             39717 non-null  float64
```

```
 38  total_rec_int               39717 non-null  float64
 39  total_rec_late_fee          39717 non-null  float64
 40  recoveries                  39717 non-null  float64
 41  collection_recovery_fee     39717 non-null  float64
 42  last_pymnt_d                39646 non-null  object
 43  last_pymnt_amnt             39717 non-null  float64
 44  last_credit_pull_d          39715 non-null  object
 45  collections_12_mths_ex_med  39661 non-null  float64
 46  policy_code                 39717 non-null  int64
 47  application_type            39717 non-null  object
 48  acc_now_delinq              39717 non-null  int64
 49  chargeoff_within_12_mths    39661 non-null  float64
 50  delinq_amnt                 39717 non-null  int64
 51  pub_rec_bankruptcies        39020 non-null  float64
 52  tax_liens                   39678 non-null  float64
dtypes: float64(18), int64(13), object(22)
memory usage: 16.1+ MB
```

In [18]:

```
# The column int_rate is character type, let's convert it to float
loan['int_rate'] = loan['int_rate'].apply(lambda x: pd.to_numeric(x.split("%")[0]))
```

In [19]:

```
# checking the data types
loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 53 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   id                          39717 non-null  int64  
 1   member_id                   39717 non-null  int64  
 2   loan_amnt                   39717 non-null  int64  
 3   funded_amnt                 39717 non-null  int64  
 4   funded_amnt_inv             39717 non-null  float64
 5   term                        39717 non-null  object 
 6   int_rate                    39717 non-null  float64
 7   installment                 39717 non-null  float64
 8   grade                       39717 non-null  object 
 9   sub_grade                   39717 non-null  object 
 10  emp_title                   37258 non-null  object 
 11  emp_length                  38642 non-null  object 
 12  home_ownership              39717 non-null  object 
 13  annual_inc                  39717 non-null  float64
 14  verification_status         39717 non-null  object 
 15  issue_d                     39717 non-null  object 
 16  loan_status                 39717 non-null  object 
 17  pymnt_plan                  39717 non-null  object 
 18  url                         39717 non-null  object 
 19  purpose                     39717 non-null  object 
 20  title                       39706 non-null  object 
 21  zip_code                    39717 non-null  object 
 22  addr_state                  39717 non-null  object 
 23  dti                         39717 non-null  float64
 24  delinq_2yrs                 39717 non-null  int64  
 25  earliest_cr_line            39717 non-null  object 
 26  inq_last_6mths              39717 non-null  int64  
 27  open_acc                    39717 non-null  int64  
 28  pub_rec                     39717 non-null  int64  
 29  revol_bal                   39717 non-null  int64  
 30  revol_util                  39667 non-null  object 
 31  total_acc                   39717 non-null  int64  
 32  initial_list_status         39717 non-null  object 
 33  out_prncp                   39717 non-null  float64
 34  out_prncp_inv               39717 non-null  float64
 35  total_pymnt                 39717 non-null  float64
 36  total_pymnt_inv             39717 non-null  float64
 37  total_rec_prncp             39717 non-null  float64
```

```
 38  total_rec_int               39717 non-null  float64
 39  total_rec_late_fee          39717 non-null  float64
 40  recoveries                  39717 non-null  float64
 41  collection_recovery_fee     39717 non-null  float64
 42  last_pymnt_d                39646 non-null  object
 43  last_pymnt_amnt             39717 non-null  float64
 44  last_credit_pull_d          39715 non-null  object
 45  collections_12_mths_ex_med  39661 non-null  float64
 46  policy_code                 39717 non-null  int64
 47  application_type            39717 non-null  object
 48  acc_now_delinq              39717 non-null  int64
 49  chargeoff_within_12_mths    39661 non-null  float64
 50  delinq_amnt                 39717 non-null  int64
 51  pub_rec_bankruptcies        39020 non-null  float64
 52  tax_liens                   39678 non-null  float64
dtypes: float64(19), int64(13), object(21)
memory usage: 16.1+ MB
```

In [20]:

```
# also, lets extract the numeric part from the variable employment length

# first, let's drop the missing values from the column (otherwise the regex code below throws error)
loan = loan[~loan['emp_length'].isnull()]

# using regular expression to extract numeric values from the string
import re
loan['emp_length'] = loan['emp_length'].apply(lambda x: re.findall('\d+', str(x))[0])

# convert to numeric
loan['emp_length'] = loan['emp_length'].apply(lambda x: pd.to_numeric(x))
```

In [21]:

```
# looking at type of the columns again
loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 38642 entries, 0 to 39716
Data columns (total 53 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       38642 non-null  int64  
 1   member_id                38642 non-null  int64  
 2   loan_amnt                38642 non-null  int64  
 3   funded_amnt              38642 non-null  int64  
 4   funded_amnt_inv          38642 non-null  float64
 5   term                     38642 non-null  object 
 6   int_rate                 38642 non-null  float64
 7   installment              38642 non-null  float64
 8   grade                    38642 non-null  object 
 9   sub_grade                38642 non-null  object 
 10  emp_title                37202 non-null  object 
 11  emp_length               38642 non-null  int64  
 12  home_ownership           38642 non-null  object 
 13  annual_inc               38642 non-null  float64
 14  verification_status      38642 non-null  object 
 15  issue_d                  38642 non-null  object 
 16  loan_status              38642 non-null  object 
 17  pymnt_plan               38642 non-null  object 
 18  url                      38642 non-null  object 
 19  purpose                  38642 non-null  object 
 20  title                    38632 non-null  object 
 21  zip_code                 38642 non-null  object 
 22  addr_state               38642 non-null  object 
 23  dti                      38642 non-null  float64
 24  delinq_2yrs              38642 non-null  int64  
 25  earliest_cr_line         38642 non-null  object 
 26  inq_last_6mths           38642 non-null  int64  
 27  open_acc                 38642 non-null  int64  
 28  pub_rec                  38642 non-null  int64  
 29  revol_bal                38642 non-null  int64  
 30  revol_util               38595 non-null  object 
 31  total_acc                38642 non-null  int64  
 32  initial_list_status      38642 non-null  object 
 33  out_prncp                38642 non-null  float64
 34  out_prncp_inv            38642 non-null  float64
 35  total_pymnt              38642 non-null  float64
 36  total_pymnt_inv          38642 non-null  float64
 37  total_rec_prncp          38642 non-null  float64
```

```
 38  total_rec_int               38642 non-null  float64
 39  total_rec_late_fee          38642 non-null  float64
 40  recoveries                  38642 non-null  float64
 41  collection_recovery_fee     38642 non-null  float64
 42  last_pymnt_d                38576 non-null  object
 43  last_pymnt_amnt             38642 non-null  float64
 44  last_credit_pull_d          38640 non-null  object
 45  collections_12_mths_ex_med  38586 non-null  float64
 46  policy_code                 38642 non-null  int64
 47  application_type            38642 non-null  object
 48  acc_now_delinq              38642 non-null  int64
 49  chargeoff_within_12_mths    38586 non-null  float64
 50  delinq_amnt                 38642 non-null  int64
 51  pub_rec_bankruptcies        37945 non-null  float64
 52  tax_liens                   38603 non-null  float64
dtypes: float64(19), int64(14), object(20)
memory usage: 15.9+ MB
```

Data Analysis

Let's now move to data analysis. To start with, let's understand the objective of the analysis clearly and identify the variables that we want to consider for analysis.

The objective is to identify predictors of default so that at the time of loan application, we can use those variables for approval/rejection of the loan. Now, there are broadly three types of variables - 1. those which are related to the applicant (demographic variables such as age, occupation, employment details etc.), 2. loan characteristics (amount of loan, interest rate, purpose of loan etc.) and 3. Customer behaviour variables (those which are generated after the loan is approved such as delinquent 2 years, revolving balance, next payment date etc.).

Now, the customer behaviour variables are not available at the time of loan application, and thus they cannot be used as predictors for credit approval.

Thus, going forward, we will use only the other two types of variables.

In [22]:

```
behaviour_var =  [
  "delinq_2yrs",
  "earliest_cr_line",
  "inq_last_6mths",
  "open_acc",
  "pub_rec",
  "revol_bal",
  "revol_util",
  "total_acc",
  "out_prncp",
  "out_prncp_inv",
  "total_pymnt",
  "total_pymnt_inv",
  "total_rec_prncp",
  "total_rec_int",
  "total_rec_late_fee",
  "recoveries",
  "collection_recovery_fee",
  "last_pymnt_d",
  "last_pymnt_amnt",
  "last_credit_pull_d",
  "application_type"]
behaviour_var
```

Out[22]:
```
['delinq_2yrs',
 'earliest_cr_line',
 'inq_last_6mths',
 'open_acc',
 'pub_rec',
 'revol_bal',
 'revol_util',
 'total_acc',
 'out_prncp',
 'out_prncp_inv',
 'total_pymnt',
 'total_pymnt_inv',
 'total_rec_prncp',
 'total_rec_int',
 'total_rec_late_fee',
 'recoveries',
 'collection_recovery_fee',
 'last_pymnt_d',
 'last_pymnt_amnt',
 'last_credit_pull_d',
 'application_type']
```

In [23]:

```
# let's now remove the behaviour variables from analysis
df = loan.drop(behaviour_var, axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 38642 entries, 0 to 39716
Data columns (total 32 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   id                          38642 non-null  int64  
 1   member_id                   38642 non-null  int64  
 2   loan_amnt                   38642 non-null  int64  
 3   funded_amnt                 38642 non-null  int64  
 4   funded_amnt_inv             38642 non-null  float64
 5   term                        38642 non-null  object 
 6   int_rate                    38642 non-null  float64
 7   installment                 38642 non-null  float64
 8   grade                       38642 non-null  object 
 9   sub_grade                   38642 non-null  object 
 10  emp_title                   37202 non-null  object 
 11  emp_length                  38642 non-null  int64  
 12  home_ownership              38642 non-null  object 
 13  annual_inc                  38642 non-null  float64
 14  verification_status         38642 non-null  object 
 15  issue_d                     38642 non-null  object 
 16  loan_status                 38642 non-null  object 
 17  pymnt_plan                  38642 non-null  object 
 18  url                         38642 non-null  object 
 19  purpose                     38642 non-null  object 
 20  title                       38632 non-null  object 
 21  zip_code                    38642 non-null  object 
 22  addr_state                  38642 non-null  object 
 23  dti                         38642 non-null  float64
 24  initial_list_status         38642 non-null  object 
 25  collections_12_mths_ex_med  38586 non-null  float64
 26  policy_code                 38642 non-null  int64  
 27  acc_now_delinq              38642 non-null  int64  
 28  chargeoff_within_12_mths    38586 non-null  float64
 29  delinq_amnt                 38642 non-null  int64  
 30  pub_rec_bankruptcies        37945 non-null  float64
 31  tax_liens                   38603 non-null  float64
dtypes: float64(9), int64(8), object(15)
memory usage: 9.7+ MB
```

Typically, variables such as acc_now_delinquent, chargeoff within 12 months etc. (which are related to the applicant's past loans) are

In [24]:
```
# also, we will not be able to use the variables zip code, address, state etc.
# the variable 'title' is derived from the variable 'purpose'
# thus let get rid of all these variables as well

df = df.drop(['title', 'url', 'zip_code', 'addr_state'], axis=1)
```

Next, let's have a look at the target variable - loan_status. We need to relabel the values to a binary form - 0 or 1, 1 indicating that the person has defaulted and 0 otherwise.

In [25]:
```
df['loan_status'] = df['loan_status'].astype('category')
df['loan_status'].value_counts()
```

Out[25]:
```
Fully Paid     32145
Charged Off     5399
Current         1098
Name: loan_status, dtype: int64
```

You can see that fully paid comprises most of the loans. The ones marked 'current' are neither fully paid not defaulted, so let's get rid of the current loans. Also, let's tag the other two values as 0 or 1.

In [26]:
```
# filtering only fully paid or charged-off
df = df[df['loan_status'] != 'Current']
df['loan_status'] = df['loan_status'].apply(lambda x: 0 if x=='Fully Paid' else 1)

# converting loan_status to integer type
df['loan_status'] = df['loan_status'].apply(lambda x: pd.to_numeric(x))

# summarising the values
df['loan_status'].value_counts()
```

Out[26]:
```
0    32145
1     5399
Name: loan_status, dtype: int64
```

Next, let's start with univariate analysis and then move to bivariate analysis.

Univariate Analysis

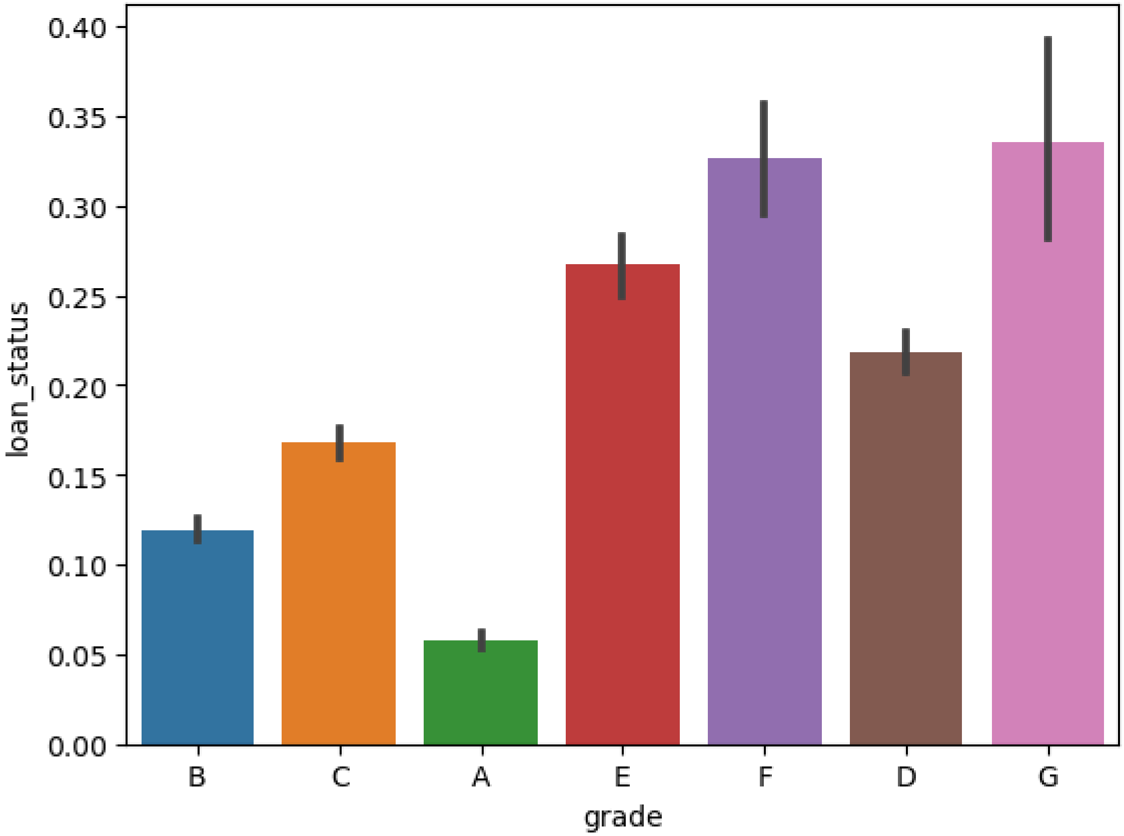
In [27]:
```
# default rate
round(np.mean(df['loan_status']), 2)
```

Out[27]:
```
0.14
```

The overall default rate is about 14%.

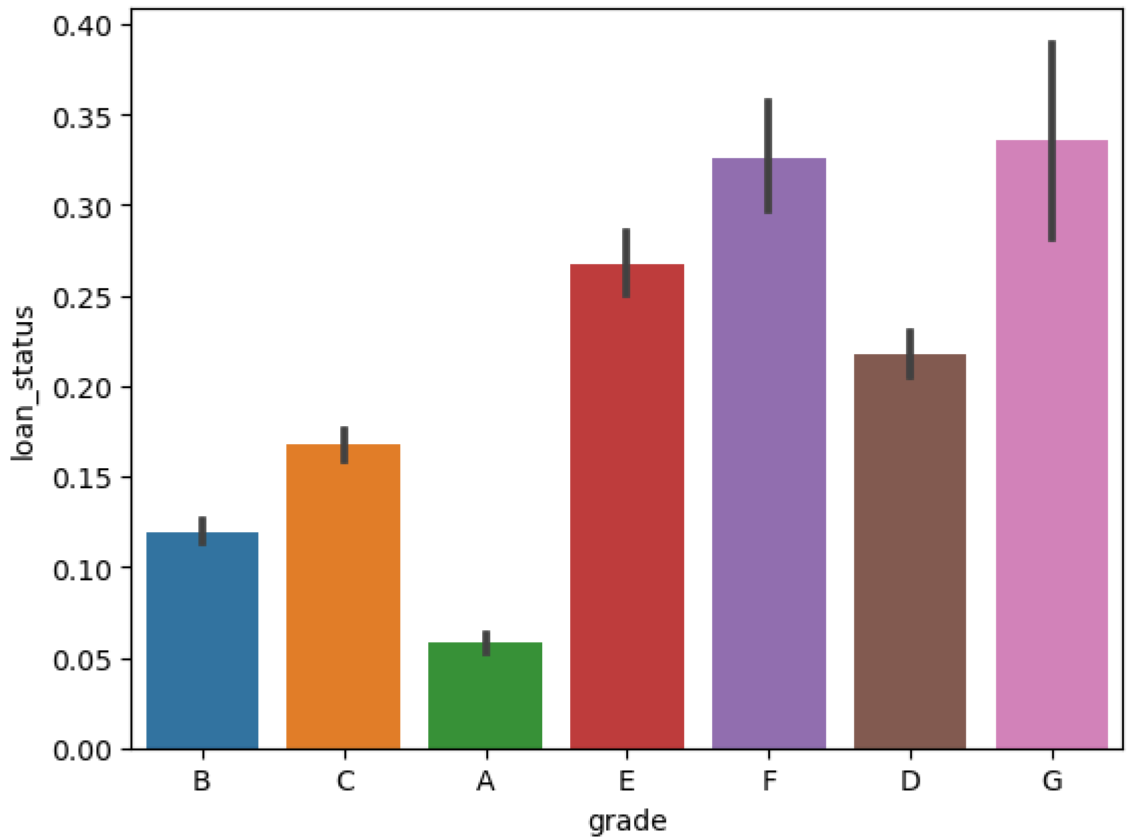
Let's first visualise the average default rates across categorical variables.

In [28]:
```
# plotting default rates across grade of the loan
sns.barplot(x='grade', y='loan_status', data=df)
plt.show()
```



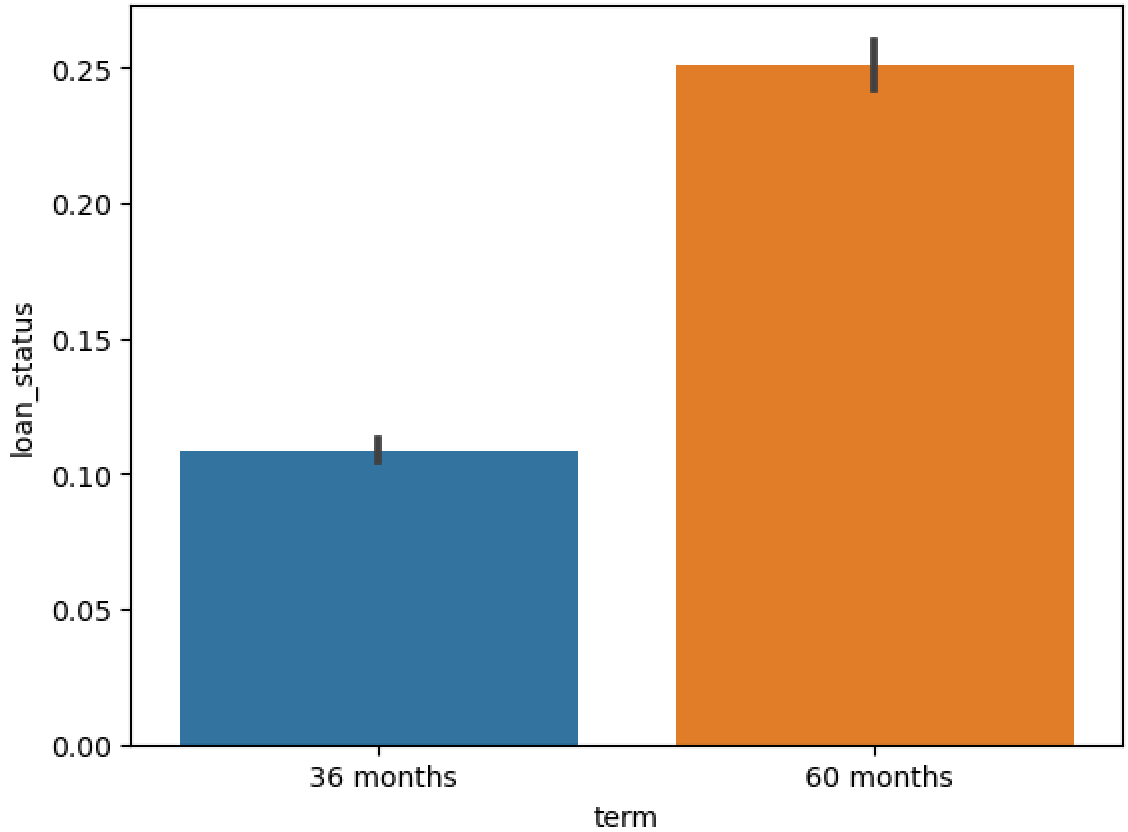
In [29]:
```
# lets define a function to plot loan_status across categorical variables
def plot_cat(cat_var):
    sns.barplot(x=cat_var, y='loan_status', data=df,orient='v')
    plt.show()
```

In [30]:
```
# compare default rates across grade of loan
plot_cat('grade')
```

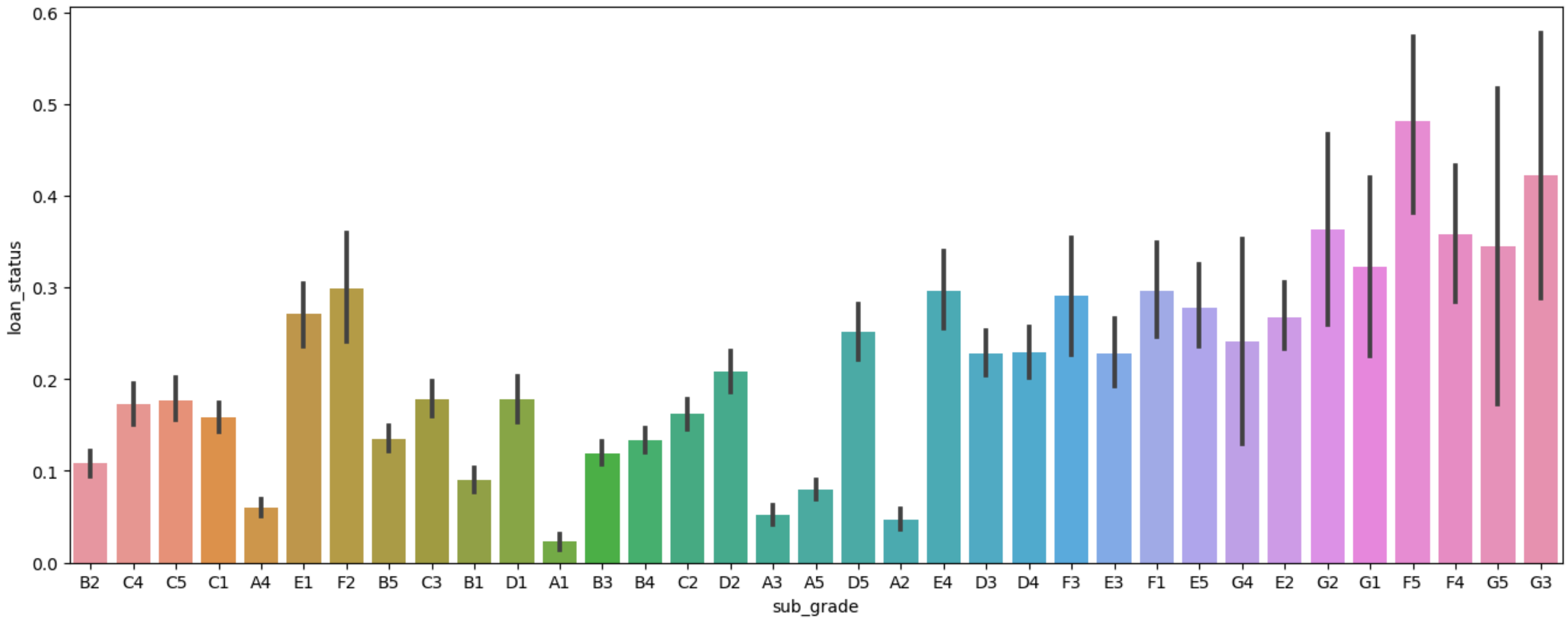


Clearly, as the grade of loan goes from A to G, the default rate increases. This is expected because the grade is decided by Lending Club based on the riskiness of the loan.

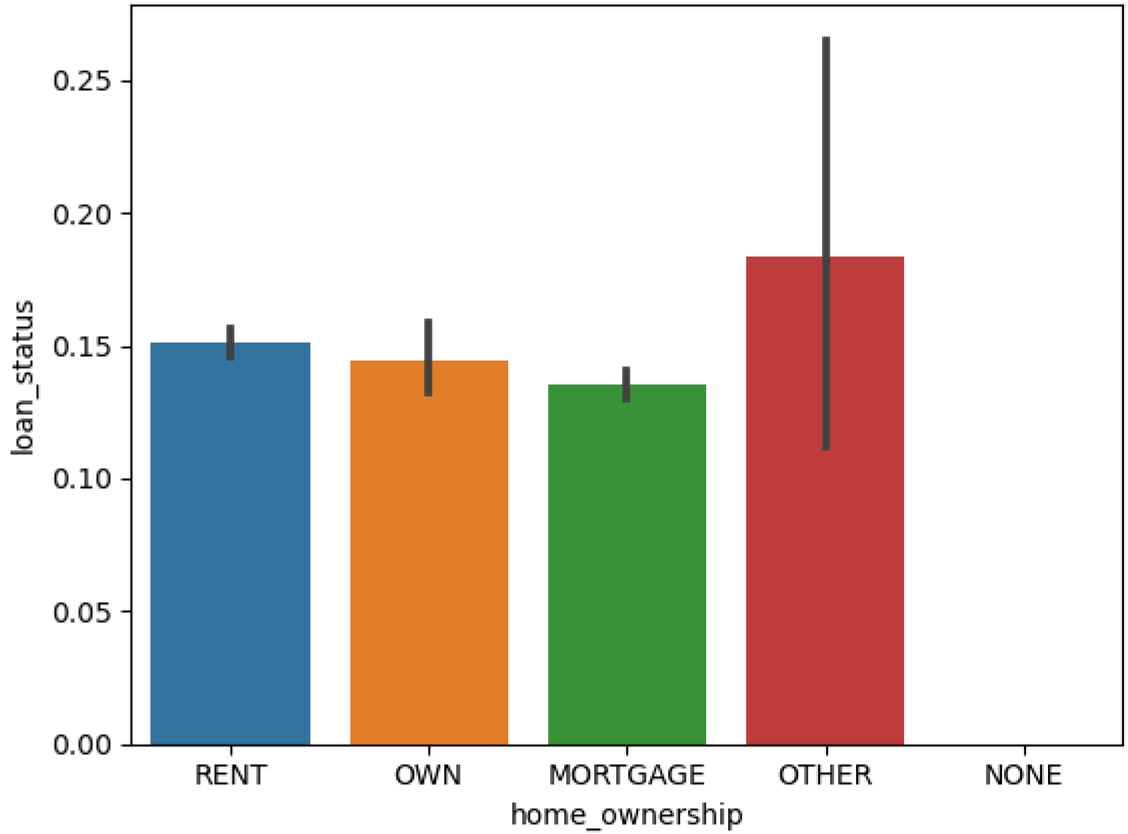
In [31]:
```
# term: 60 months loans default more than 36 months loans
plot_cat('term')
```



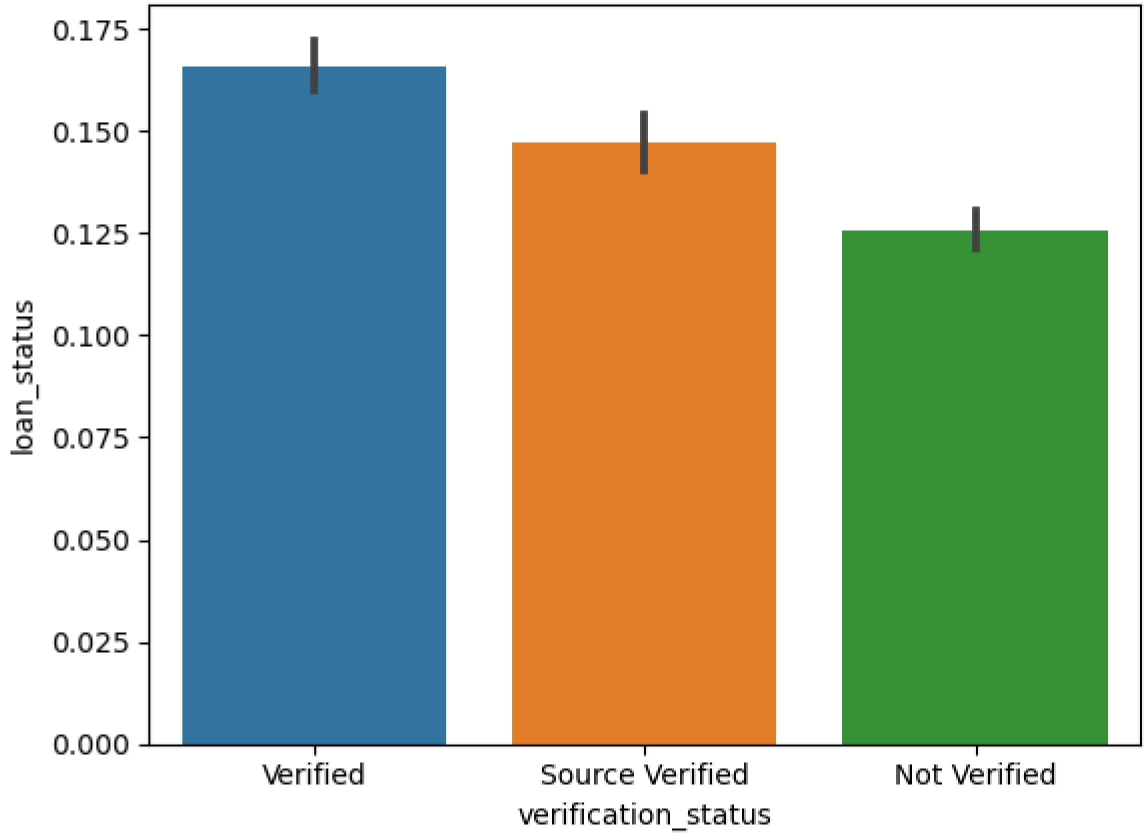
In [32]:
```
# sub-grade: as expected - A1 is better than A2 better than A3 and so on
plt.figure(figsize=(16, 6))
plot_cat('sub_grade')
```



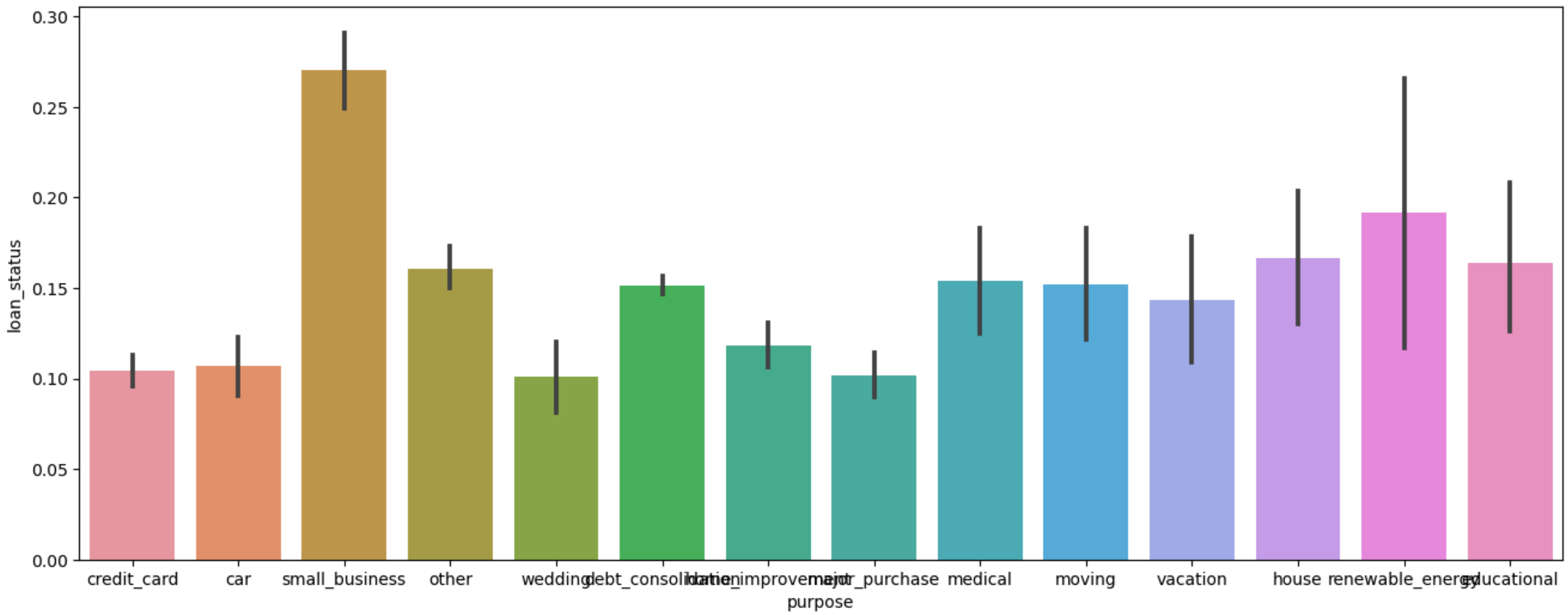
In [33]:
```
# home ownership: not a great discriminator
plot_cat('home_ownership')
```



In [34]:
```
# verification_status: surprisingly, verified loans default more than not verifiedb
plot_cat('verification_status')
```



In [35]:
```
# purpose: small business loans defualt the most, then renewable energy and education
plt.figure(figsize=(16, 6))
plot_cat('purpose')
```



In [36]:
```
# let's also observe the distribution of loans across years
# first lets convert the year column into datetime and then extract year and month from it
df['issue_d'].head()
```

Out[36]:
```
0    Dec-11
1    Dec-11
2    Dec-11
3    Dec-11
5    Dec-11
Name: issue_d, dtype: object
```

In [37]:
```
from datetime import datetime
df['issue_d'] = df['issue_d'].apply(lambda x: datetime.strptime(x, '%b-%y'))
```

In [38]:

```
# extracting month and year from issue_date
df['month'] = df['issue_d'].apply(lambda x: x.month)
df['year'] = df['issue_d'].apply(lambda x: x.year)
```

In [39]:

```
# let's first observe the number of loans granted across years
df.groupby('year').year.count()
```

Out[39]:

```
year
2007      251
2008     1562
2009     4716
2010    11214
2011    19801
Name: year, dtype: int64
```

You can see that the number of loans has increased steadily across years.

In [40]:

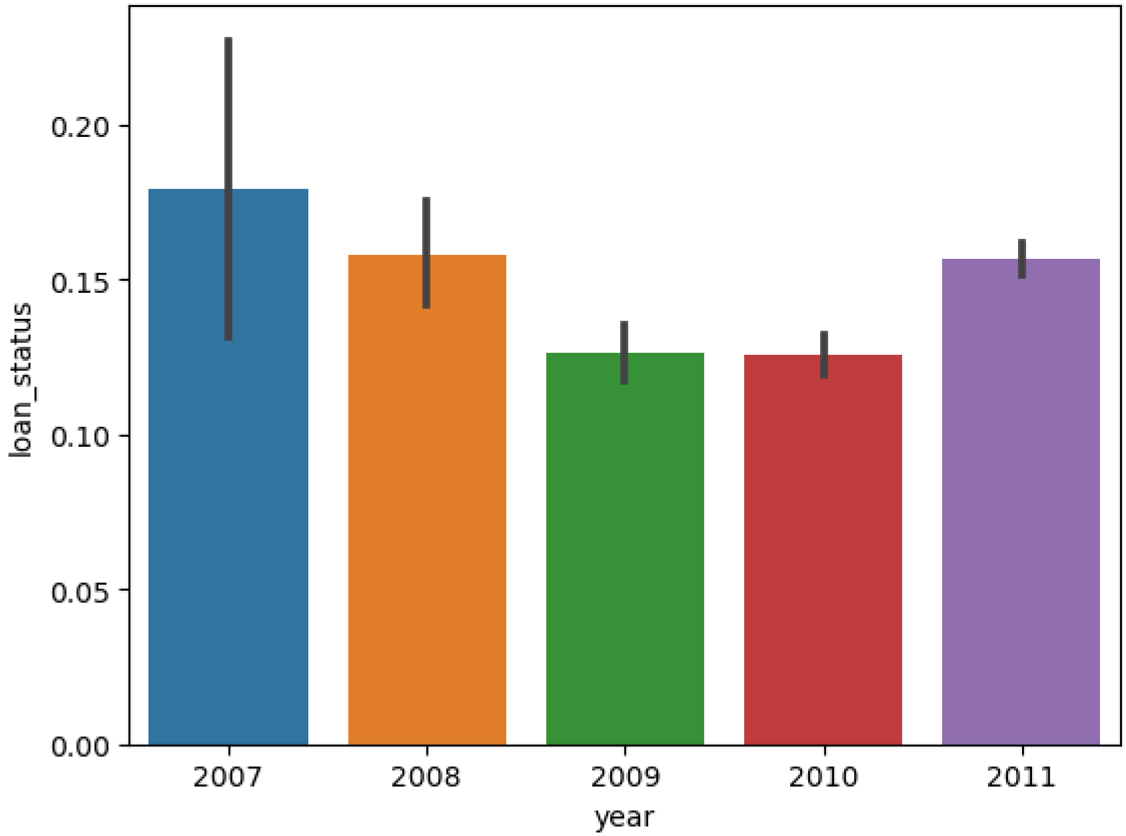
```
# number of loans across months
df.groupby('month').month.count()
```

Out[40]:

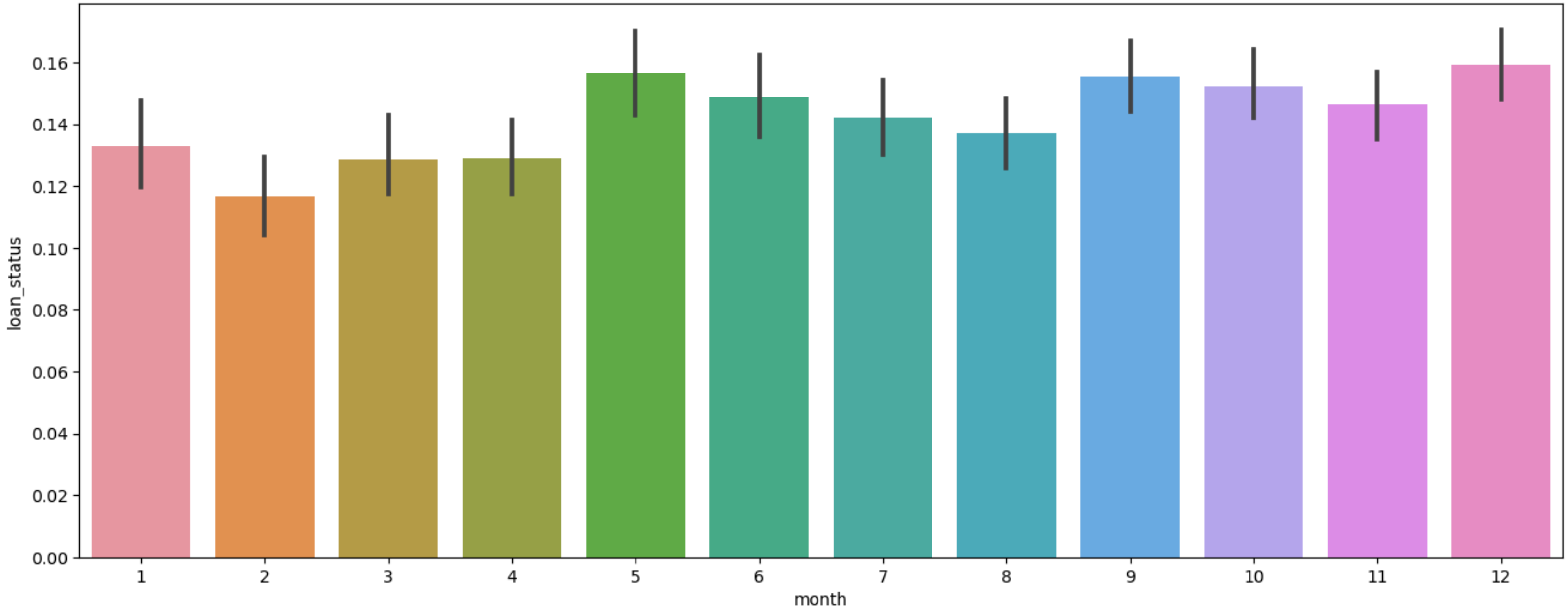
```
month
1     2331
2     2278
3     2632
4     2756
5     2838
6     3094
7     3253
8     3321
9     3394
10    3637
11    3890
12    4120
Name: month, dtype: int64
```

Most loans are granted in December, and in general in the latter half of the year.

In [41]:
```
# lets compare the default rates across years
# the default rate had suddenly increased in 2011, inspite of reducing from 2008 till 2010
plot_cat('year')
```



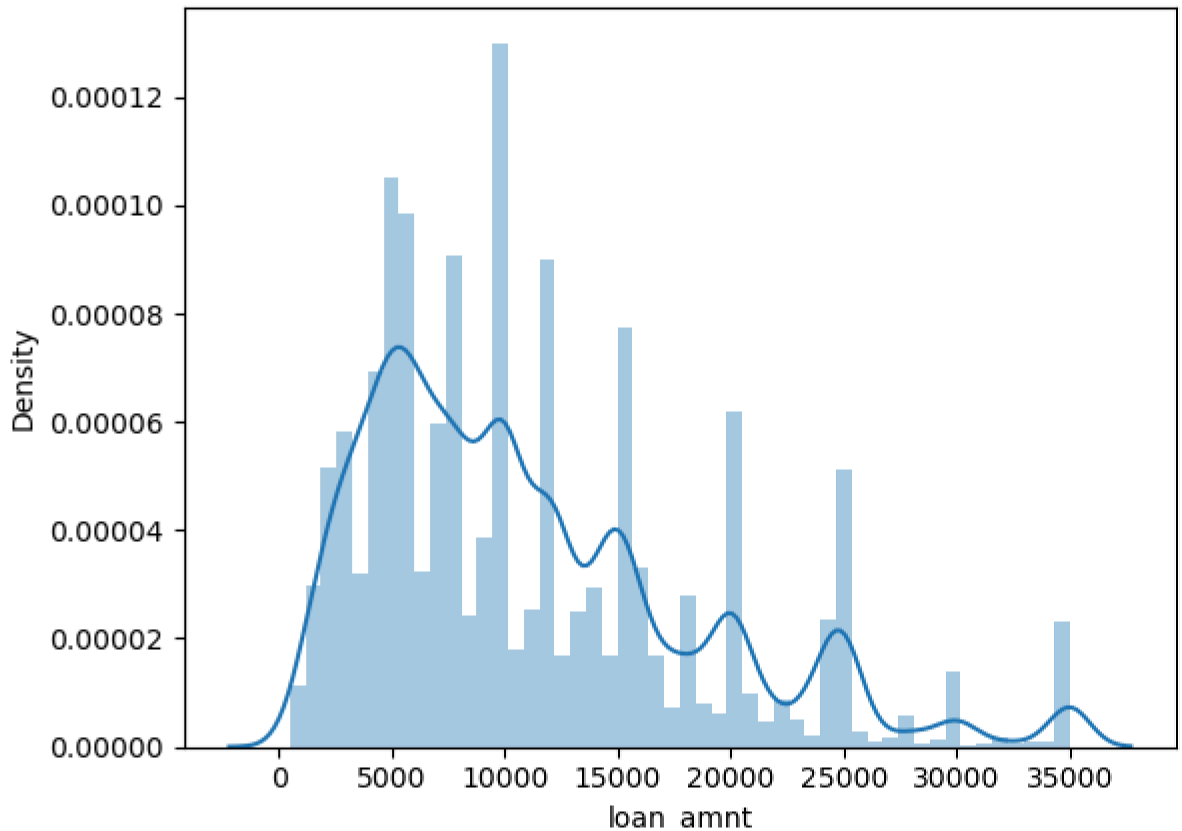
In [42]:
```
# comparing default rates across months: not much variation across months
plt.figure(figsize=(16, 6))
plot_cat('month')
```



Let's now analyse how the default rate varies across continuous variables.

In [43]:
```
# Loan amount: the median loan amount is around 10,000
sns.distplot(df['loan_amnt'])
plt.show()
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_11208\2122829423.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://gist.github.com/mwaskom/de4414
7ed2974457ad6372750bbe5751)

  sns.distplot(df['loan_amnt'])
```



The easiest way to analyse how default rates vary across continous variables is to bin the variables into discrete categories.

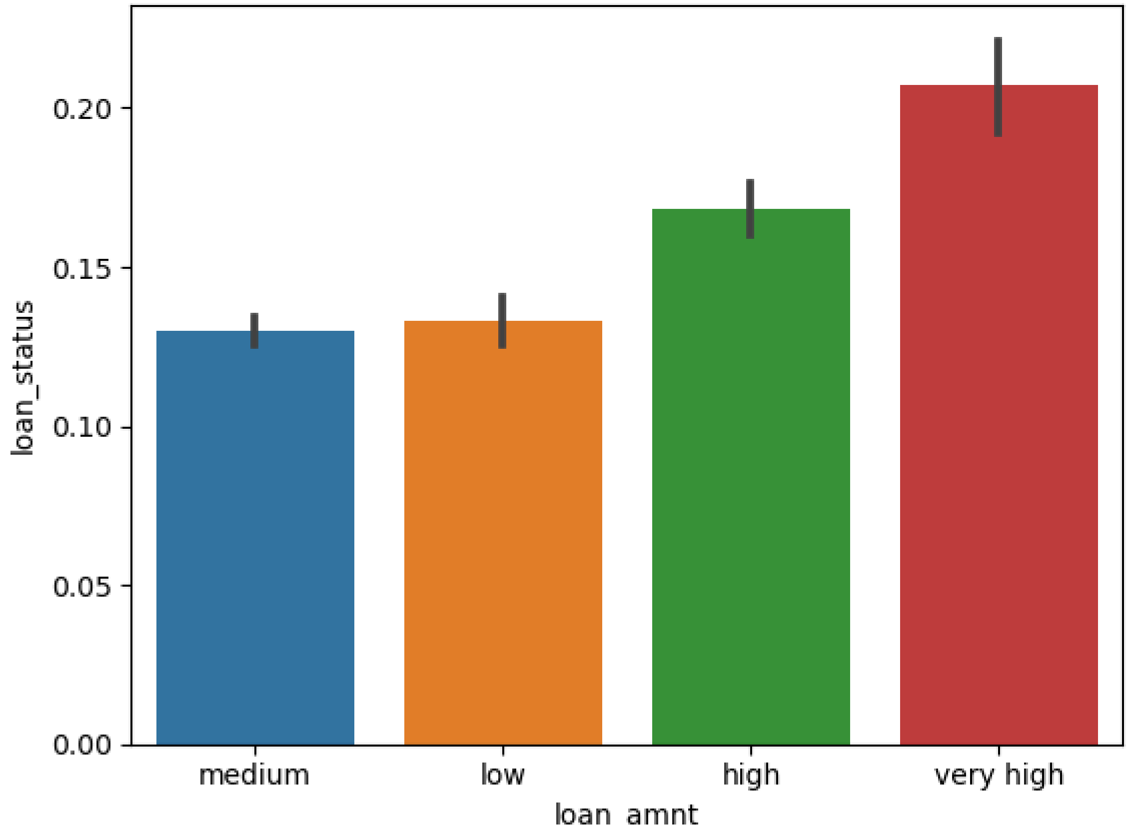
Let's bin the loan amount variable into small, medium, high, very high.

In [44]:
```
# binning loan amount
def loan_amount(n):
    if n < 5000:
        return 'low'
    elif n >=5000 and n < 15000:
        return 'medium'
    elif n >= 15000 and n < 25000:
        return 'high'
    else:
        return 'very high'

df['loan_amnt'] = df['loan_amnt'].apply(lambda x: loan_amount(x))
```

In [45]:
```
df['loan_amnt'].value_counts()
```

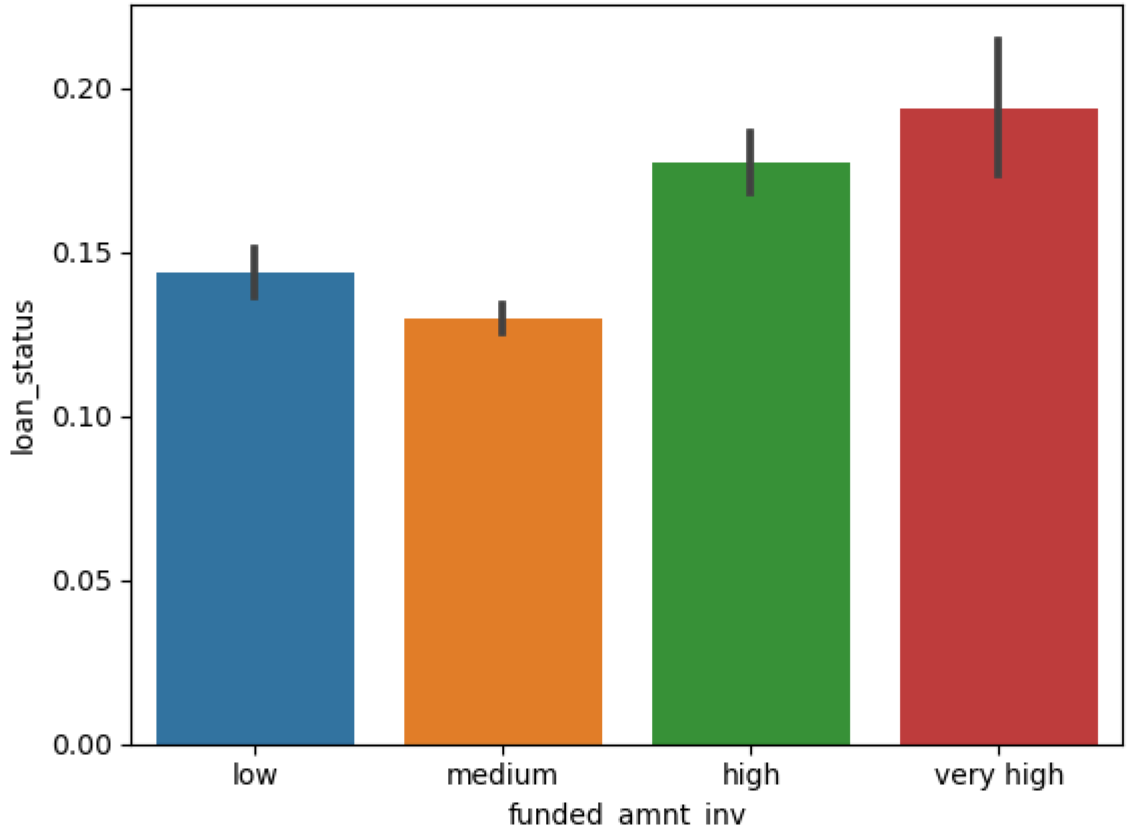
Out[45]:
```
medium       20157
high          7572
low           7095
very high     2720
Name: loan_amnt, dtype: int64
```

In [46]:
```
# let's compare the default rates across loan amount type
# higher the loan amount, higher the default rate
plot_cat('loan_amnt')
```



In [47]:
```
# let's also convert funded amount invested to bins
df['funded_amnt_inv'] = df['funded_amnt_inv'].apply(lambda x: loan_amount(x))
```

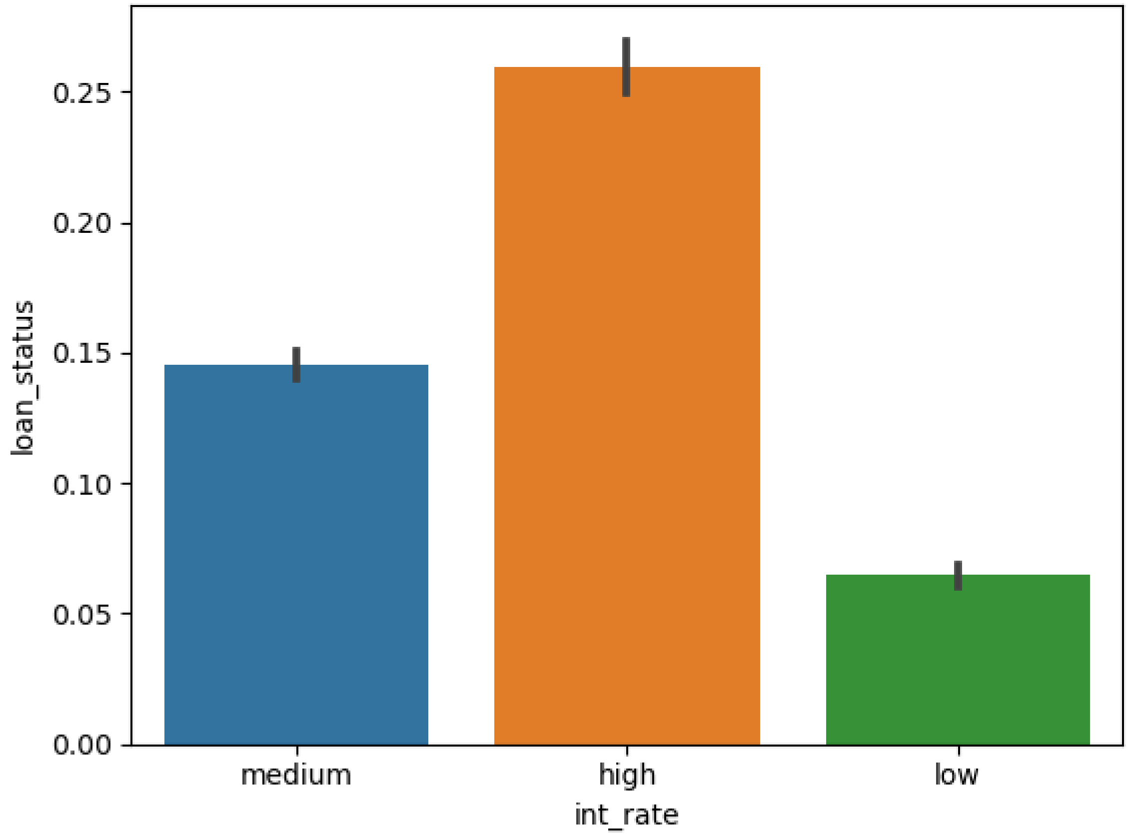
In [48]:
```
# funded amount invested
plot_cat('funded_amnt_inv')
```



In [49]:

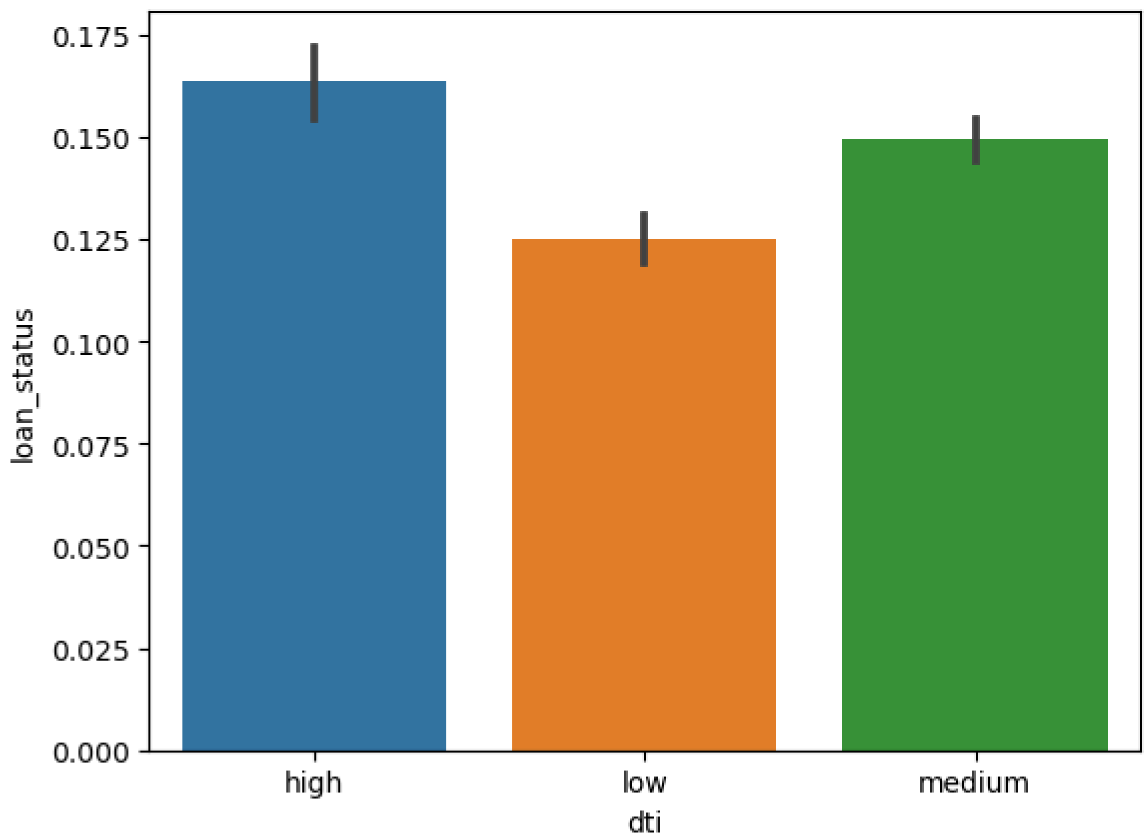
```
# lets also convert interest rate to low, medium, high
# binning loan amount
def int_rate(n):
    if n <= 10:
        return 'low'
    elif n > 10 and n <=15:
        return 'medium'
    else:
        return 'high'


df['int_rate'] = df['int_rate'].apply(lambda x: int_rate(x))
```

In [50]:
```
# comparing default rates across rates of interest
# high interest rates default more, as expected
plot_cat('int_rate')
```



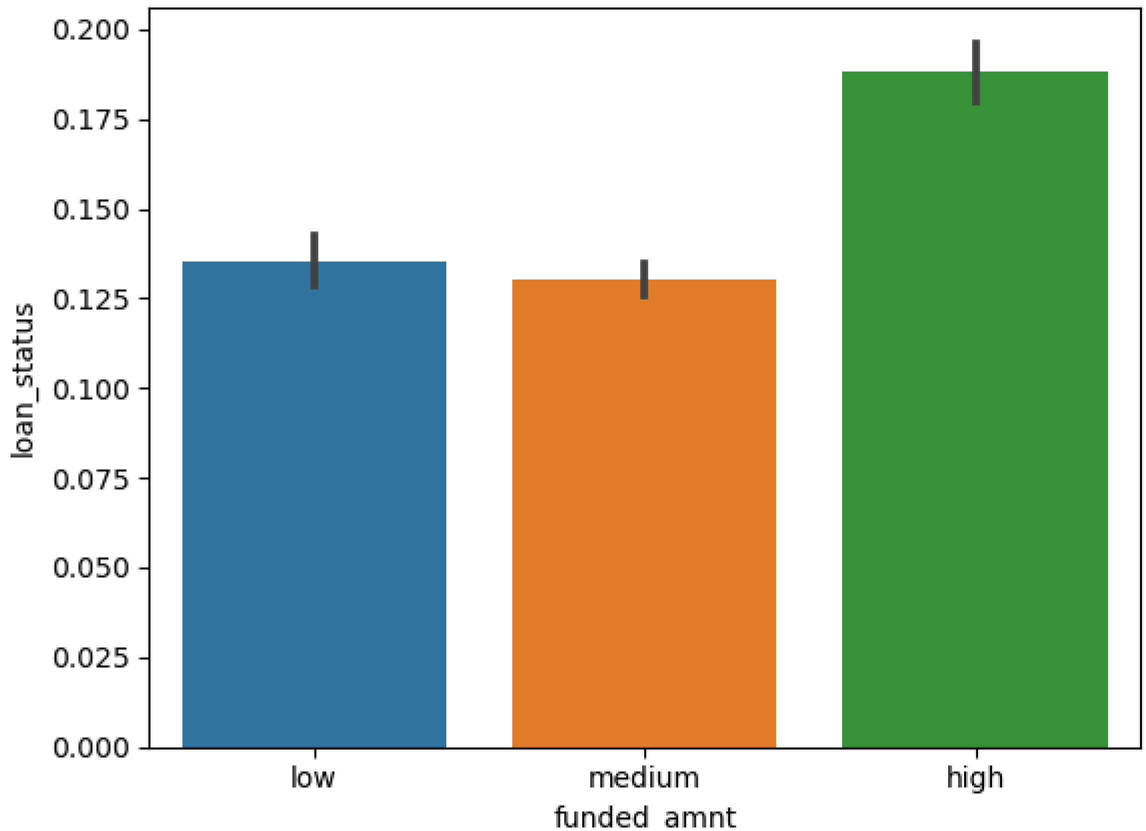
In [51]:
```
# debt to income ratio
def dti(n):
    if n <= 10:
        return 'low'
    elif n > 10 and n <=20:
        return 'medium'
    else:
        return 'high'


df['dti'] = df['dti'].apply(lambda x: dti(x))
```

In [52]:
```
# comparing default rates across debt to income ratio
# high dti translates into higher default rates, as expected
plot_cat('dti')
```



In [53]:
```
# Segregating the funded amount into the respective bins into Low, Medium and High
def funded_amount(n):
    if n <= 5000:
        return 'low'
    elif n > 5000 and n <=15000:
        return 'medium'
    else:
        return 'high'

df['funded_amnt'] = df['funded_amnt'].apply(lambda x: funded_amount(x))
```

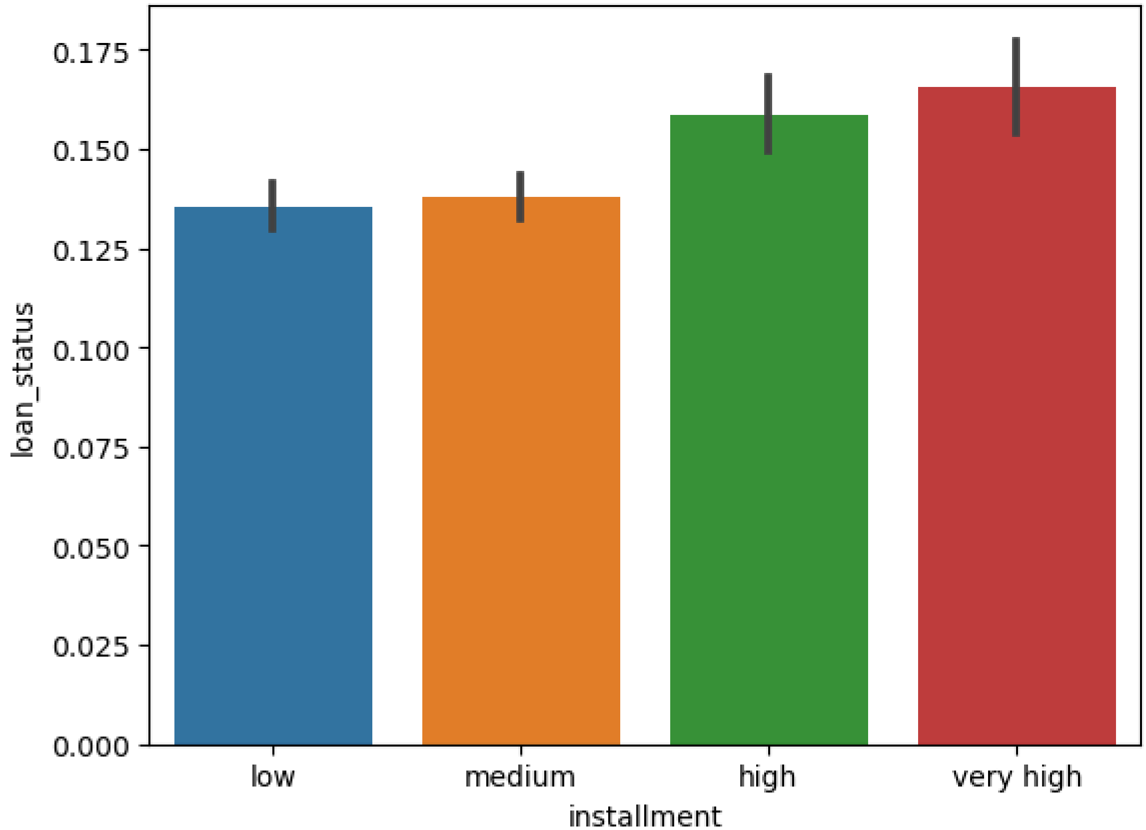
In [54]:
```
plot_cat('funded_amnt')
```



In [55]:

```
# installment dividing into the respective bins into Low, Medium, High and very High
def installment(n):
    if n <= 200:
        return 'low'
    elif n > 200 and n <=400:
        return 'medium'
    elif n > 400 and n <=600:
        return 'high'
    else:
        return 'very high'

df['installment'] = df['installment'].apply(lambda x: installment(x))
```

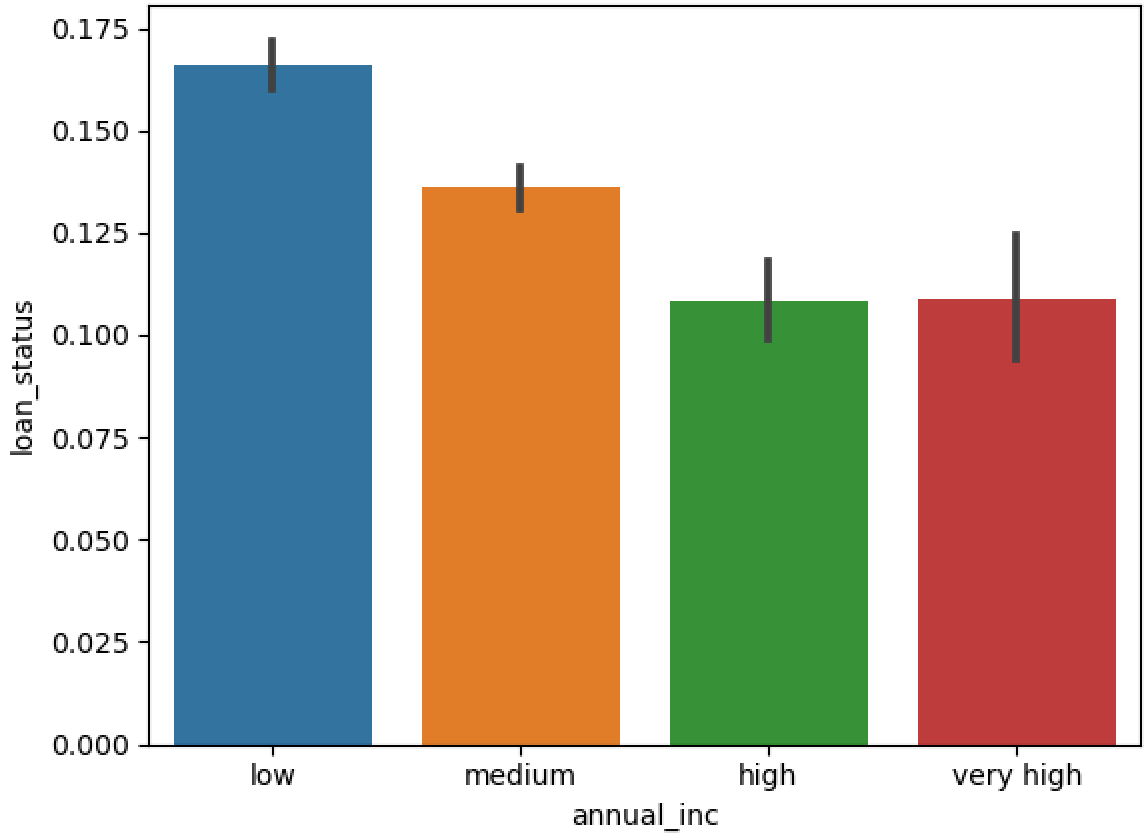
In [56]:
```
# comparing default rates across installment
# the higher the installment amount, the higher the default rate
plot_cat('installment')
```



In [57]:

```
# annual income dividing into the respective bins into Low, Medium, High and very High
def annual_income(n):
    if n <= 50000:
        return 'low'
    elif n > 50000 and n <=100000:
        return 'medium'
    elif n > 100000 and n <=150000:
        return 'high'
    else:
        return 'very high'

df['annual_inc'] = df['annual_inc'].apply(lambda x: annual_income(x))
```

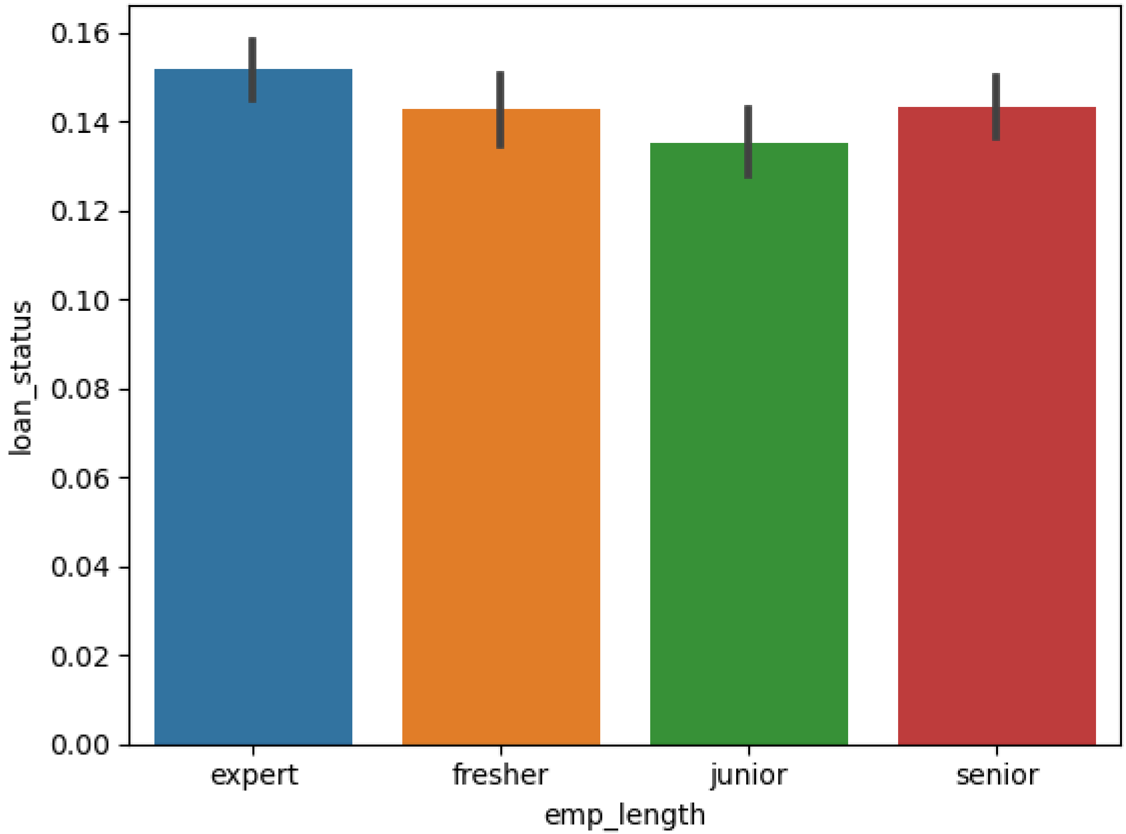
In [58]:
```
# annual income and default rate
# lower the annual income, higher the default rate
plot_cat('annual_inc')
```



In [59]:

```
# employment length
# first, let's drop the missing value observations in emp length
df = df[~df['emp_length'].isnull()]

# binning the variable
def emp_length(n):
    if n <= 1:
        return 'fresher'
    elif n > 1 and n <=3:
        return 'junior'
    elif n > 3 and n <=7:
        return 'senior'
    else:
        return 'expert'

df['emp_length'] = df['emp_length'].apply(lambda x: emp_length(x))
```

In [60]:
```
# emp_length and default rate
# not much of a predictor of default
plot_cat('emp_length')
```



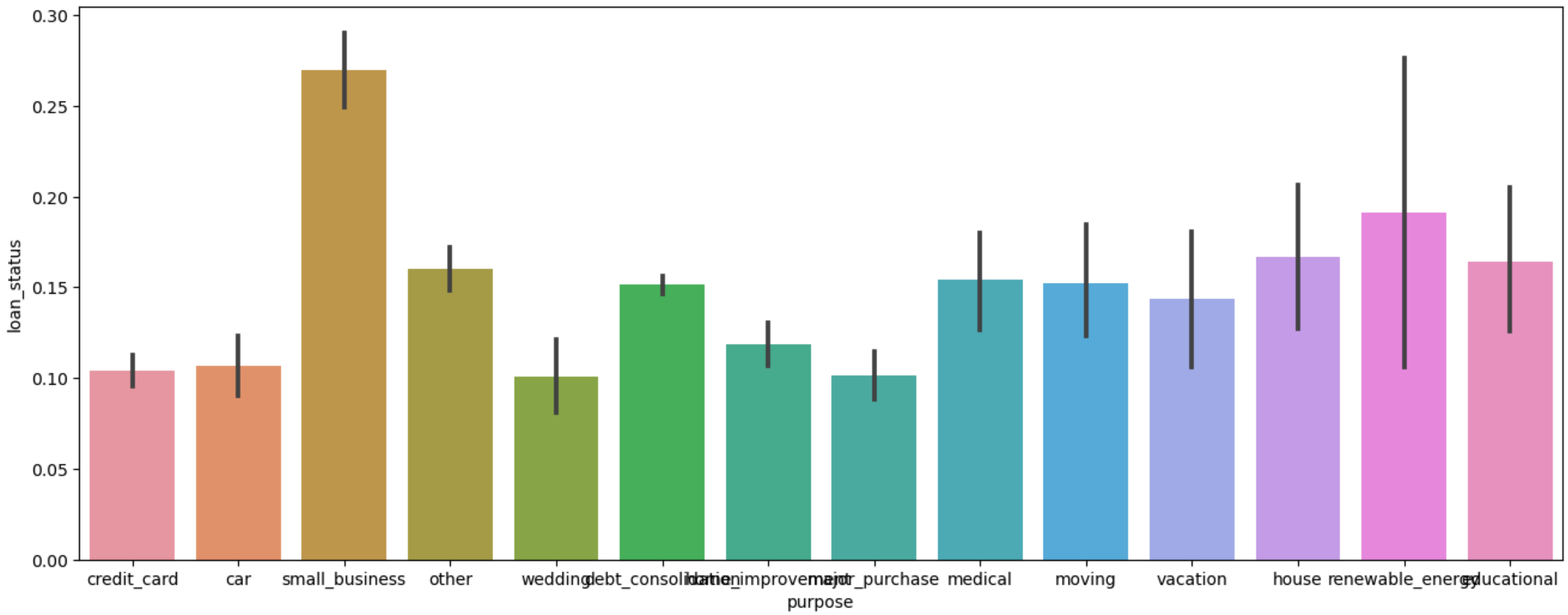
Segmented Univariate Analysis

We have now compared the default rates across various variables, and some of the important predictors are purpose of the loan, interest rate, annual income, grade etc.

In the credit industry, one of the most important factors affecting default is the purpose of the loan - home loans perform differently than credit cards, credit cards are very different from debt condolidation loans etc.

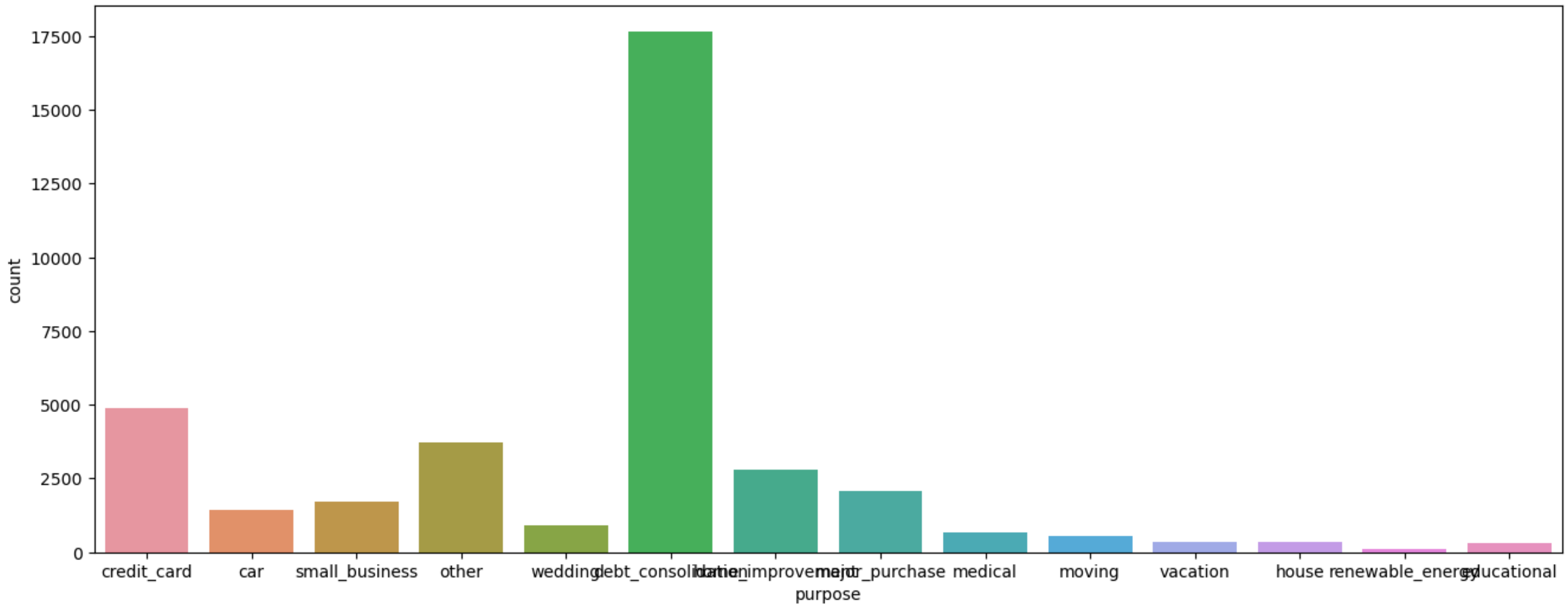
This comes from business understanding, though let's again have a look at the default rates across the purpose of the loan.

In [61]:
```
# purpose: small business loans defualt the most, then renewable energy and education
plt.figure(figsize=(16, 6))
plot_cat('purpose')
```



In the upcoming analyses, we will segment the loan applications across the purpose of the loan, since that is a variable affecting many other variables - the type of applicant, interest rate, income, and finally the default rate.

In [62]:
```
# lets first look at the number of loans for each type (purpose) of the loan
# most loans are debt consolidation (to repay otehr debts), then credit card, major purchase etc.
plt.figure(figsize=(16, 6))
sns.countplot(x='purpose', data=df)
plt.show()
```

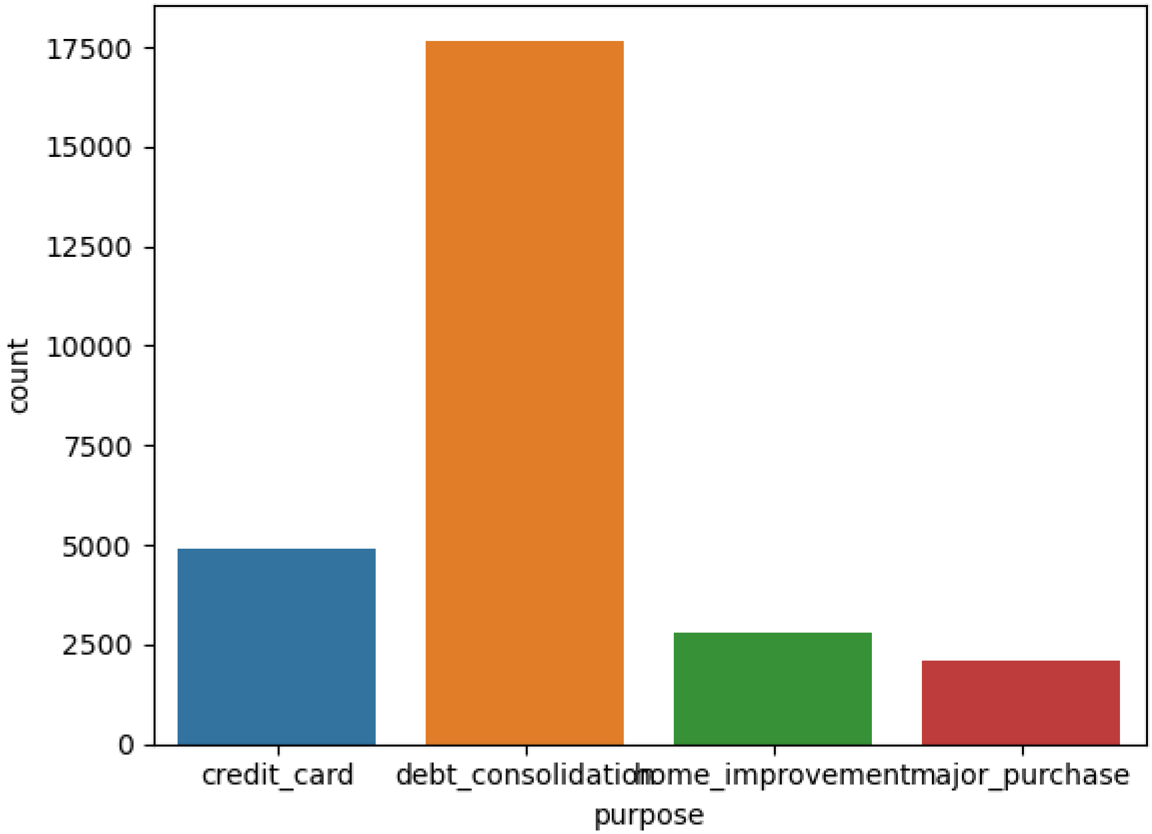


Let's analyse the top 4 types of loans based on purpose: consolidation, credit card, home improvement and major purchase.

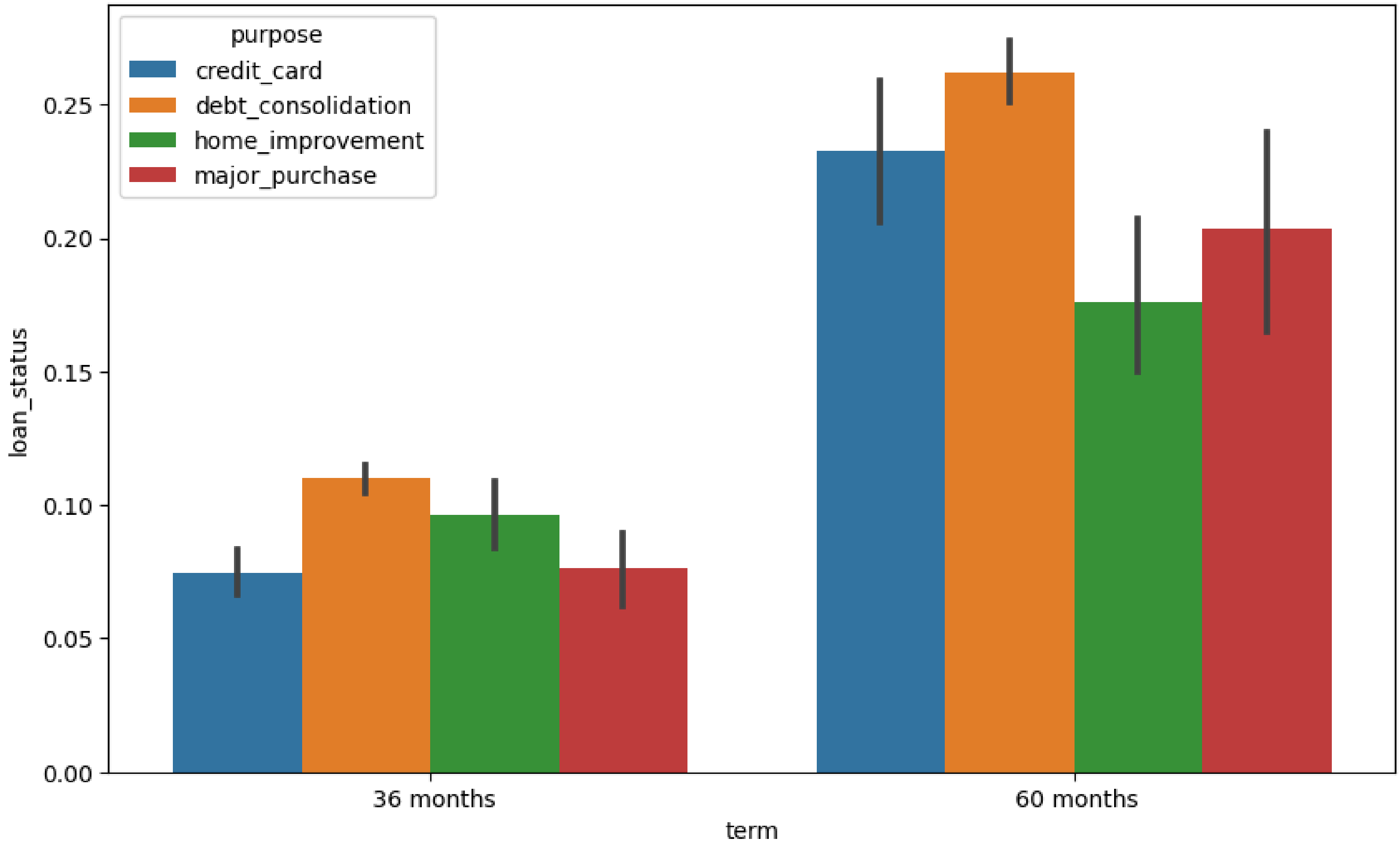
In [63]:
```
# filtering the df for the 4 types of loans mentioned above
main_purposes = ["credit_card","debt_consolidation","home_improvement","major_purchase"]
df = df[df['purpose'].isin(main_purposes)]
df['purpose'].value_counts()
```

Out[63]:
```
debt_consolidation    17675
credit_card            4899
home_improvement       2785
major_purchase         2080
Name: purpose, dtype: int64
```

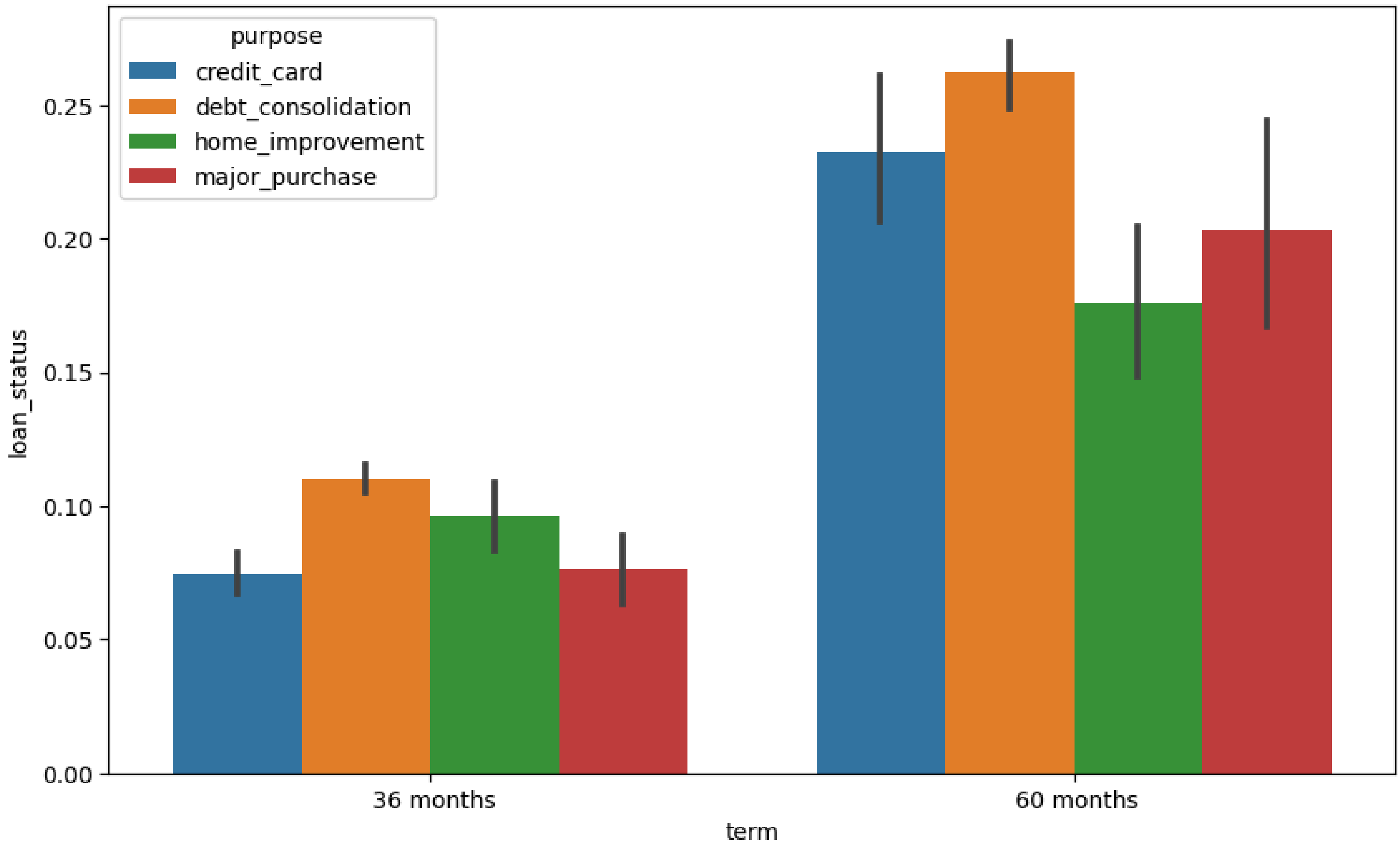
In [64]:
```
# plotting number of loans by purpose
sns.countplot(x=df['purpose'])
plt.show()
```



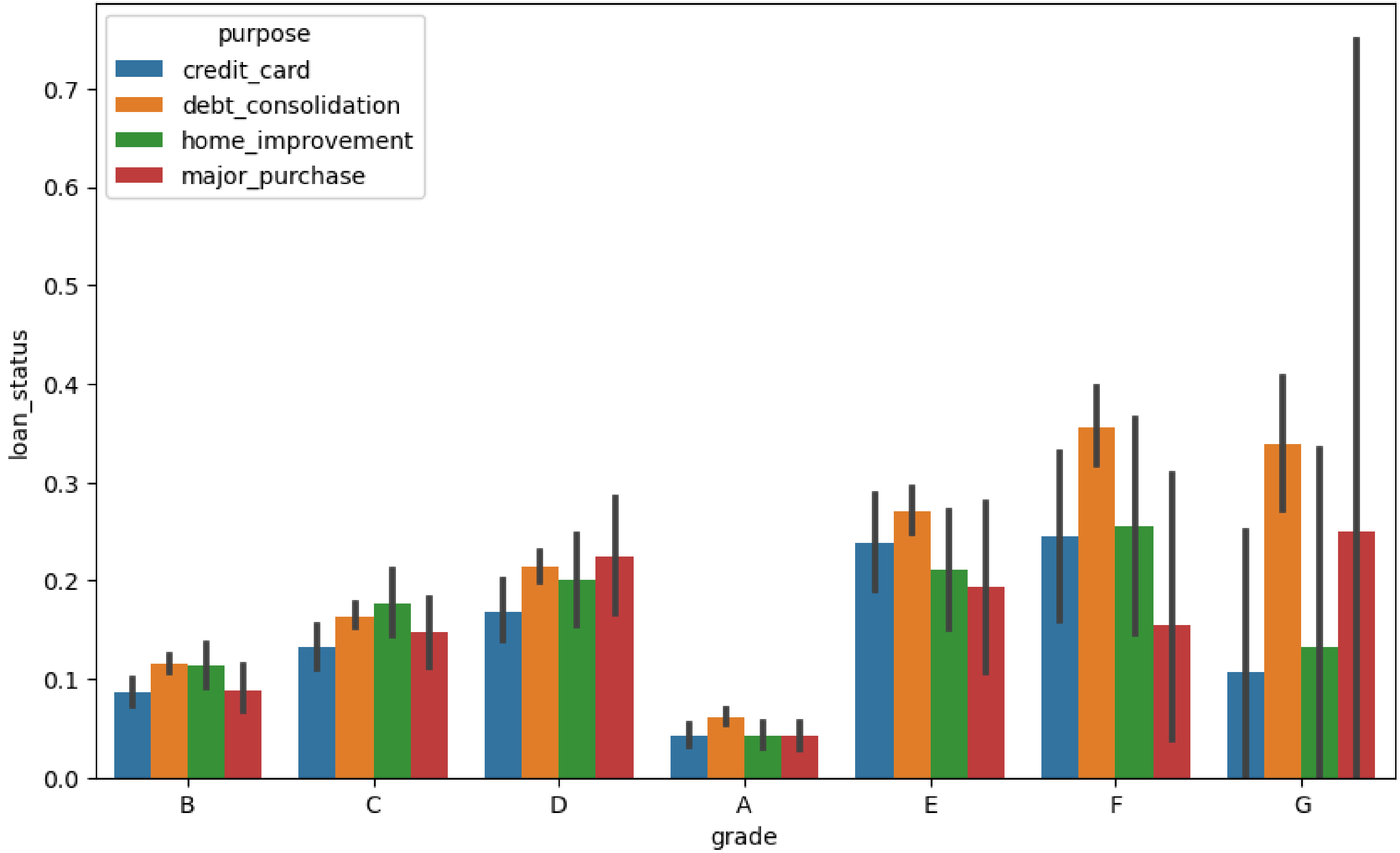
In [65]:
```
# let's now compare the default rates across two types of categorical variables
# purpose of loan (constant) and another categorical variable (which changes)

plt.figure(figsize=[10, 6])
sns.barplot(x='term', y="loan_status", hue='purpose', data=df)
plt.show()
```



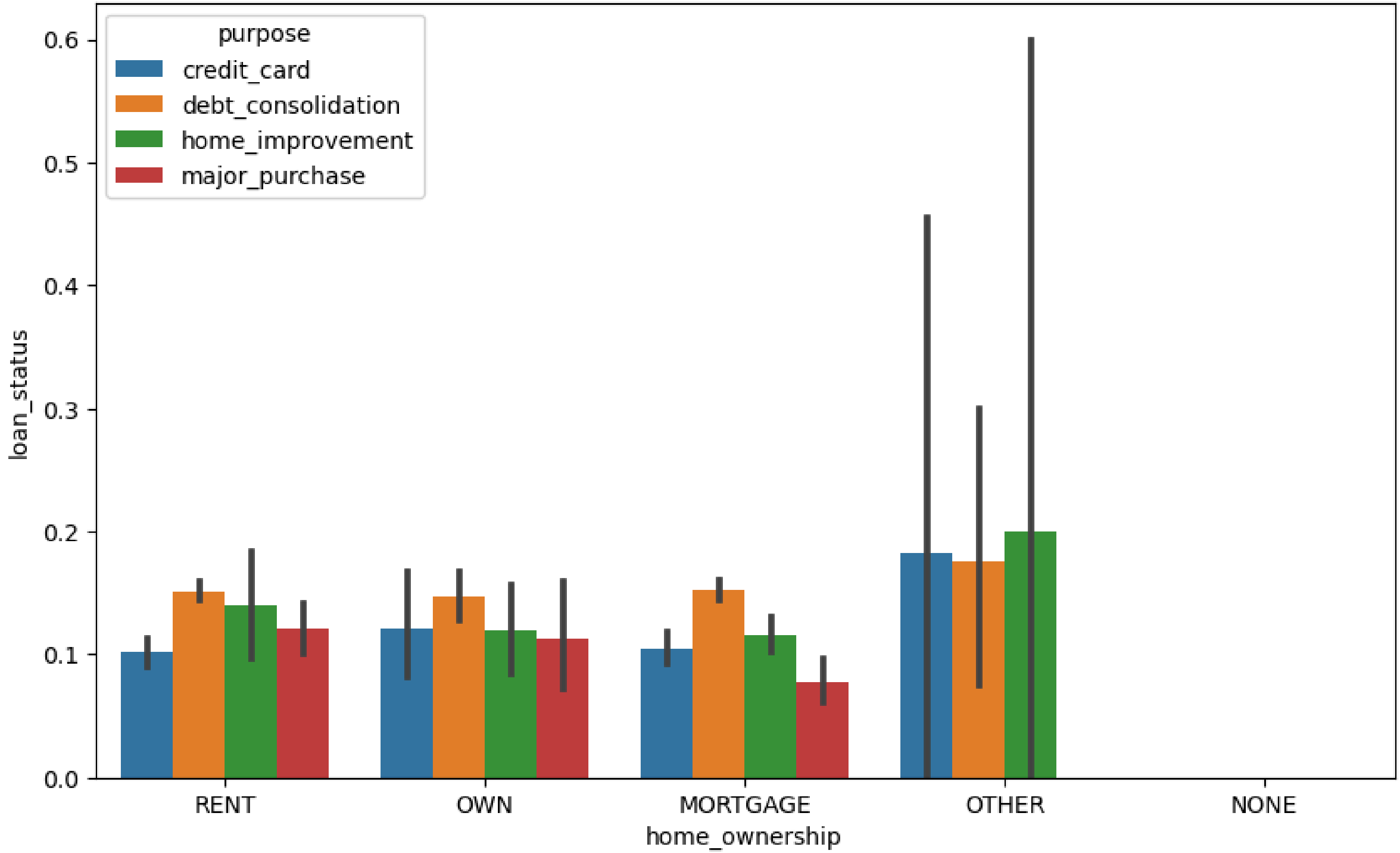
In [66]:
```
# lets write a function which takes a categorical variable and plots the default rate
# segmented by purpose

def plot_segmented(cat_var):
    plt.figure(figsize=(10, 6))
    sns.barplot(x=cat_var, y='loan_status', hue='purpose', data=df)
    plt.show()


plot_segmented('term')
```



In [67]:
```
# grade of Loan
plot_segmented('grade')
```

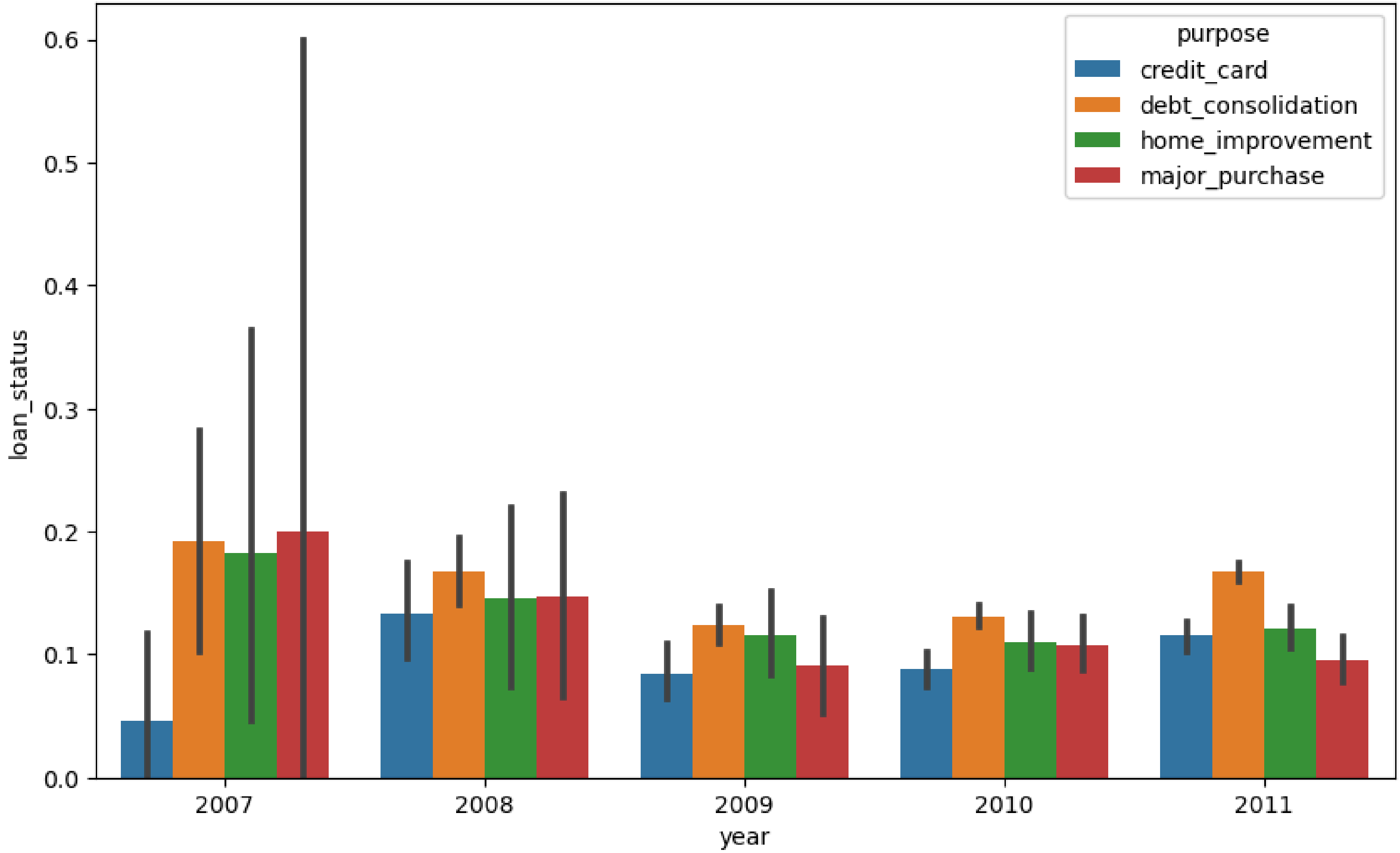


In [68]:
```
# home ownership
plot_segmented('home_ownership')
```

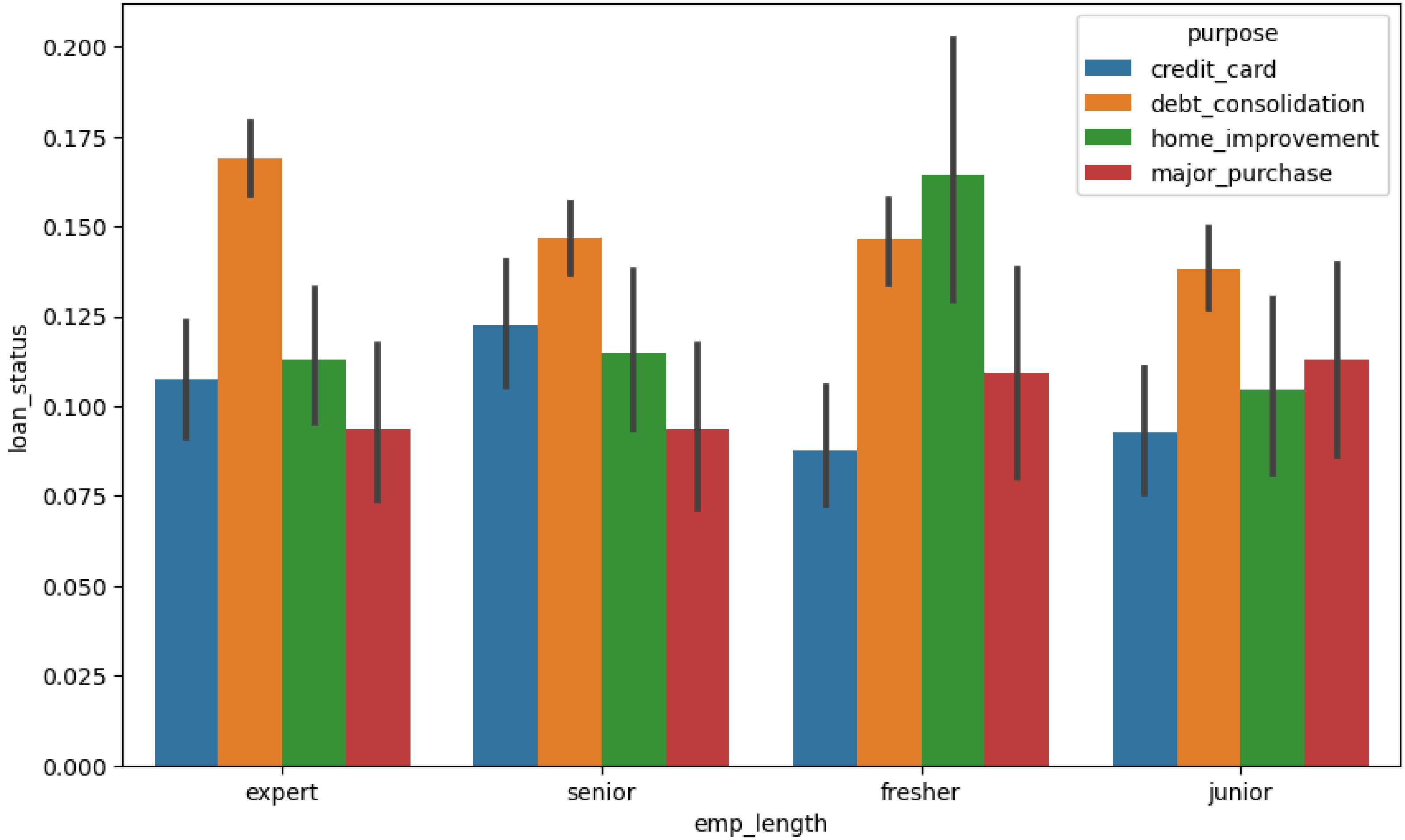


In general, debt consolidation loans have the highest default rates. Lets compare across other categories as well.

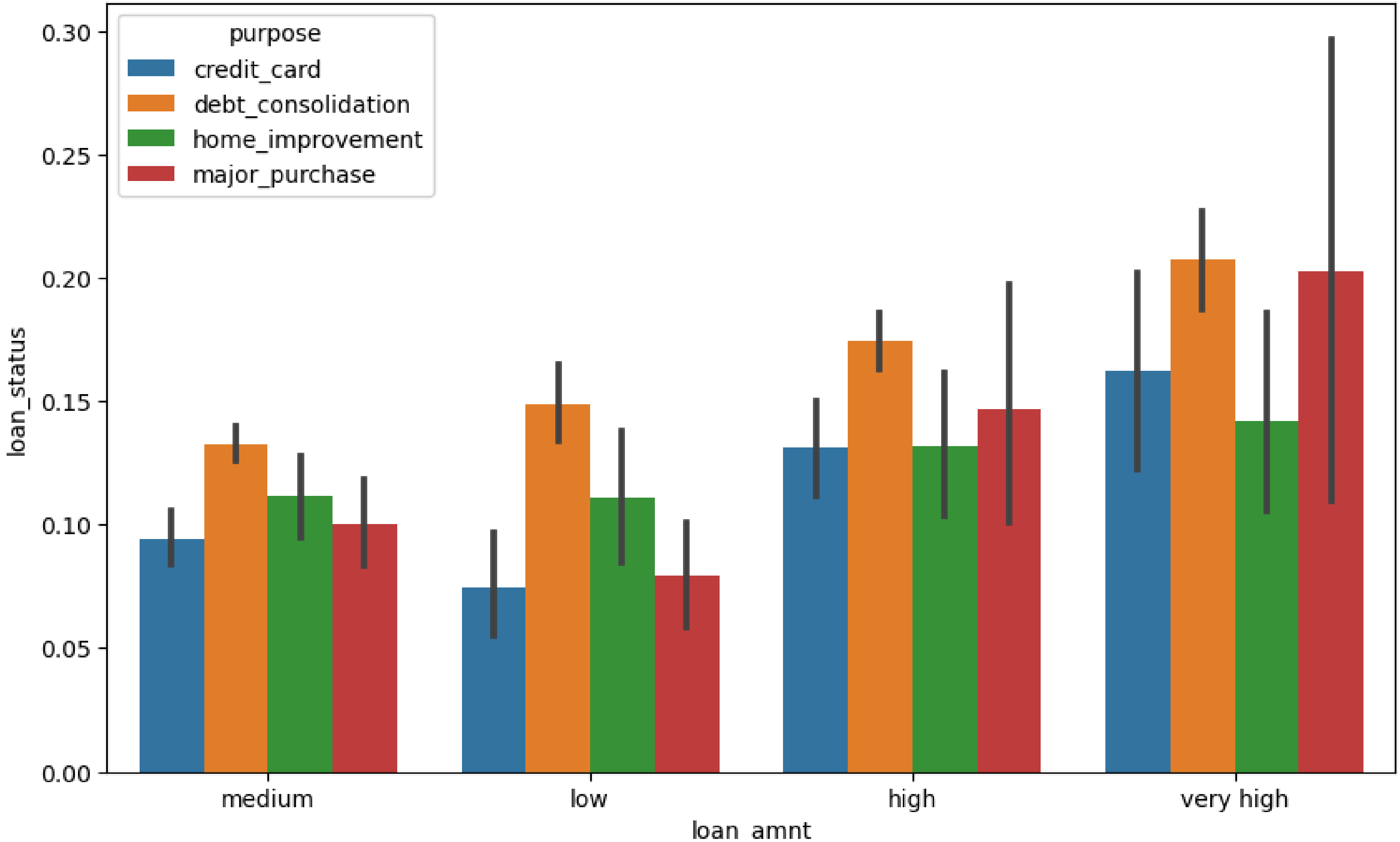
In [69]:
```
# year
plot_segmented('year')
```



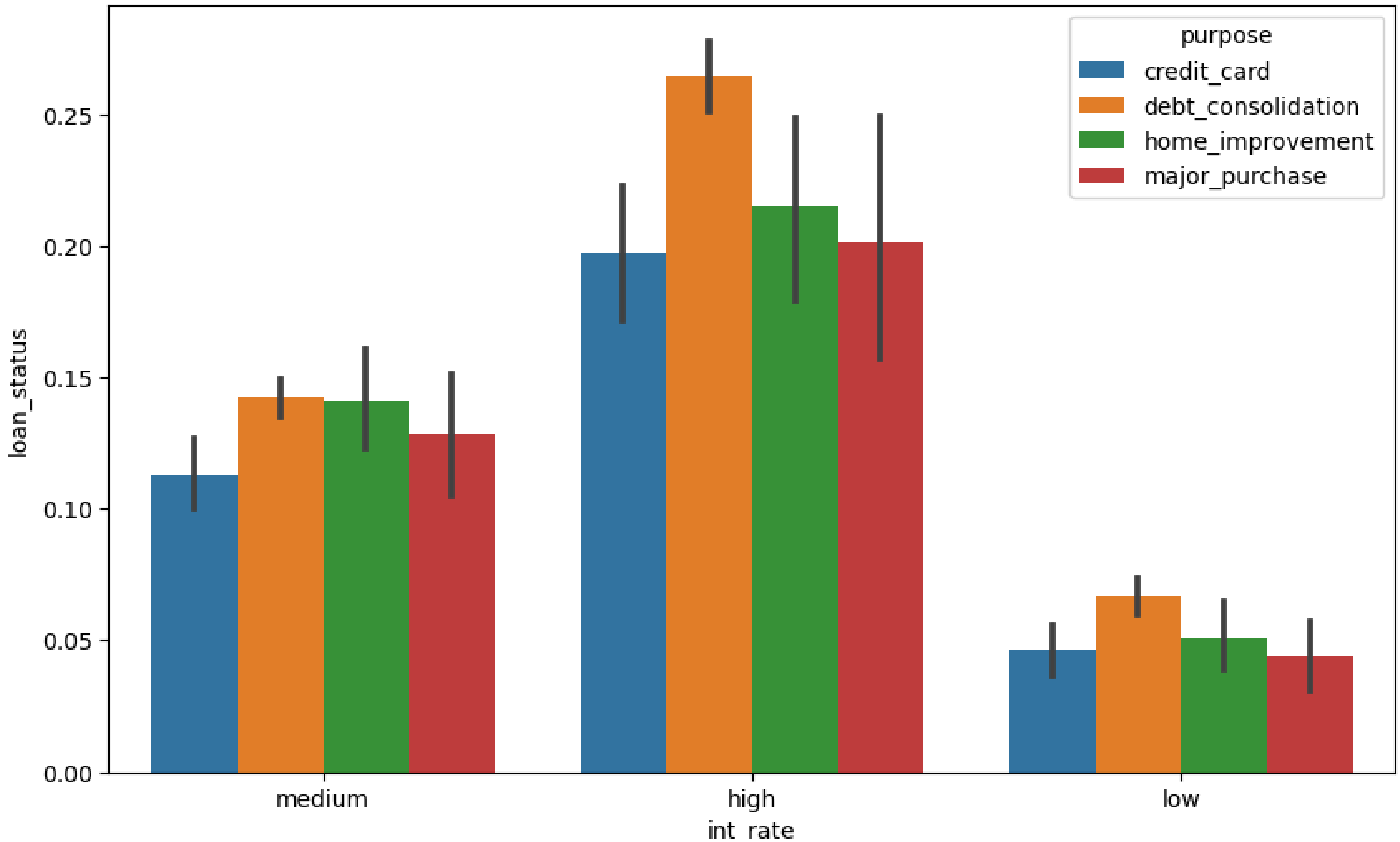
In [70]:
```
# emp_length
plot_segmented('emp_length')
```



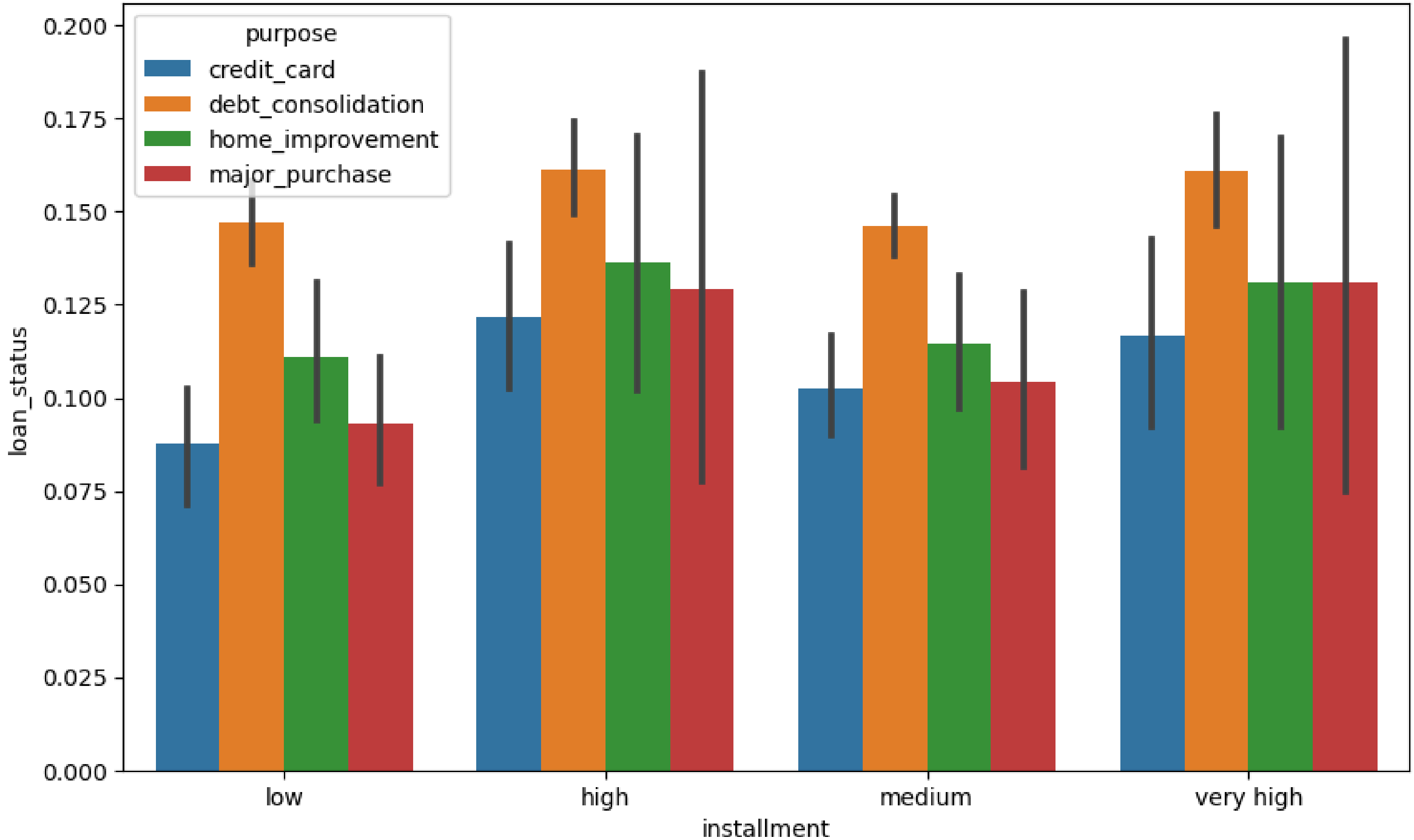
In [71]:
```
# loan_amnt: same trend across loan purposes
plot_segmented('loan_amnt')
```



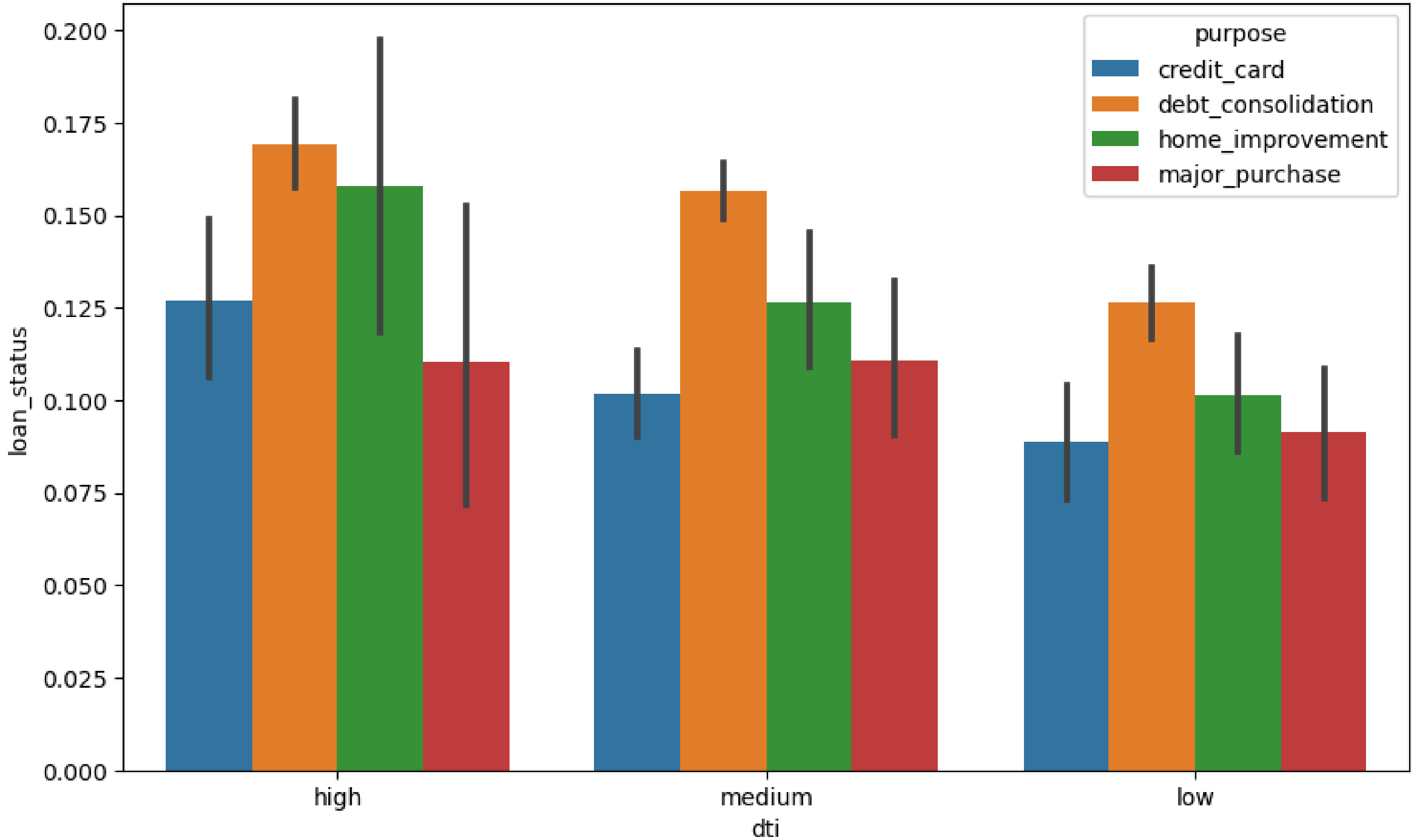
In [72]:
```
# interest rate
plot_segmented('int_rate')
```



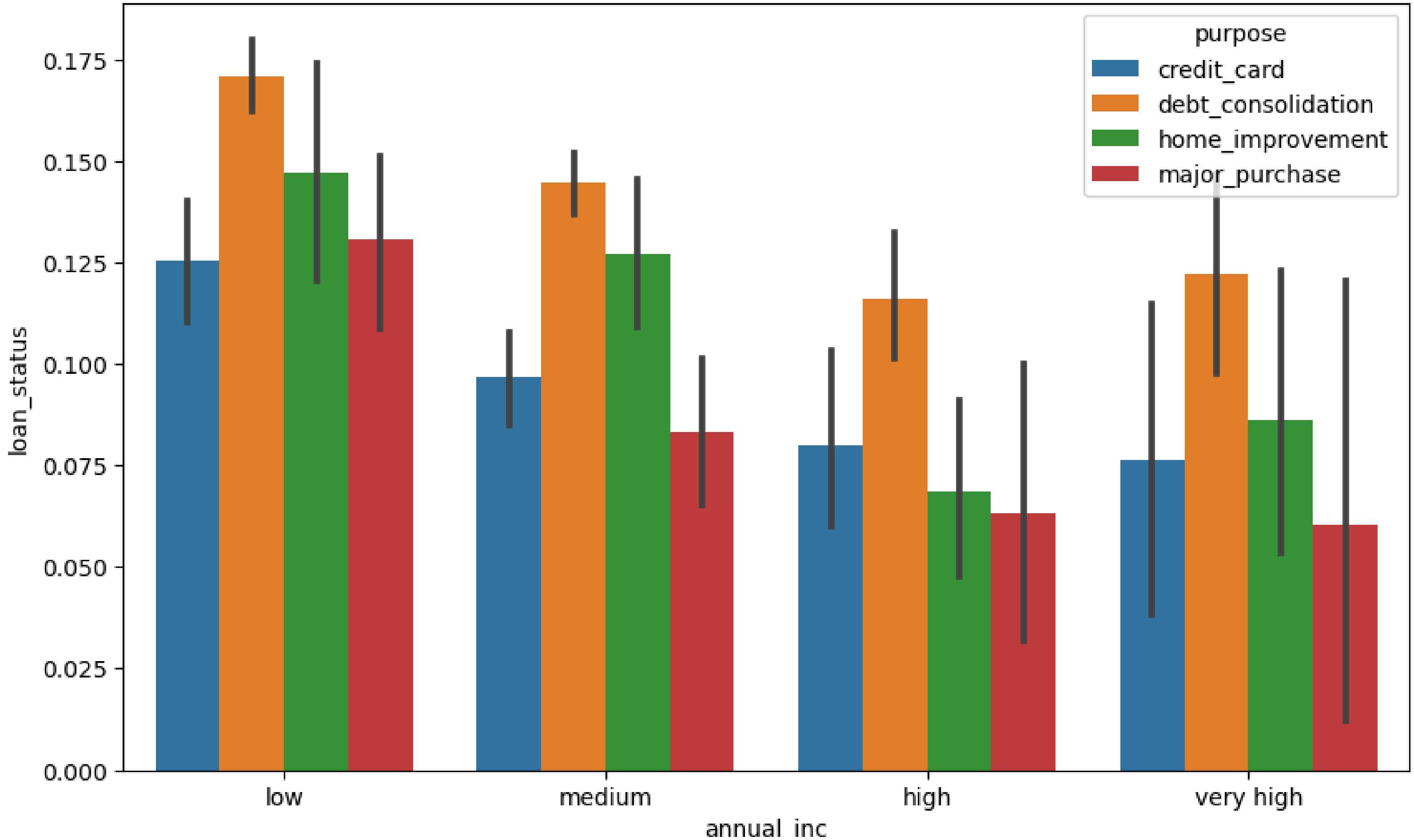
In [73]:
```
# installment
plot_segmented('installment')
```



In [74]:
```
# debt to income ratio
plot_segmented('dti')
```



In [75]:
```
# annual income
plot_segmented('annual_inc')
```



A good way to quantify th effect of a categorical variable on default rate is to see 'how much does the default rate vary across the categories'.

Let's see an example using annual_inc as the categorical variable

In [76]:
```
# variation of default rate across annual_inc
df.groupby('annual_inc').loan_status.mean().sort_values(ascending=False)
```

Out[76]:
```
annual_inc
low          0.157966
medium       0.130075
very high    0.101570
high         0.097749
Name: loan_status, dtype: float64
```

In [77]:
```
# one can write a function which takes in a categorical variable and computed the average
# default rate across the categories
# It can also compute the 'difference between the highest and the lowest default rate' across the
# categories, which is a decent metric indicating the effect of the varaible on default rate

def diff_rate(cat_var):
    default_rates = df.groupby(cat_var).loan_status.mean().sort_values(ascending=False)
    return (round(default_rates, 2), round(default_rates[0] - default_rates[-1], 2))

default_rates, diff = diff_rate('annual_inc')
print(default_rates)
print(diff)
```

```
annual_inc
low          0.16
medium       0.13
very high    0.10
high         0.10
Name: loan_status, dtype: float64
0.06
```

Thus, there is a 6% increase in default rate as you go from high to low annual income. We can compute this difference for all the variables and roughly identify the ones that affect default rate the most.

In [78]:

```
# filtering all the object type variables
df_categorical = df.loc[:, df.dtypes == object]
df_categorical['loan_status'] = df['loan_status']

# Now, for each variable, we can compute the incremental diff in default rates
print([i for i in df.columns])
```

```
['id', 'member_id', 'loan_amnt', 'funded_amnt', 'funded_amnt_inv', 'term', 'int_rate', 'installment', 'g
rade', 'sub_grade', 'emp_title', 'emp_length', 'home_ownership', 'annual_inc', 'verification_status', 'i
ssue_d', 'loan_status', 'pymnt_plan', 'purpose', 'dti', 'initial_list_status', 'collections_12_mths_ex_m
ed', 'policy_code', 'acc_now_delinq', 'chargeoff_within_12_mths', 'delinq_amnt', 'pub_rec_bankruptcies',
'tax_liens', 'month', 'year']

C:\Users\hp\AppData\Local\Temp\ipykernel_11208\2256099650.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.h
tml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df_categorical['loan_status'] = df['loan_status']
```

In [81]:

```
# storing the diff of default rates for each column in a dict
d = {key: diff_rate(key)[1]*100 for key in df_categorical.columns if key != 'loan_status'}
d
```

Out[81]:

```
{'loan_amnt': 7.000000000000001,
 'funded_amnt': 5.0,
 'funded_amnt_inv': 6.0,
 'term': 15.0,
 'int_rate': 19.0,
 'installment': 3.0,
 'grade': 27.0,
 'sub_grade': 46.0,
 'emp_title': 100.0,
 'emp_length': 2.0,
 'home_ownership': 16.0,
 'annual_inc': 6.0,
 'verification_status': 4.0,
 'pymnt_plan': 0.0,
 'purpose': 5.0,
 'dti': 5.0,
 'initial_list_status': 0.0}
```

In [ ]: