Task 3 - Predict the PD (Probability of default) for a borrower

Aim Use the provided data to train a function that will estimate the probability of default for a borrower.

Objectives

1. Produce a function that can take in the properties of a loan and output the expected loss.
2. Explore some technique including

> - Simple regression: -- Accuracy of the Logistic Regression model is: 0.99; Accuracy of Logisitic Regression model after replace variable is: 0.9979
> - XGBoost: -- Accuracy of the XGBoost is 0.9998
> - Random forest: -- Accuracy of the Random Forest model is 0.9997

1. Use multiple methods and provide a comparative analysis.

Raw data info:

- borrower
- income
- total loans outstanding
- Previsouly defaulted on a loan
- Assuming a recovery rate of 10%, this can be used to give the expected loss on a loan.

In [1]:
```
import numpy as np
import pandas as pd
from datetime import datetime, date
import matplotlib.pyplot as plt
import seaborn as sns
import os
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics  import classification_report, accuracy_score, confu
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:
```
url = 'https://raw.githubusercontent.com/Hongyan-Wang/JP_Morgan_Project/m
df = pd.read_csv(url)
df.describe()
```

Out[2]:

	customer_id	credit_lines_outstanding	loan_amt_outstanding	total_debt_outstan
count	1.000000e+04	10000.000000	10000.000000	10000.00(
mean	4.974577e+06	1.461200	4159.677034	8718.91
std	2.293890e+06	1.743846	1421.399078	6627.16
min	1.000324e+06	0.000000	46.783973	31.65
25%	2.977661e+06	0.000000	3154.235371	4199.83(
50%	4.989502e+06	1.000000	4052.377228	6732.40
75%	6.967210e+06	2.000000	5052.898103	11272.26
max	8.999789e+06	5.000000	10750.677810	43688.78

Exploratory Data Analaysis

1. Check out the misssing data

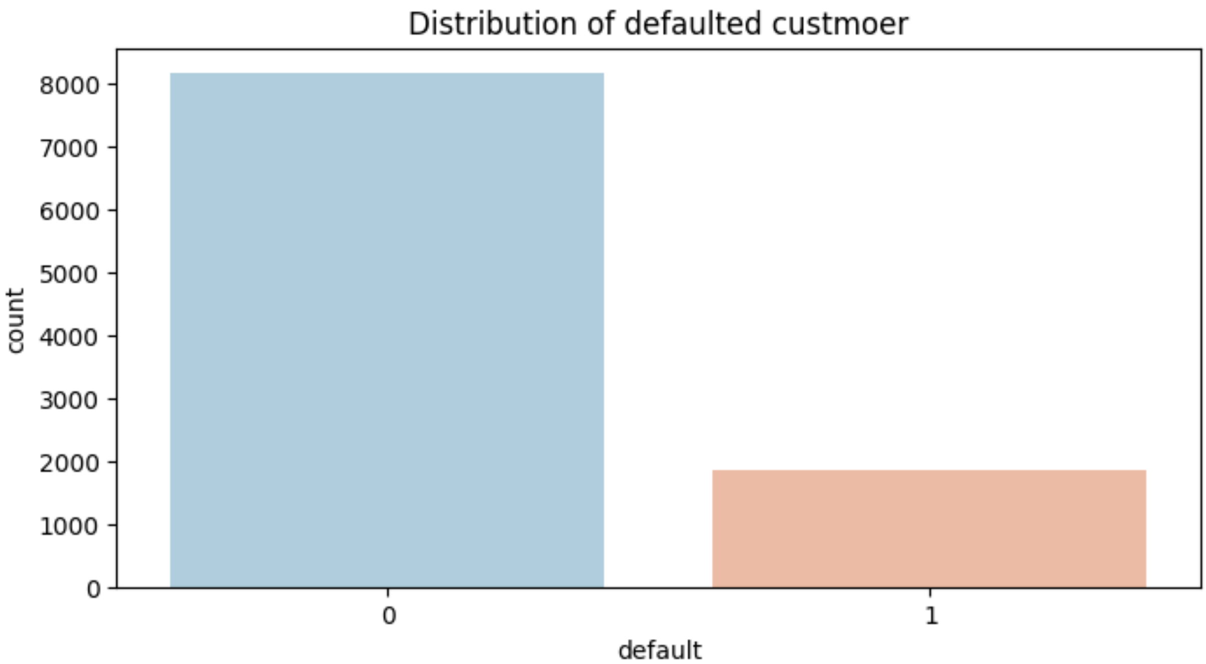
- It is found that their is no missing data in this data set
- No need to conduct pre-processing/ data wrangling for now

2. Check the distribution of some key variables

In [3]:

```
fig, ax1 = plt.subplots(figsize = (8,3))
sns.heatmap(df.isnull(),yticklabels=False, cbar = False, cmap = 'viridis'
plt.show()
```

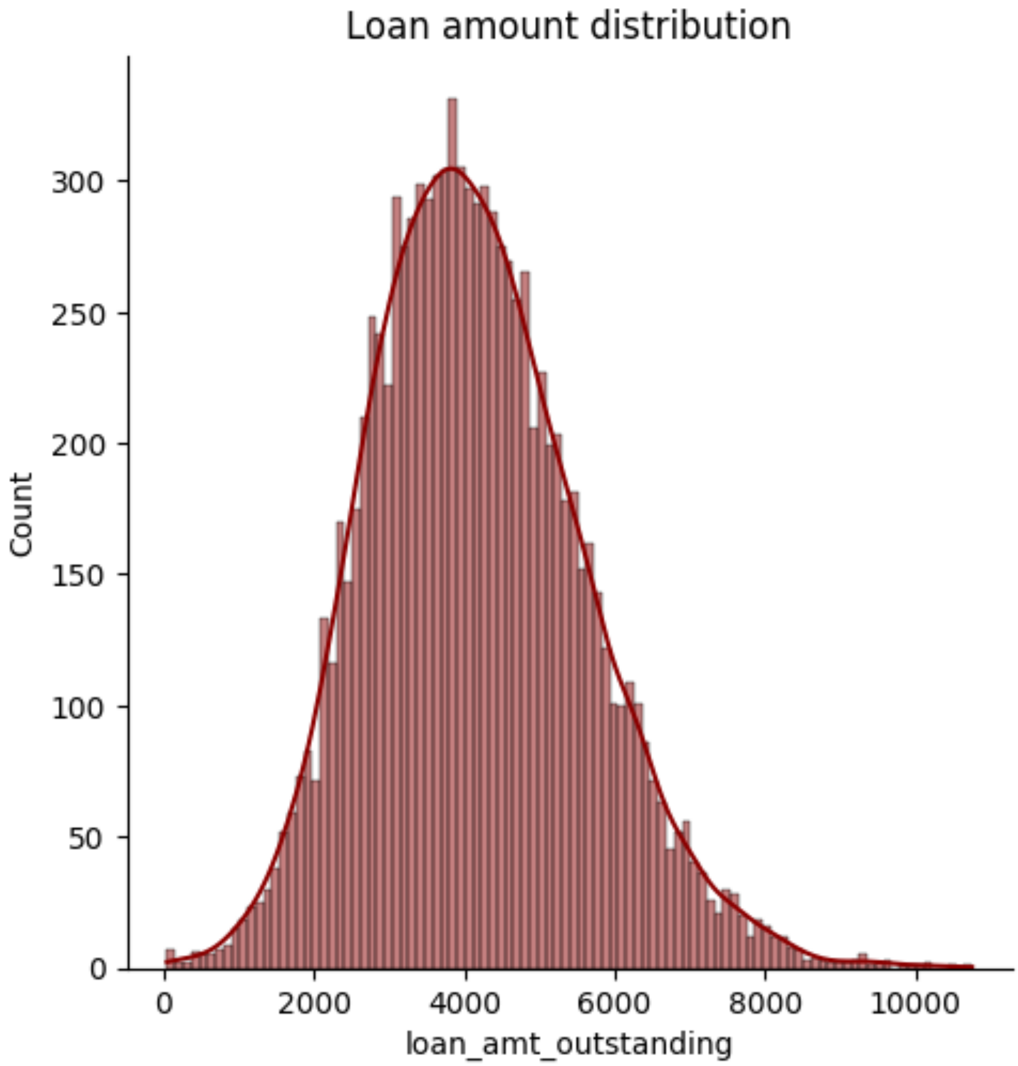
In [4]:
```
fig,ax1 =plt.subplots(figsize = (8, 4))
sns.countplot(x = 'default', data =df, palette= 'RdBu_r').set(title = 'Di
plt.show()
print('the percentage of defaulted customer is: ', sum(df.default)/len(df
```

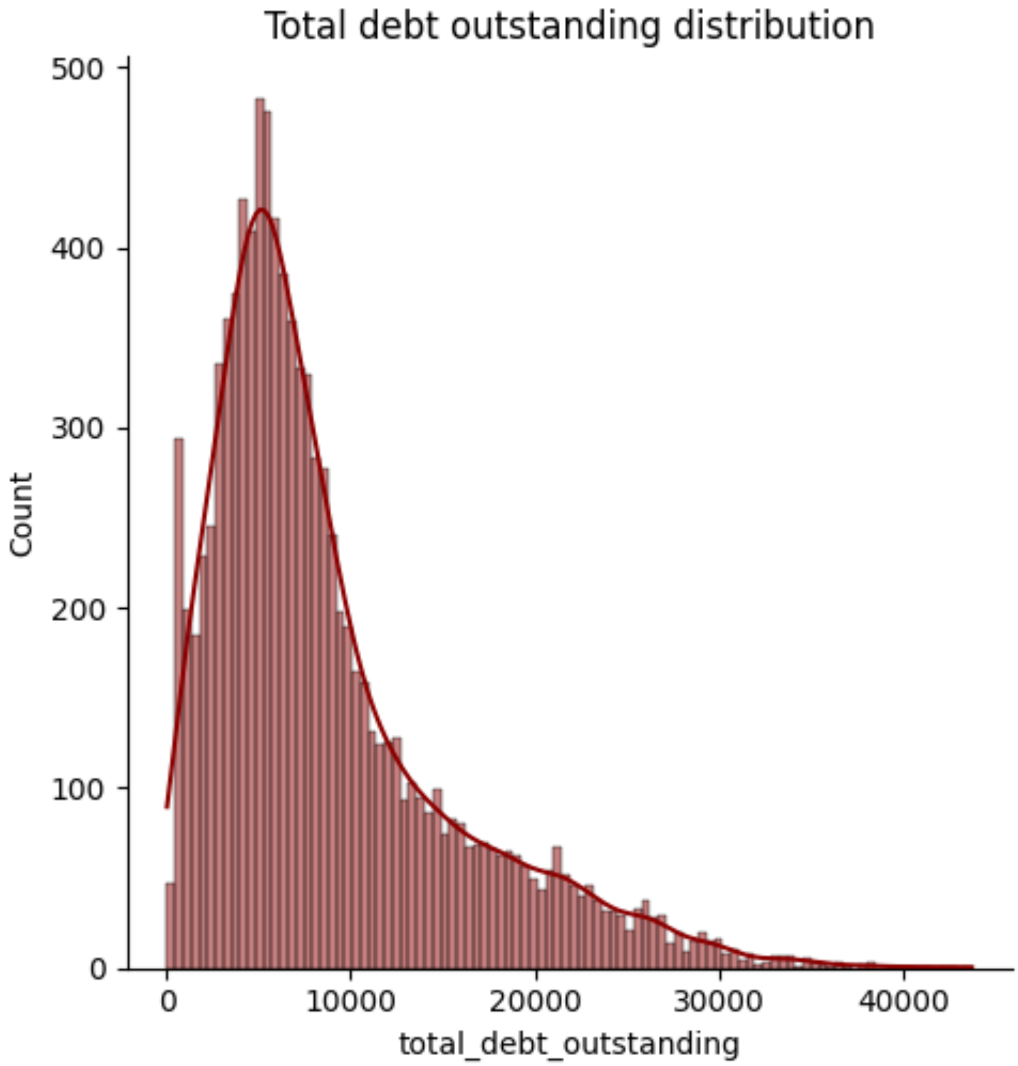



```
the percentage of defaulted customer is:  18.509999999999998  %
```

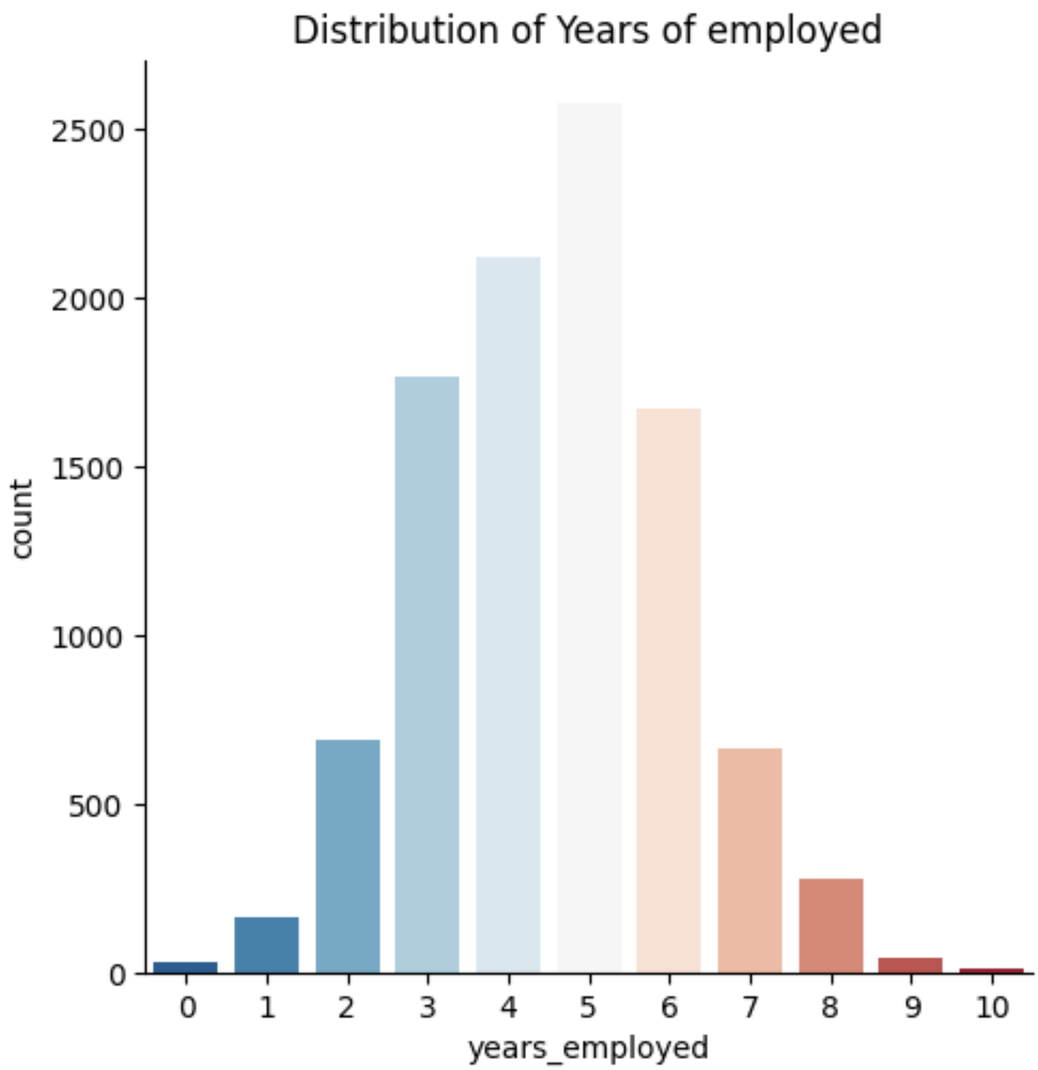
In [5]:
```
sns.displot(df.loan_amt_outstanding, kde = True, color = 'darkred', bins
sns.displot(df.total_debt_outstanding, kde = True, color = 'darkred', bin
sns.displot(df.income, kde = True, color = 'darkred', bins = 100).set(tit
sns.countplot(x = 'years_employed', data =df, palette= 'RdBu_r').set(titl
```

Out[5]:
```
[Text(0.5, 1.0, 'Distribution of Years of employed')]
```


Loan amount distribution
Count
300
250
200
150
100
50
0
0
2000
4000
6000
8000
10000
loan_amt_outstanding

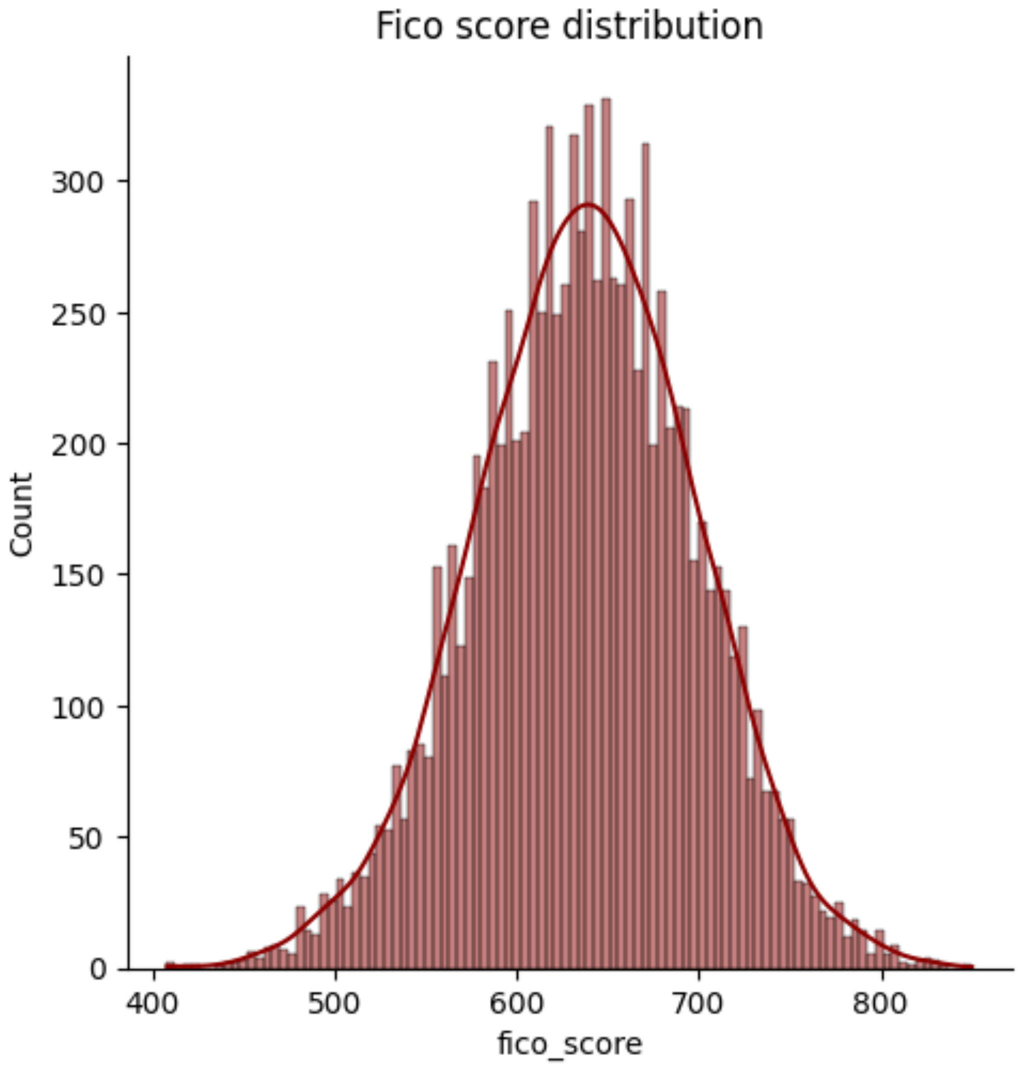


Total debt outstanding distribution
Count
total_debt_outstanding
0
100
200
300
400
500
10000
20000
30000
40000

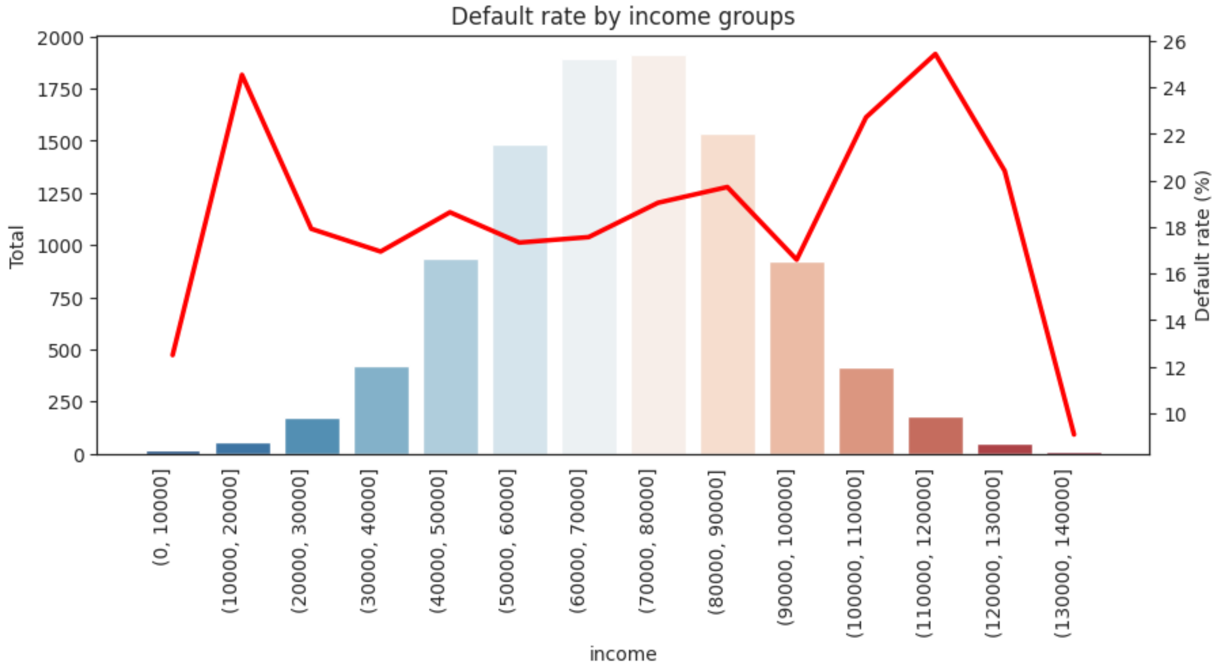


In [6]:
```
sns.displot(df.fico_score, kde = True, color = 'darkred', bins = 100).set
```

Out[6]:
```
<seaborn.axisgrid.FacetGrid at 0x7dedc4c3ff40>
```

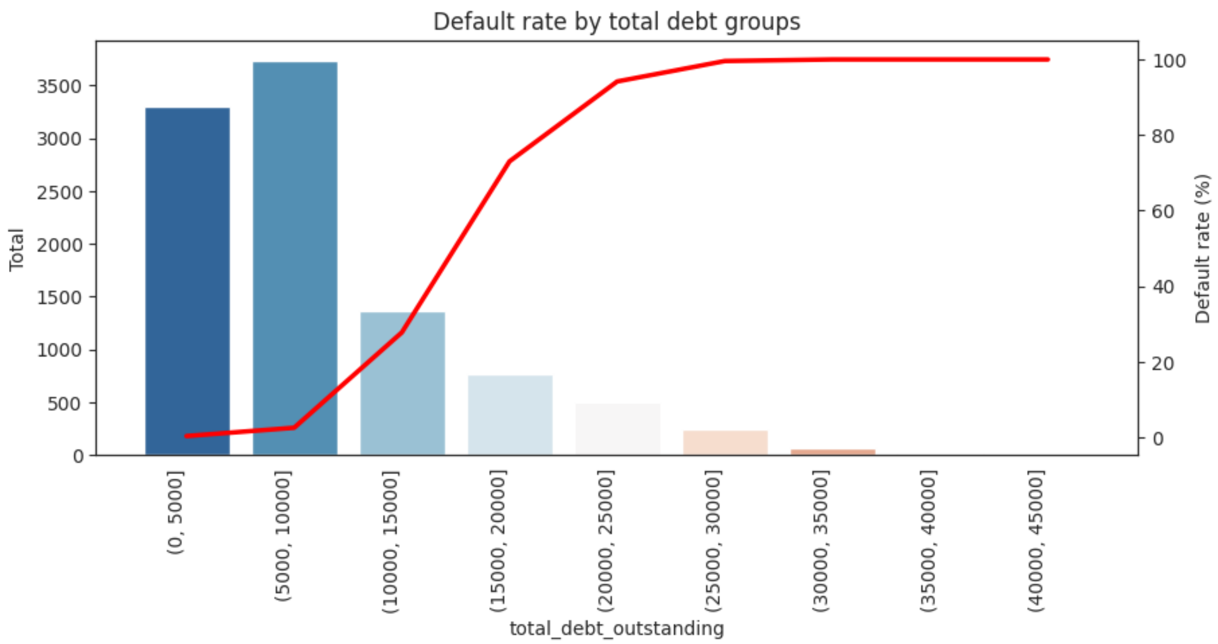


In [8]:
```
sns.set_style('white')
df_grouped = df.groupby([pd.cut(df['income'],np.arange(0, 150000, 10000))
df_grouped1 = df_grouped.groupby(level = 0).apply(lambda x:x/x.sum() * 10
df_grouped1['Default rate (%)'] = df_grouped1[1]
df_grouped = df_grouped.groupby(level = 0).apply(lambda x: x).unstack(lev
df_grouped['Total'] = df_grouped[0]+df_grouped[1]
fig, ax1 = plt.subplots(figsize = (10,4))
sns.barplot(data = df_grouped, x = 'income', y = 'Total', ax= ax1, palett
ax1.set_xticklabels(ax1.get_xticklabels(), rotation=90, horizontalalignme
ax2 = ax1.twinx()
sns.lineplot(data = df_grouped1, x = df_grouped1['income'].astype(str), y
plt.show()
```



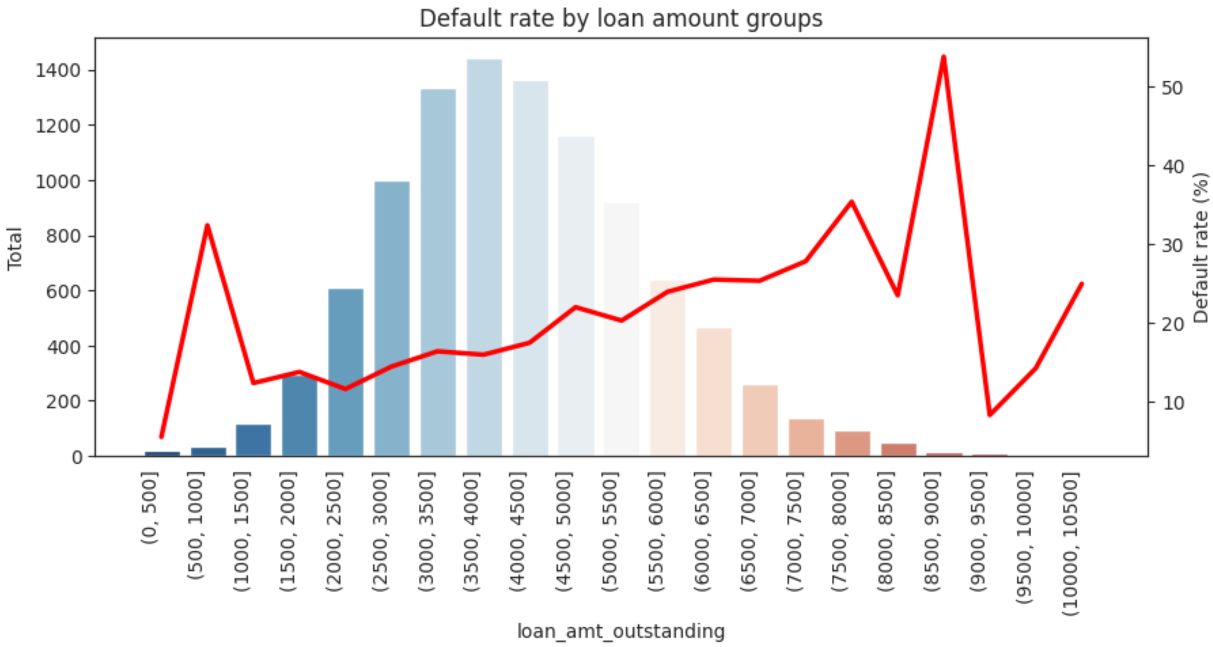
In [9]:

```
sns.set_style('white')
df_grouped = df.groupby([pd.cut(df['total_debt_outstanding'],np.arange(0,
df_grouped1 = df_grouped.groupby(level = 0).apply(lambda x:x/x.sum() * 10
df_grouped1['Default rate (%)'] = df_grouped1[1]
df_grouped = df_grouped.groupby(level = 0).apply(lambda x: x).unstack(lev
df_grouped['Total'] = df_grouped[0]+df_grouped[1]
fig, ax1 = plt.subplots(figsize = (10,4))
sns.barplot(data = df_grouped, x = 'total_debt_outstanding', y = 'Total',
ax1.set_xticklabels(ax1.get_xticklabels(), rotation=90, horizontalalignme
ax2 = ax1.twinx()
sns.lineplot(data = df_grouped1, x = df_grouped1['total_debt_outstanding'
plt.show()
```



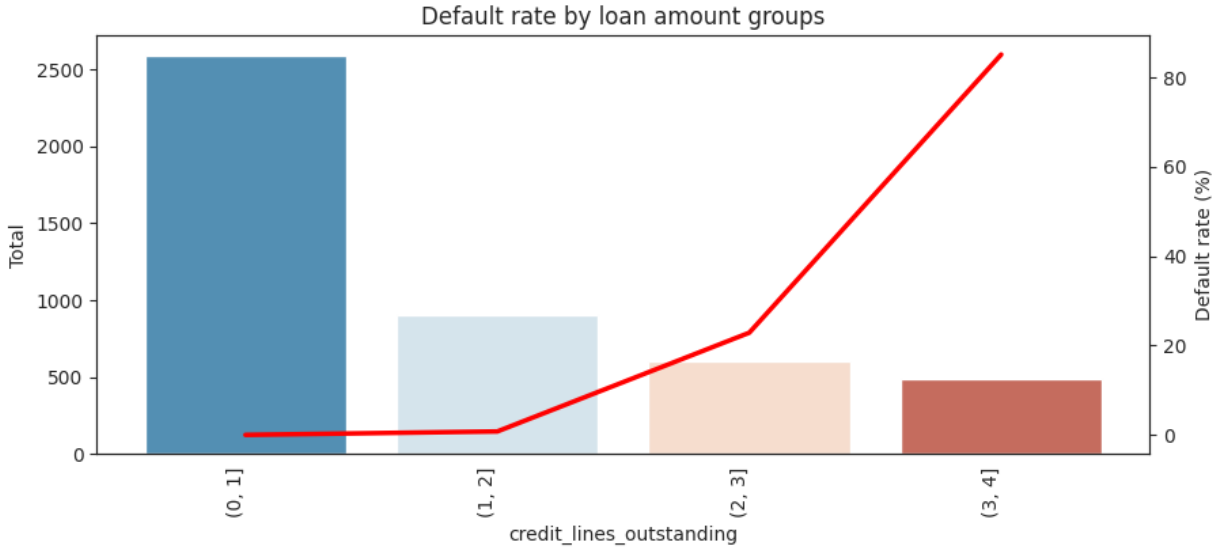
In [10]:

```
sns.set_style('white')
df_grouped = df.groupby([pd.cut(df['loan_amt_outstanding'],np.arange(0, 1
df_grouped1 = df_grouped.groupby(level = 0).apply(lambda x:x/x.sum() * 10
df_grouped1['Default rate (%)'] = df_grouped1[1]
df_grouped = df_grouped.groupby(level = 0).apply(lambda x: x).unstack(lev
df_grouped['Total'] = df_grouped[0]+df_grouped[1]
fig, ax1 = plt.subplots(figsize = (10,4))
sns.barplot(data = df_grouped, x = 'loan_amt_outstanding', y = 'Total', a
ax1.set_xticklabels(ax1.get_xticklabels(), rotation=90, horizontalalignme
ax2 = ax1.twinx()
sns.lineplot(data = df_grouped1, x = df_grouped1['loan_amt_outstanding'].
plt.show()
```

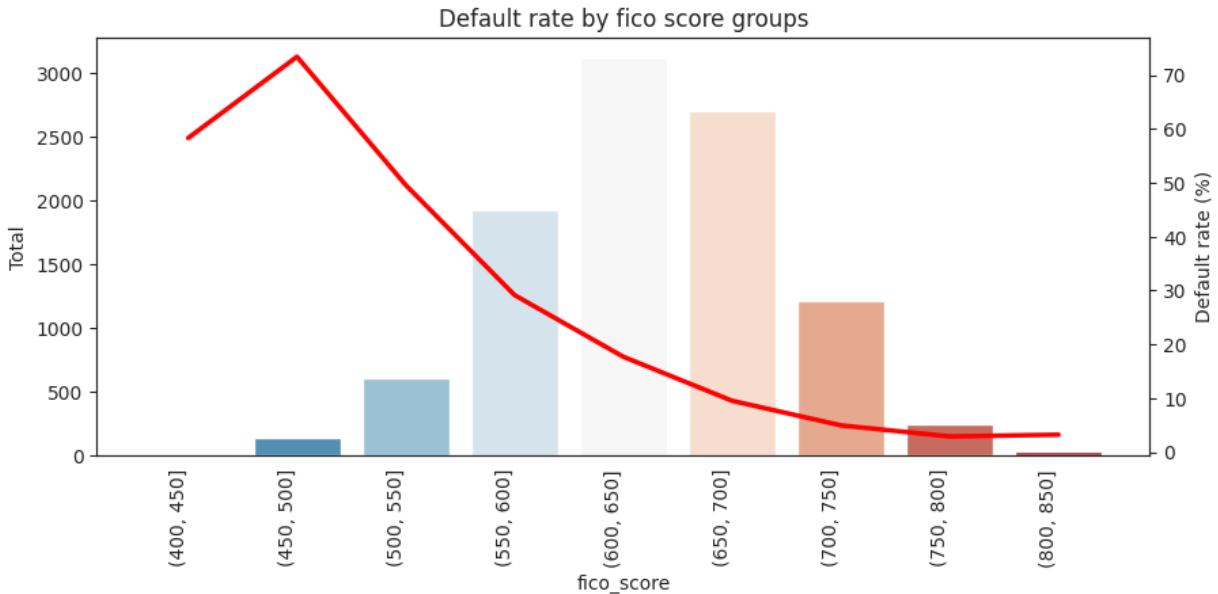


In [11]:

```
sns.set_style('white')
df_grouped = df.groupby([pd.cut(df['credit_lines_outstanding'],np.arange(
df_grouped1 = df_grouped.groupby(level = 0).apply(lambda x:x/x.sum() * 10
df_grouped1['Default rate (%)'] = df_grouped1[1]
df_grouped = df_grouped.groupby(level = 0).apply(lambda x: x).unstack(lev
df_grouped['Total'] = df_grouped[0]+df_grouped[1]
fig, ax1 = plt.subplots(figsize = (10,4))
sns.barplot(data = df_grouped, x = 'credit_lines_outstanding', y = 'Total
ax1.set_xticklabels(ax1.get_xticklabels(), rotation=90, horizontalalignme
ax2 = ax1.twinx()
sns.lineplot(data = df_grouped1, x = df_grouped1['credit_lines_outstandin
plt.show()
```



In [12]:
```
sns.set_style('white')
df_grouped = df.groupby([pd.cut(df['fico_score'],np.arange(400, 900, 50))
df_grouped1 = df_grouped.groupby(level = 0).apply(lambda x:x/x.sum() * 10
df_grouped1['Default rate (%)'] = df_grouped1[1]
df_grouped = df_grouped.groupby(level = 0).apply(lambda x: x).unstack(lev
df_grouped['Total'] = df_grouped[0]+df_grouped[1]
fig, ax1 = plt.subplots(figsize = (10,4))
sns.barplot(data = df_grouped, x = 'fico_score', y = 'Total', ax= ax1, pa
ax1.set_xticklabels(ax1.get_xticklabels(), rotation=90, horizontalalignme
ax2 = ax1.twinx()
sns.lineplot(data = df_grouped1, x = df_grouped1['fico_score'].astype(str
plt.show()
```

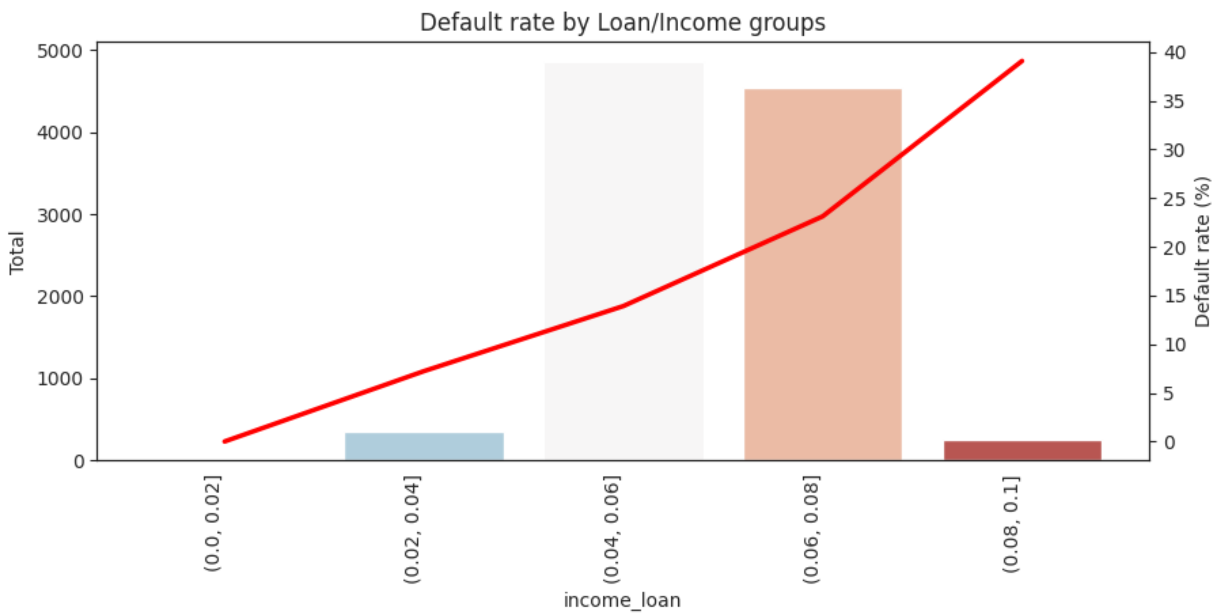


In [13]:
```
correlation_features = ['credit_lines_outstanding','loan_amt_outstanding'
ccorrelation_Transaction = df[correlation_features].corr()
plt.subplots(figsize = (10, 6))
sns.heatmap(ccorrelation_Transaction,annot=True, cmap = 'Greens')
```

Out[13]: <Axes: >

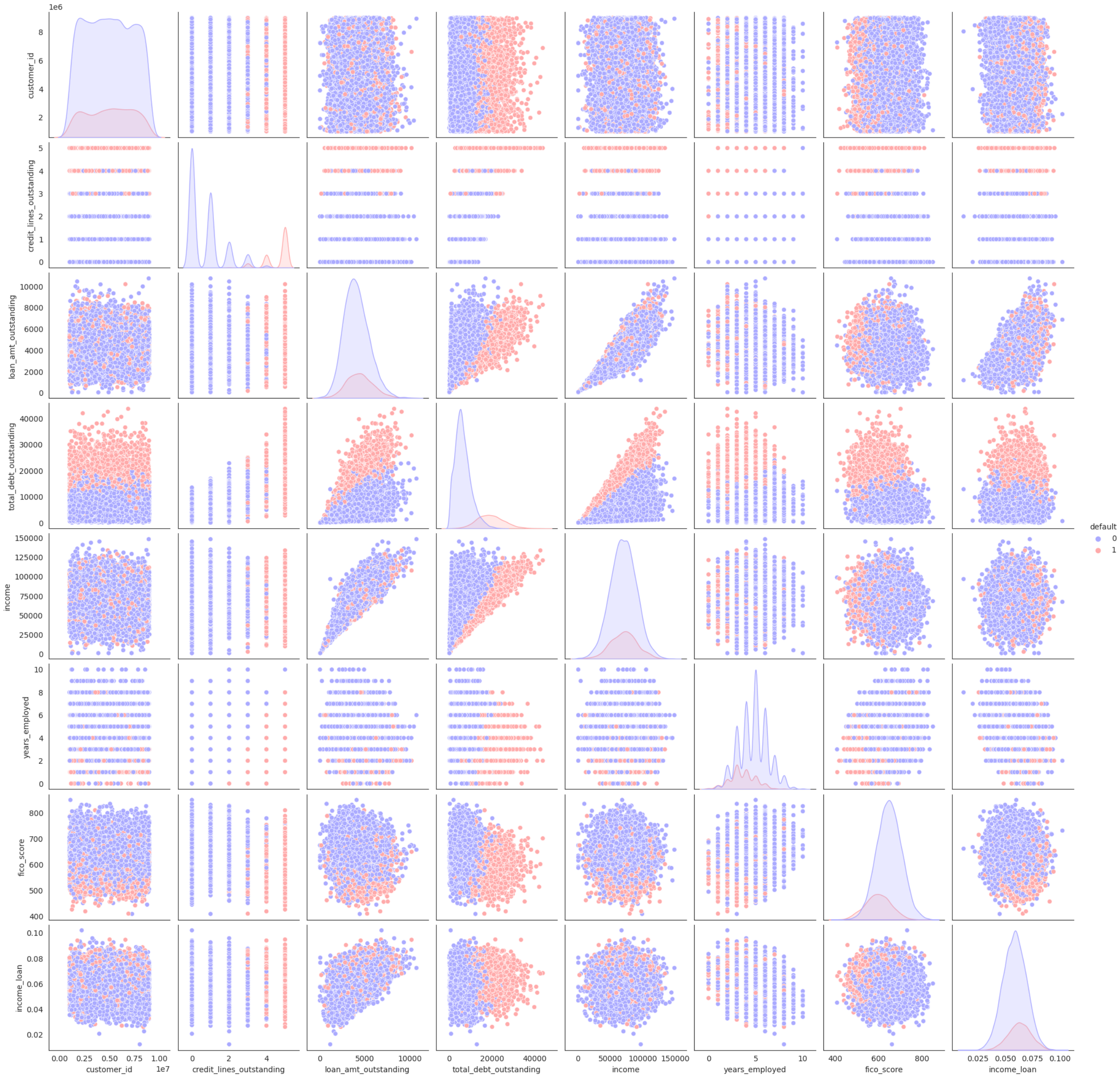
In [19]:

```
# To creat a new variable, to combine 'income' and 'loan_amount' together
df['income_loan'] = df['loan_amt_outstanding']/df['income']
sns.set_style('white')
df_grouped = df.groupby([pd.cut(df['income_loan'],np.arange(0, 0.12, 0.02
df_grouped1 = df_grouped.groupby(level = 0).apply(lambda x:x/x.sum() * 10
df_grouped1['Default rate (%)'] = df_grouped1[1]
df_grouped = df_grouped.groupby(level = 0).apply(lambda x: x).unstack(lev
df_grouped['Total'] = df_grouped[0]+df_grouped[1]
fig, ax1 = plt.subplots(figsize = (10,4))
sns.barplot(data = df_grouped, x = 'income_loan', y = 'Total', ax= ax1, p
ax1.set_xticklabels(ax1.get_xticklabels(), rotation=90, horizontalalignme
ax2 = ax1.twinx()
sns.lineplot(data = df_grouped1, x = df_grouped1['income_loan'].astype(st
plt.show()
```



In [22]:
```
sns.pairplot(data=df, hue='default', palette='bwr')
```

Out[22]:
```
<seaborn.axisgrid.PairGrid at 0x7dedc0718b80>
```



Building a Logistic Regression model

In [37]:
```
trainX = df[['credit_lines_outstanding','loan_amt_outstanding','total_deb
trainY = df[['default']]
X_train, X_test, Y_train, Y_test = train_test_split(trainX, trainY, test_
```

In [38]:
```
logmodel = LogisticRegression(max_iter = 500)
logmodel.fit(X_train, Y_train)
```

Out[38]:
```
▾ LogisticRegression
LogisticRegression(max_iter=500)
```

In [39]:
```
Predictions = logmodel.predict(X_test)
```

In [40]:
```
print(classification_report(Y_test, Predictions))
```

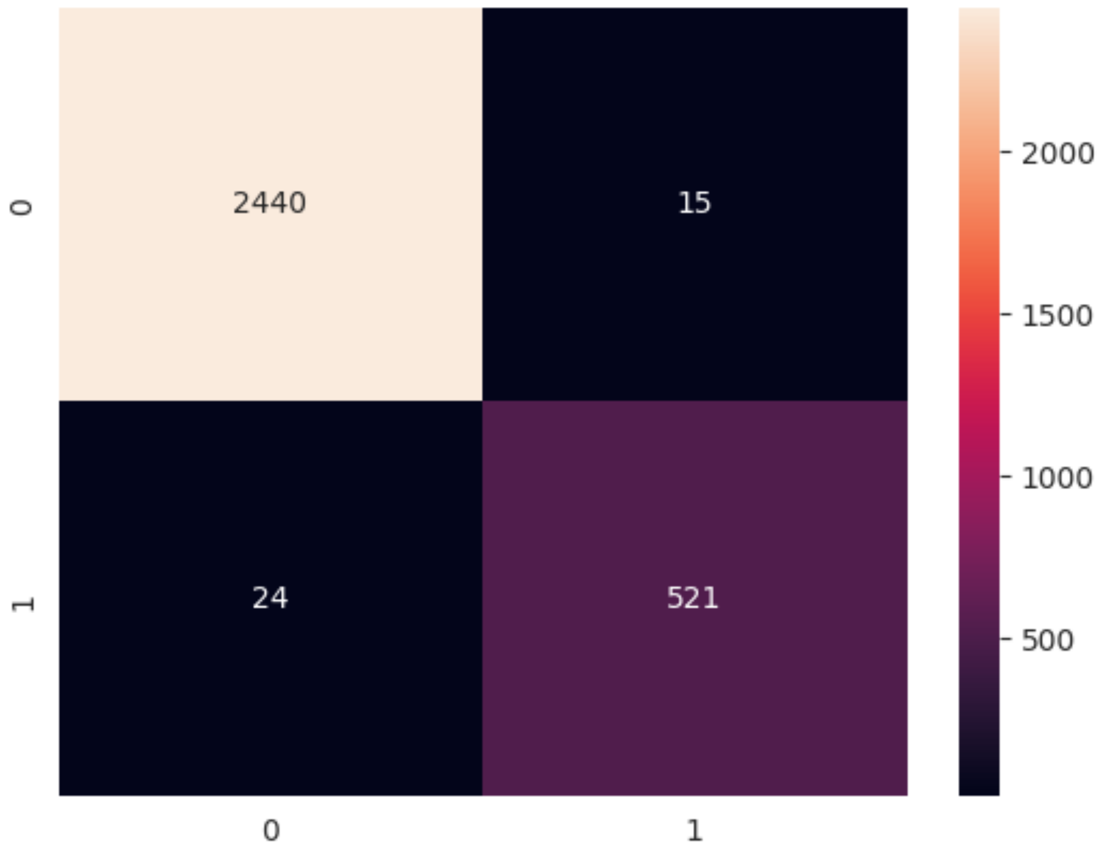
```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      2455
           1       0.97      0.96      0.96       545

    accuracy                           0.99      3000
   macro avg       0.98      0.97      0.98      3000
weighted avg       0.99      0.99      0.99      3000
```

In [41]:
```python
cm = confusion_matrix(Y_test, Predictions)
sns.heatmap(cm, annot=True, fmt='d')
```

Out[41]: <Axes: >



In [42]:
```python
print("Accuracy of the Logistic Regression model is: ", round(accuracy_sc
```

```
Accuracy of the Logistic Regression model is:  0.99
```

if use the new variable load_income_ratio to replace these two varibles

In [33]:
```python
trainX = df[['credit_lines_outstanding','income_loan','total_debt_outstan
trainY = df[['default']]
X_train, X_test, Y_train, Y_test = train_test_split(trainX, trainY, test_
logmodel = LogisticRegression(max_iter = 500)
logmodel.fit(X_train, Y_train)
```

Out[33]:
```
▾ LogisticRegression
LogisticRegression(max_iter=500)
```

In [34]:
```
Predictions = logmodel.predict(X_test)
print(classification_report(Y_test, Predictions))
```

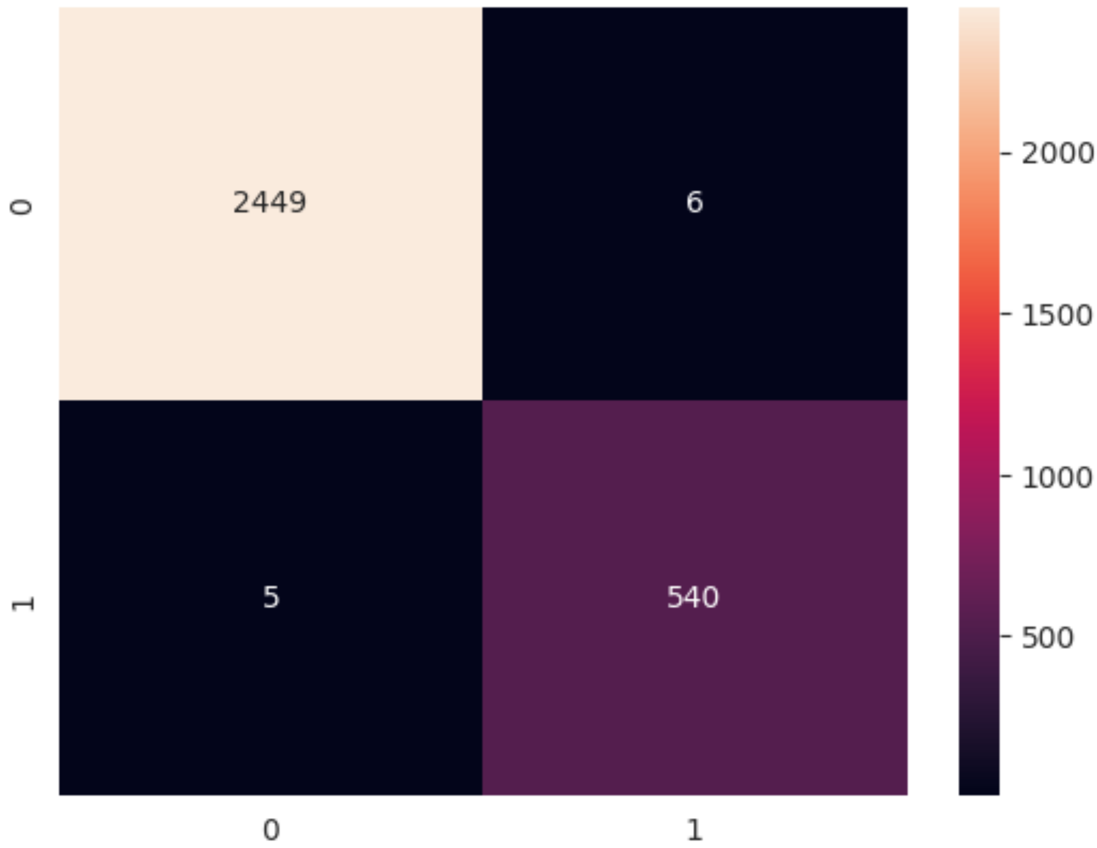
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2455
           1       0.99      0.99      0.99       545

    accuracy                           1.00      3000
   macro avg       0.99      0.99      0.99      3000
weighted avg       1.00      1.00      1.00      3000
```

In [35]:
```
cm = confusion_matrix(Y_test, Predictions)
sns.heatmap(cm, annot=True, fmt='d')
```

Out[35]: <Axes: >

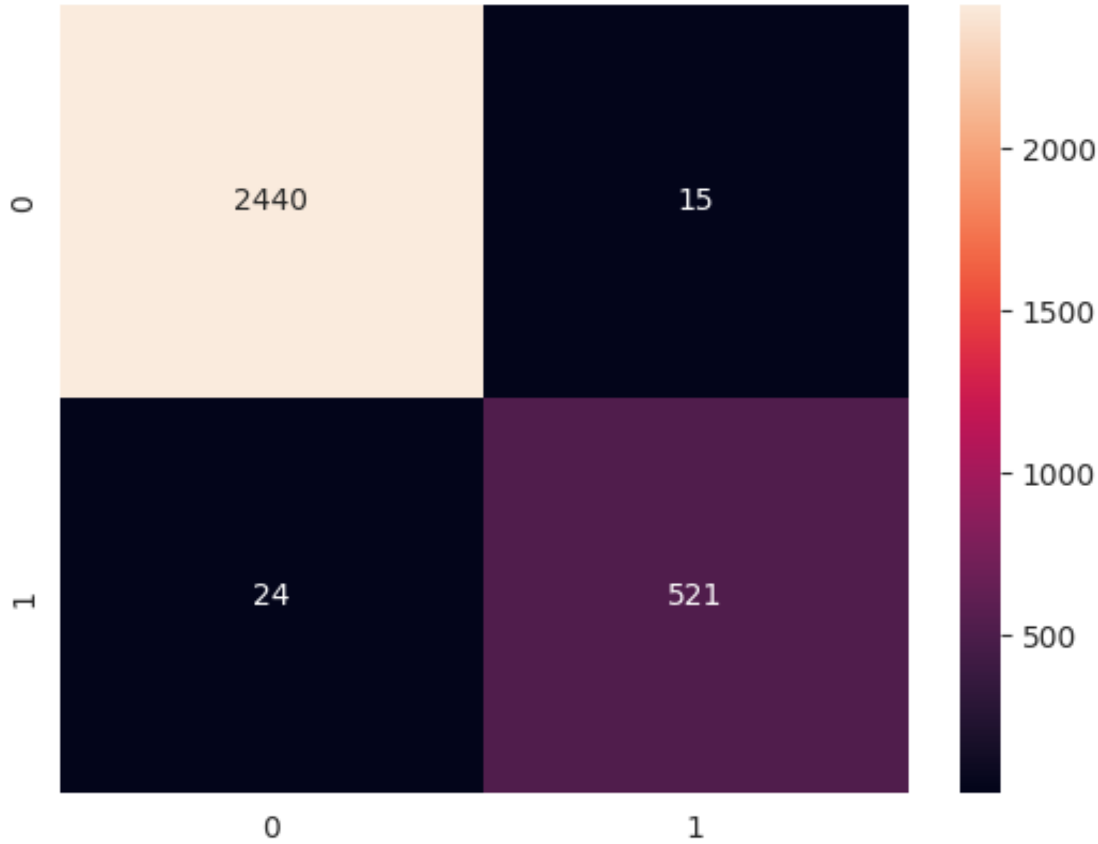


In [36]:
```
print("Accuracy of the Logistic Regression model is: ", round(accuracy_sc
```

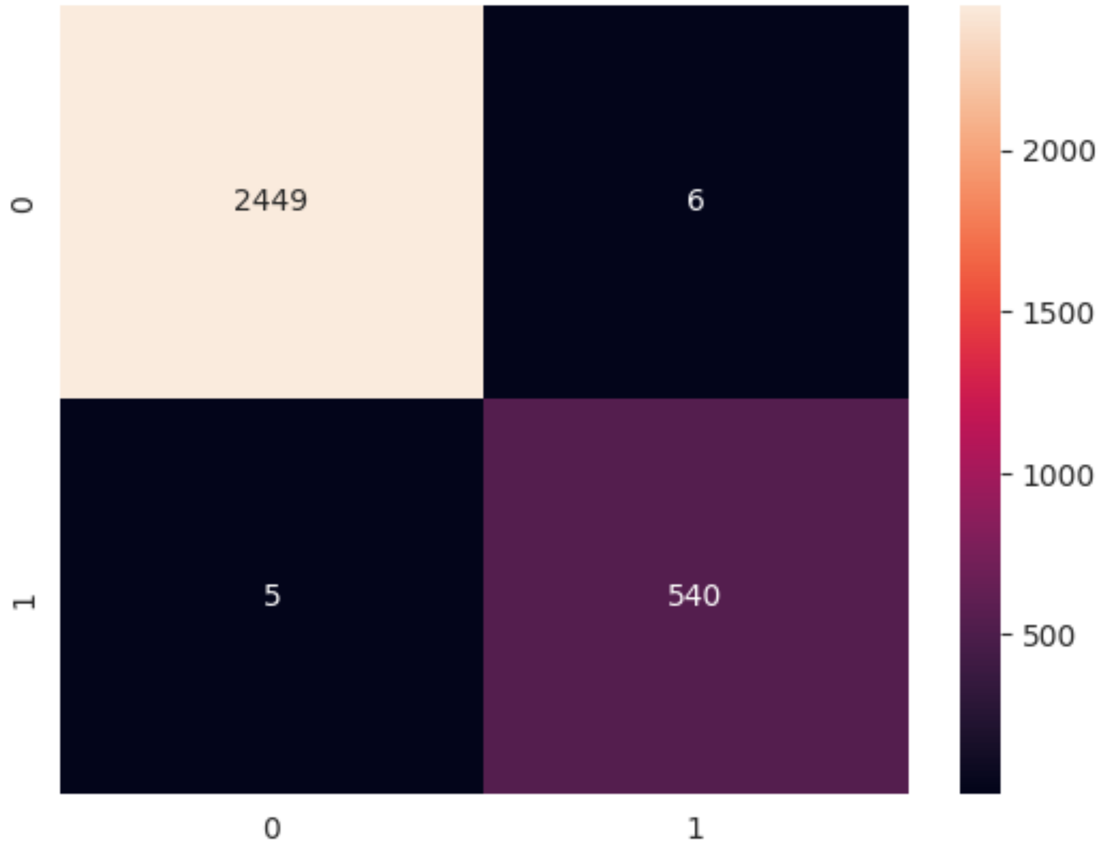
```
Accuracy of the Logistic Regression model is:  1.0
```

To compare:

- Before replace the variable:



- After replace the varible:



Building a Random Forest Model

In [44]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

In [45]:
```
rfmodel = RandomForestClassifier(max_depth = 8, n_estimators = 100, rando
rfmodel.fit(X_train, Y_train)
```

Out[45]:
```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=8, random_state=20)
```

In [46]:
```
Predictions_rf = rfmodel.predict(X_test)
print(classification_report(Y_test, Predictions_rf))
```

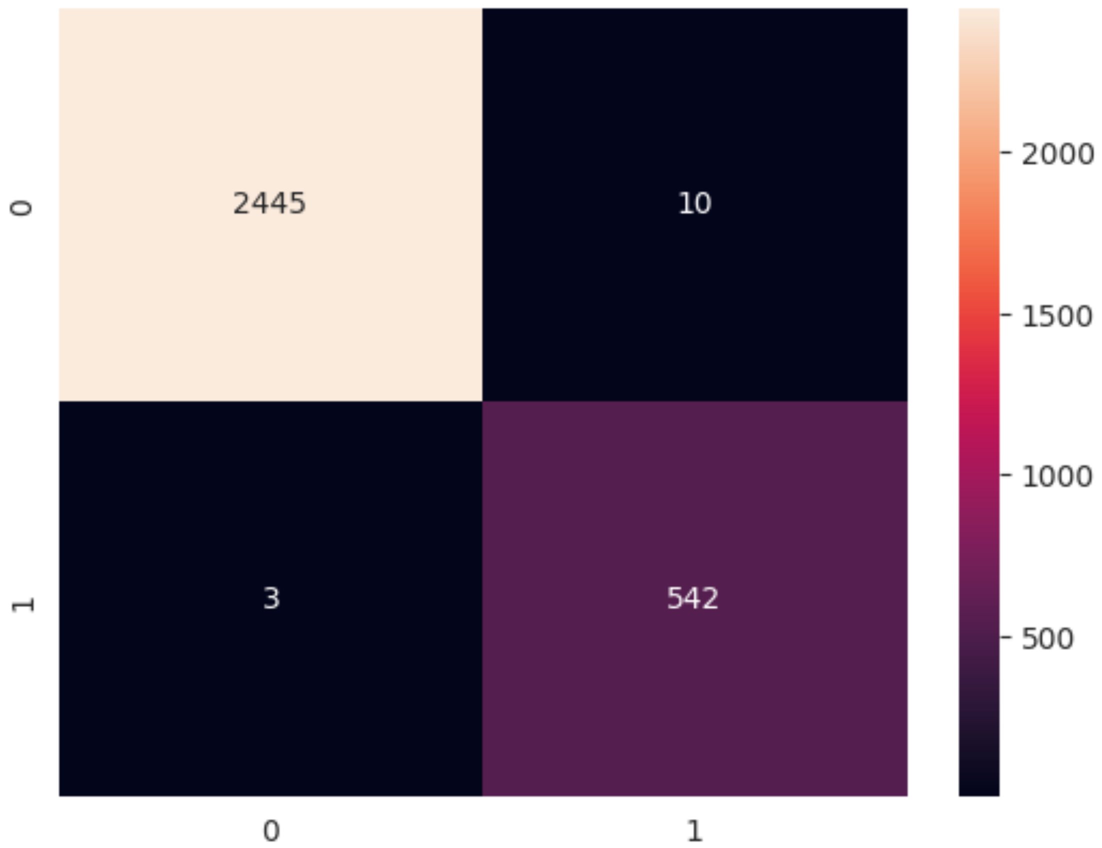
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2455
           1       0.98      0.99      0.99       545

    accuracy                           1.00      3000
   macro avg       0.99      1.00      0.99      3000
weighted avg       1.00      1.00      1.00      3000
```

In [47]:
```
cm = confusion_matrix(Y_test, Predictions_rf)
sns.heatmap(cm, annot=True, fmt='d')
```

Out[47]: <Axes: >



In [48]:
```
print('Accuracy of the Random Forest model is', round(accuracy_score(Y_te
```

```
Accuracy of the Random Forest model is 1.0
```

In [49]:
```
importances = rfmodel.feature_importances_

sorted_indices = np.argsort(importances)[::-1]
for i in sorted_indices:
    print("{0:25} {1:6}".format(X_train.columns[i],round(importances[i],4
```

```
credit_lines_outstanding  0.5577
total_debt_outstanding    0.3065
years_employed            0.0513
fico_score                0.0369
income                    0.0338
loan_amt_outstanding      0.0139
```

Building a XGBoost predictions

In [56]:
```
from xgboost import XGBClassifier
xgb_clf = XGBClassifier(use_label_encoder = False)
xgb_clf.fit(X_train, Y_train)
Predictions_xgb = xgb_clf.predict(X_test)
print(classification_report(Y_test, Predictions_xgb))
```

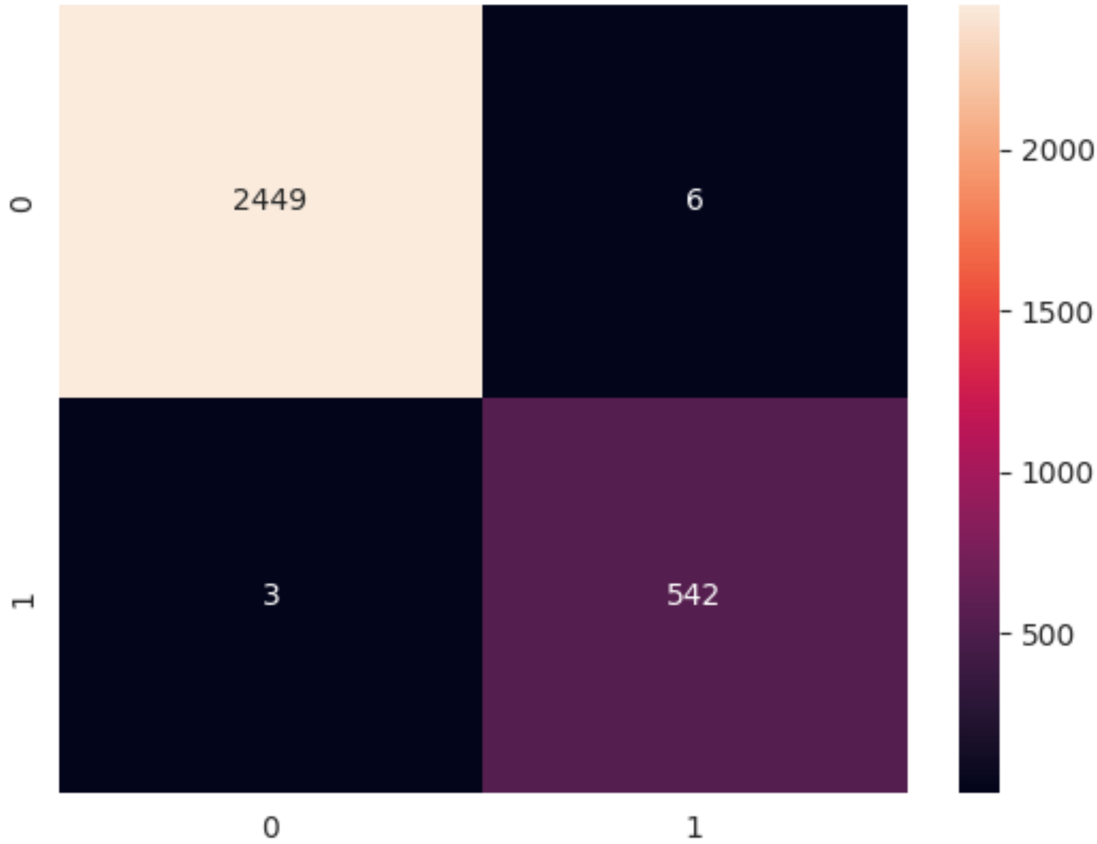
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2455
           1       0.99      0.99      0.99       545

    accuracy                           1.00      3000
   macro avg       0.99      1.00      0.99      3000
weighted avg       1.00      1.00      1.00      3000
```

In [57]:
```
cm = confusion_matrix(Y_test, Predictions_xgb)
sns.heatmap(cm, annot=True, fmt='d')
```

Out[57]: <Axes: >



Compare Gini performance for both algorithms

The Gini coefficient is an industry standard measure of assessing the effectiveness of a scorecard in discriminating between good and bads.

Further details on how it's used and calculated :

https://towardsdatascience.com/clearly-explained-gini-coefficient-and-lorenz-curve-fe6f5dcdc07

https://www.thoughtco.com/calculate-the-gini-coefficient-1147711

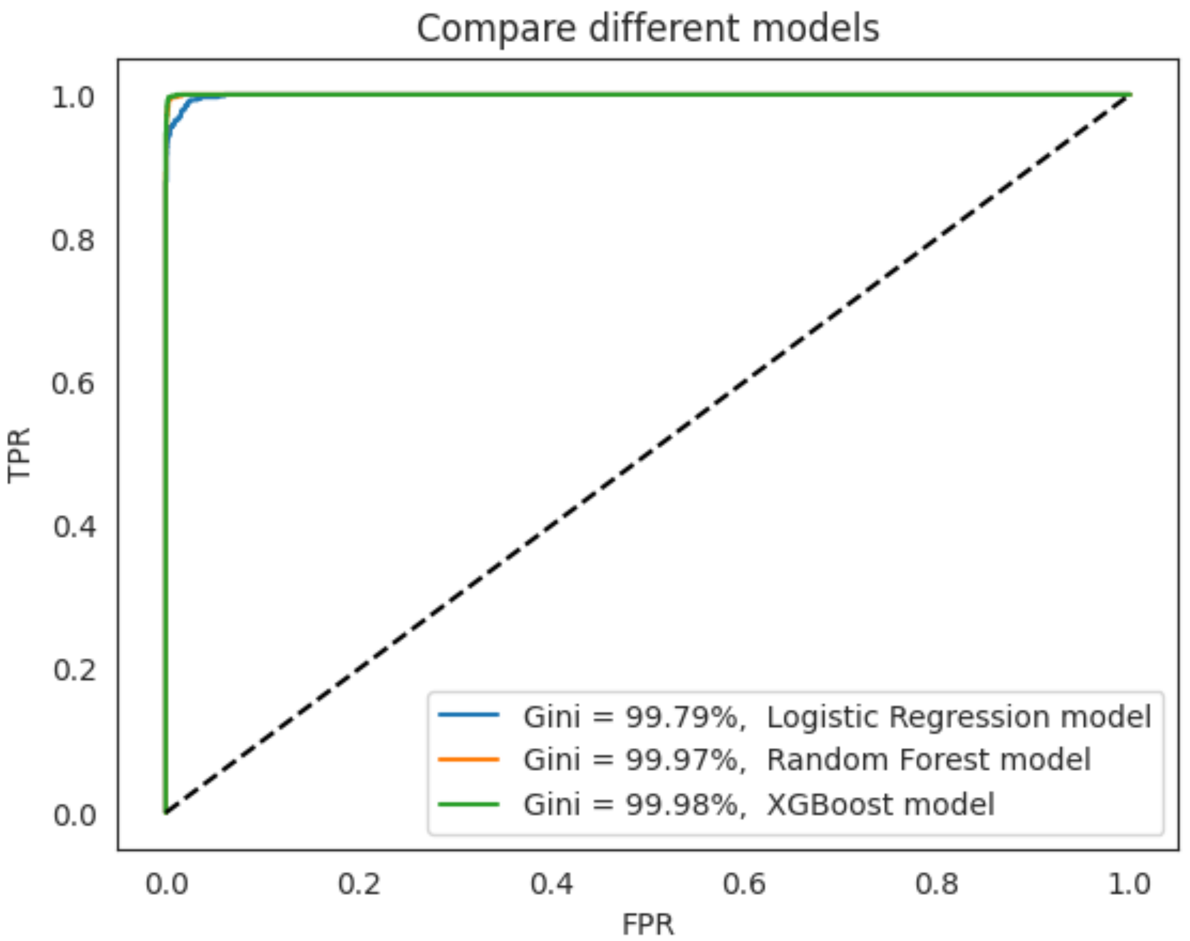
In [52]:
```
# Function to calculate and plot gini curve
def plot_roc(y_true, scores_names):
    '''
    plot ROC curves for the specified model scores

            Parameters:
                    y_true (num): Target variable
                    scores_names (tuple): a tuple of model predictions an
    '''

    for score, label in scores_names:
        fpr, tpr, _ = roc_curve(y_true, y_score=score, drop_intermediate=
        AUC = roc_auc_score(y_true, score)
        gini = 2 * AUC - 1
        label = 'Gini = {:.2%},  {}'.format(gini, label)
        plt.plot(fpr, tpr, label=label)
    plt.plot([0,1],[0,1], '--k')
    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.legend(loc="lower right")
    plt.show();
```

In [59]:
```
# Calculate probability outcome to feed into Gini function
log_proba = logmodel.predict_proba(X_test)[:, 1]
rf_proba = rfmodel.predict_proba(X_test)[:, 1]
xgb_proba = xgb_clf.predict_proba(X_test)[:,1]
```

In [60]:
```
plt.title('Compare different models')
plot_roc(Y_test, [(log_proba, 'Logistic Regression model'), (rf_proba, 'R
```



In [ ]:

```

```