"Risk Mitigation through EDA: Unveiling Patterns in Client Payment Behavior for Informed Lending Decisions in Banking Sector"

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Reading the Data

In [2]:
```
# Load datasets
previous_application = pd.read_csv('previous_application.csv')
application_data = pd.read_csv('application_data.csv')
```

In [3]:
```
# Display the first few rows of each dataset
print("Previous Application Data:")
previous_application.head()
```

```
Previous Application Data:
```

Out[3]:

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION
0	2030495	271877	Consumer loans	1730.430	17145.0
1	2802425	108129	Cash loans	25188.615	607500.0
2	2523466	122040	Cash loans	15060.735	112500.0
3	2819243	176158	Cash loans	47041.335	450000.0
4	1784265	202054	Cash loans	31924.395	337500.0

5 rows × 37 columns

In [4]:
```
print("\nApplication Data:")
application_data.head()
```

```
Application Data:
```

Out[4]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_(
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	

5 rows × 122 columns

Dropping Unnecessary Columns

In [5]:

```
# Drop unnecessary columns in previous applications dataset
unnecessary_cols_previous = [
    'SK_ID_PREV', 'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY', 'SELLERP
]
previous_application = previous_application.drop(unnecessary_cols_previous, axis=1)

# Drop unnecessary columns in application data dataset
unnecessary_cols_app = [
    'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE', 'FLAG_PH
    'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY', 'FLAG_DOCUMENT_2', 'FLAG
    'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5', 'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_7', 'FL
    'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11', 'FLAG_DOCUMENT_12',
    'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15', 'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17',
    'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21'
]
application_data = application_data.drop(unnecessary_cols_app, axis=1)

# Display the remaining columns in each dataset
print("Remaining columns in Previous Applications Data:")
print(previous_application.columns)

print("\nRemaining columns in Application Data:")
print(application_data.columns)
```

```
Remaining columns in Previous Applications Data:
Index(['SK_ID_CURR', 'NAME_CONTRACT_TYPE', 'AMT_ANNUITY', 'AMT_APPLICATION',
       'AMT_CREDIT', 'AMT_DOWN_PAYMENT', 'AMT_GOODS_PRICE',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
       'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
       'CHANNEL_TYPE', 'NAME_SELLER_INDUSTRY', 'CNT_PAYMENT',
       'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION', 'DAYS_FIRST_DRAWING',
       'DAYS_FIRST_DUE', 'DAYS_LAST_DUE_1ST_VERSION', 'DAYS_LAST_DUE',
       'DAYS_TERMINATION', 'NFLAG_INSURED_ON_APPROVAL'],
      dtype='object')

Remaining columns in Application Data:
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
       'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',
       'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE',
       'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS',
       'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH',
       'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OWN_CAR_AGE',
       'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS', 'WEEKDAY_APPR_PROCESS_START',
       'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION',
       'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION',
       'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY',
       'LIVE_CITY_NOT_WORK_CITY', 'ORGANIZATION_TYPE', 'EXT_SOURCE_1',
       'EXT_SOURCE_2', 'EXT_SOURCE_3', 'APARTMENTS_AVG', 'BASEMENTAREA_AVG',
       'YEARS_BEGINEXPLUATATION_AVG', 'YEARS_BUILD_AVG', 'COMMONAREA_AVG',
       'ELEVATORS_AVG', 'ENTRANCES_AVG', 'FLOORSMAX_AVG', 'FLOORSMIN_AVG',
       'LANDAREA_AVG', 'LIVINGAPARTMENTS_AVG', 'LIVINGAREA_AVG',
       'NONLIVINGAPARTMENTS_AVG', 'NONLIVINGAREA_AVG', 'APARTMENTS_MODE',
       'BASEMENTAREA_MODE', 'YEARS_BEGINEXPLUATATION_MODE', 'YEARS_BUILD_MODE',
       'COMMONAREA_MODE', 'ELEVATORS_MODE', 'ENTRANCES_MODE', 'FLOORSMAX_MODE',
       'FLOORSMIN_MODE', 'LANDAREA_MODE', 'LIVINGAPARTMENTS_MODE',
       'LIVINGAREA_MODE', 'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_MODE',
       'APARTMENTS_MEDI', 'BASEMENTAREA_MEDI', 'YEARS_BEGINEXPLUATATION_MEDI',
       'YEARS_BUILD_MEDI', 'COMMONAREA_MEDI', 'ELEVATORS_MEDI',
       'ENTRANCES_MEDI', 'FLOORSMAX_MEDI', 'FLOORSMIN_MEDI', 'LANDAREA_MEDI',
       'LIVINGAPARTMENTS_MEDI', 'LIVINGAREA_MEDI', 'NONLIVINGAPARTMENTS_MEDI',
       'NONLIVINGAREA_MEDI', 'FONDKAPREMONT_MODE', 'HOUSETYPE_MODE',
       'TOTALAREA_MODE', 'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE',
       'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE',
       'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
       'DAYS_LAST_PHONE_CHANGE', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object')
```

Handling Missing Values in both datasets

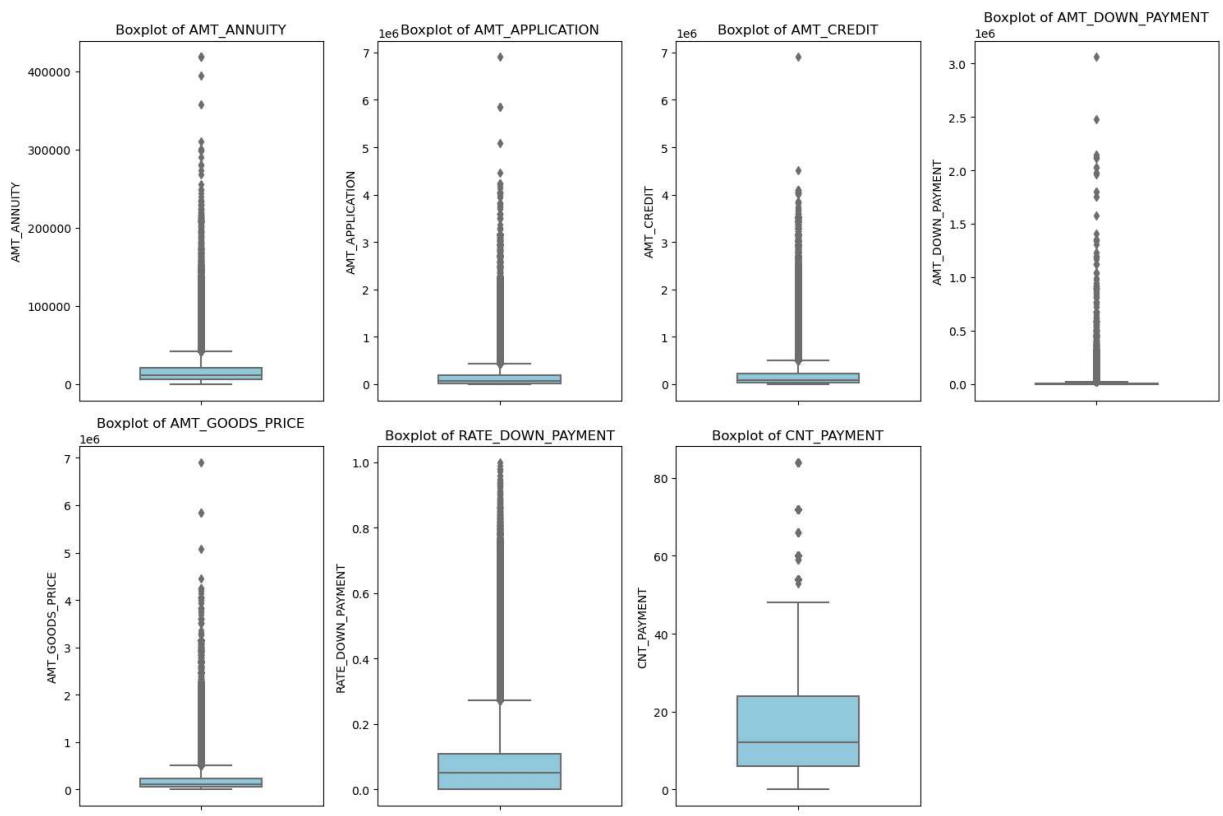
In [6]:
```
# Check for missing values in previous_application dataset
print("Missing values in Previous Applications Data:")
print(previous_application.isnull().sum())
```

```python
# Check for missing values in application_data dataset
print("\nMissing values in Application Data:")
print(application_data.isnull().sum())
```

```
Missing values in Previous Applications Data:
SK_ID_CURR                          0
NAME_CONTRACT_TYPE                  0
AMT_ANNUITY                    372235
AMT_APPLICATION                     0
AMT_CREDIT                          1
AMT_DOWN_PAYMENT               895844
AMT_GOODS_PRICE                385515
WEEKDAY_APPR_PROCESS_START          0
HOUR_APPR_PROCESS_START             0
RATE_DOWN_PAYMENT              895844
RATE_INTEREST_PRIMARY         1664263
RATE_INTEREST_PRIVILEGED      1664263
NAME_CASH_LOAN_PURPOSE              0
NAME_CONTRACT_STATUS                0
DAYS_DECISION                       0
NAME_PAYMENT_TYPE                   0
CODE_REJECT_REASON                  0
NAME_TYPE_SUITE                820405
NAME_CLIENT_TYPE                    0
NAME_GOODS_CATEGORY                 0
NAME_PORTFOLIO                      0
NAME_PRODUCT_TYPE                   0
CHANNEL_TYPE                        0
NAME_SELLER_INDUSTRY                0
CNT_PAYMENT                    372230
NAME_YIELD_GROUP                    0
PRODUCT_COMBINATION               346
DAYS_FIRST_DRAWING             673065
DAYS_FIRST_DUE                 673065
DAYS_LAST_DUE_1ST_VERSION      673065
DAYS_LAST_DUE                  673065
DAYS_TERMINATION               673065
NFLAG_INSURED_ON_APPROVAL      673065
dtype: int64

Missing values in Application Data:
SK_ID_CURR                        0
TARGET                            0
NAME_CONTRACT_TYPE                0
CODE_GENDER                       0
FLAG_OWN_CAR                      0
                                ...
AMT_REQ_CREDIT_BUREAU_DAY     41519
AMT_REQ_CREDIT_BUREAU_WEEK    41519
AMT_REQ_CREDIT_BUREAU_MON     41519
AMT_REQ_CREDIT_BUREAU_QRT     41519
AMT_REQ_CREDIT_BUREAU_YEAR    41519
Length: 94, dtype: int64
```

Detecting Outliers

In [7]:
```
# Columns to check for outliers in previous_application data
columns_to_check_previous = ['AMT_ANNUITY', 'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_D

# Create individual box plots for each column in previous_application data
plt.figure(figsize=(15, 10))

for i, column in enumerate(columns_to_check_previous, 1):
    plt.subplot(2, 4, i)
    sns.boxplot(y=previous_application[column], color='skyblue', width=0.5)
    plt.title(f'Boxplot of {column}')
    plt.xticks(rotation=45)  # Rotate x-axis labels for better readability

plt.tight_layout()
plt.show()
```



In [8]:
```
# Impute numerical columns
numerical_cols_previous = ['AMT_ANNUITY', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT', 'AMT_GO
                           'RATE_DOWN_PAYMENT', 'CNT_PAYMENT']

for col in numerical_cols_previous:
    previous_application[col].fillna(previous_application[col].median(), inplace=Tr

# Impute categorical columns
categorical_cols_previous = ['NAME_TYPE_SUITE', 'PRODUCT_COMBINATION']
for col in categorical_cols_previous:
    previous_application[col].fillna(previous_application[col].mode()[0], inplace=T
```

```
# Drop columns with a high percentage of missing values
columns_to_drop_previous = ['RATE_INTEREST_PRIMARY', 'RATE_INTEREST_PRIVILEGED']
previous_application = previous_application.drop(columns=columns_to_drop_previous,

# Check again for missing values
print("Missing values in Previous Applications Data after imputation:")
print(previous_application.isnull().sum())
```

```
Missing values in Previous Applications Data after imputation:
SK_ID_CURR                        0
NAME_CONTRACT_TYPE                0
AMT_ANNUITY                       0
AMT_APPLICATION                   0
AMT_CREDIT                        0
AMT_DOWN_PAYMENT                  0
AMT_GOODS_PRICE                   0
WEEKDAY_APPR_PROCESS_START        0
HOUR_APPR_PROCESS_START           0
RATE_DOWN_PAYMENT                 0
NAME_CASH_LOAN_PURPOSE            0
NAME_CONTRACT_STATUS              0
DAYS_DECISION                     0
NAME_PAYMENT_TYPE                 0
CODE_REJECT_REASON                0
NAME_TYPE_SUITE                   0
NAME_CLIENT_TYPE                  0
NAME_GOODS_CATEGORY               0
NAME_PORTFOLIO                    0
NAME_PRODUCT_TYPE                 0
CHANNEL_TYPE                      0
NAME_SELLER_INDUSTRY              0
CNT_PAYMENT                       0
NAME_YIELD_GROUP                  0
PRODUCT_COMBINATION               0
DAYS_FIRST_DRAWING           673065
DAYS_FIRST_DUE               673065
DAYS_LAST_DUE_1ST_VERSION    673065
DAYS_LAST_DUE                673065
DAYS_TERMINATION             673065
NFLAG_INSURED_ON_APPROVAL    673065
dtype: int64
```

In [9]:

```
# Impute missing values in days-related columns with zero
days_columns_previous = ['DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', 'DAYS_LAST_DUE_1ST
                         'DAYS_LAST_DUE', 'DAYS_TERMINATION', 'NFLAG_INSURED_ON_AP

previous_application[days_columns_previous] = previous_application[days_columns_pre

# Check again for missing values
print("Missing values in Previous Applications Data after handling days-related col
print(previous_application.isnull().sum())
```

```
Missing values in Previous Applications Data after handling days-related columns:
SK_ID_CURR                    0
NAME_CONTRACT_TYPE            0
AMT_ANNUITY                   0
AMT_APPLICATION               0
AMT_CREDIT                    0
AMT_DOWN_PAYMENT              0
AMT_GOODS_PRICE               0
WEEKDAY_APPR_PROCESS_START    0
HOUR_APPR_PROCESS_START       0
RATE_DOWN_PAYMENT             0
NAME_CASH_LOAN_PURPOSE        0
NAME_CONTRACT_STATUS          0
DAYS_DECISION                 0
NAME_PAYMENT_TYPE             0
CODE_REJECT_REASON            0
NAME_TYPE_SUITE               0
NAME_CLIENT_TYPE              0
NAME_GOODS_CATEGORY           0
NAME_PORTFOLIO                0
NAME_PRODUCT_TYPE             0
CHANNEL_TYPE                  0
NAME_SELLER_INDUSTRY          0
CNT_PAYMENT                   0
NAME_YIELD_GROUP              0
PRODUCT_COMBINATION           0
DAYS_FIRST_DRAWING            0
DAYS_FIRST_DUE                0
DAYS_LAST_DUE_1ST_VERSION     0
DAYS_LAST_DUE                 0
DAYS_TERMINATION              0
NFLAG_INSURED_ON_APPROVAL     0
dtype: int64
```

In [10]:
```
# Check for missing values in application_data dataset
print("Missing values in Application Data:")
print(application_data.isnull().sum())
```

```
Missing values in Application Data:
SK_ID_CURR                        0
TARGET                            0
NAME_CONTRACT_TYPE                0
CODE_GENDER                       0
FLAG_OWN_CAR                      0
                                ...
AMT_REQ_CREDIT_BUREAU_DAY     41519
AMT_REQ_CREDIT_BUREAU_WEEK    41519
AMT_REQ_CREDIT_BUREAU_MON     41519
AMT_REQ_CREDIT_BUREAU_QRT     41519
AMT_REQ_CREDIT_BUREAU_YEAR    41519
Length: 94, dtype: int64
```

In [11]:
```
# Check for missing values in application_data
missing_values = application_data.isnull().sum()

# Display columns with missing values
```

```
columns_with_missing_values = missing_values[missing_values > 0]
print(columns_with_missing_values)
```

```
AMT_ANNUITY                      12
AMT_GOODS_PRICE                 278
NAME_TYPE_SUITE                1292
OWN_CAR_AGE                  202929
OCCUPATION_TYPE               96391
                              ...
AMT_REQ_CREDIT_BUREAU_DAY     41519
AMT_REQ_CREDIT_BUREAU_WEEK    41519
AMT_REQ_CREDIT_BUREAU_MON     41519
AMT_REQ_CREDIT_BUREAU_QRT     41519
AMT_REQ_CREDIT_BUREAU_YEAR    41519
Length: 67, dtype: int64
```

In [12]:

```
# Impute missing values in numerical columns with mean or median
numerical_cols_app = [
    'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE',
    'OWN_CAR_AGE', 'EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
    'APARTMENTS_AVG', 'BASEMENTAREA_AVG', 'YEARS_BEGINEXPLUATATION_AVG',
    'YEARS_BUILD_AVG', 'COMMONAREA_AVG', 'ELEVATORS_AVG', 'ENTRANCES_AVG',
    'FLOORSMAX_AVG', 'FLOORSMIN_AVG', 'LANDAREA_AVG', 'LIVINGAPARTMENTS_AVG',
    'LIVINGAREA_AVG', 'NONLIVINGAPARTMENTS_AVG', 'NONLIVINGAREA_AVG',
    'APARTMENTS_MODE', 'BASEMENTAREA_MODE', 'YEARS_BEGINEXPLUATATION_MODE',
    'YEARS_BUILD_MODE', 'COMMONAREA_MODE', 'ELEVATORS_MODE', 'ENTRANCES_MODE',
    'FLOORSMAX_MODE', 'FLOORSMIN_MODE', 'LANDAREA_MODE', 'LIVINGAPARTMENTS_MODE',
    'LIVINGAREA_MODE', 'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_MODE',
    'APARTMENTS_MEDI', 'BASEMENTAREA_MEDI', 'YEARS_BEGINEXPLUATATION_MEDI',
    'YEARS_BUILD_MEDI', 'COMMONAREA_MEDI', 'ELEVATORS_MEDI', 'ENTRANCES_MEDI',
    'FLOORSMAX_MEDI', 'FLOORSMIN_MEDI', 'LANDAREA_MEDI', 'LIVINGAPARTMENTS_MEDI',
    'LIVINGAREA_MEDI', 'NONLIVINGAPARTMENTS_MEDI', 'NONLIVINGAREA_MEDI',
    'TOTALAREA_MODE'
]

for col in numerical_cols_app:
    application_data[col].fillna(application_data[col].median(), inplace=True)

# Impute missing values in categorical columns with mode
categorical_cols_app = [
    'NAME_TYPE_SUITE', 'OCCUPATION_TYPE', 'FONDKAPREMONT_MODE',
    'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE'
]

for col in categorical_cols_app:
    application_data[col].fillna(application_data[col].mode()[0], inplace=True)

# Check again for missing values
print("Missing values in Application Data after imputation:")
print(application_data.isnull().sum())
```

```
Missing values in Application Data after imputation:
SK_ID_CURR                       0
TARGET                           0
NAME_CONTRACT_TYPE               0
CODE_GENDER                      0
FLAG_OWN_CAR                     0
                               ...
AMT_REQ_CREDIT_BUREAU_DAY    41519
AMT_REQ_CREDIT_BUREAU_WEEK   41519
AMT_REQ_CREDIT_BUREAU_MON    41519
AMT_REQ_CREDIT_BUREAU_QRT    41519
AMT_REQ_CREDIT_BUREAU_YEAR   41519
Length: 94, dtype: int64
```

In [13]:
```
#Imute the Amount category columns with mean, median
application_data['AMT_REQ_CREDIT_BUREAU_DAY'].fillna(application_data['AMT_REQ_CRED
application_data['AMT_REQ_CREDIT_BUREAU_WEEK'].fillna(application_data['AMT_REQ_CRE
application_data['AMT_REQ_CREDIT_BUREAU_MON'].fillna(application_data['AMT_REQ_CRED
application_data['AMT_REQ_CREDIT_BUREAU_QRT'].fillna(application_data['AMT_REQ_CRED
application_data['AMT_REQ_CREDIT_BUREAU_YEAR'].fillna(application_data['AMT_REQ_CRE
```

In [14]:
```
# Check again for missing values
print("Missing values in Application Data after imputation:")
print(application_data.isnull().sum())
```

```
Missing values in Application Data after imputation:
SK_ID_CURR                   0
TARGET                       0
NAME_CONTRACT_TYPE           0
CODE_GENDER                  0
FLAG_OWN_CAR                 0
                            ..
AMT_REQ_CREDIT_BUREAU_DAY    0
AMT_REQ_CREDIT_BUREAU_WEEK   0
AMT_REQ_CREDIT_BUREAU_MON    0
AMT_REQ_CREDIT_BUREAU_QRT    0
AMT_REQ_CREDIT_BUREAU_YEAR   0
Length: 94, dtype: int64
```

In [15]:
```
# Replace "XNA" or "XAP" in the gender column with the mode
application_data['CODE_GENDER'].replace(['XNA', 'XAP'], application_data['CODE_GEND

# Check the unique values in the gender column
print("Unique values in CODE_GENDER column after imputation:")
print(application_data['CODE_GENDER'].unique())
```

```
Unique values in CODE_GENDER column after imputation:
['M' 'F']
```

In [16]:
```
# Replace missing or unusual values in the 'ORGANIZATION_TYPE' column with the mode
application_data['ORGANIZATION_TYPE'].replace(['XNA'], application_data['ORGANIZATI

# Check the unique values in the 'ORGANIZATION_TYPE' column
print("Unique values in ORGANIZATION_TYPE column after imputation:")
print(application_data['ORGANIZATION_TYPE'].unique())
```

```
Unique values in ORGANIZATION_TYPE column after imputation:
['Business Entity Type 3' 'School' 'Government' 'Religion' 'Other'
 'Electricity' 'Medicine' 'Business Entity Type 2' 'Self-employed'
 'Transport: type 2' 'Construction' 'Housing' 'Kindergarten'
 'Trade: type 7' 'Industry: type 11' 'Military' 'Services'
 'Security Ministries' 'Transport: type 4' 'Industry: type 1' 'Emergency'
 'Security' 'Trade: type 2' 'University' 'Transport: type 3' 'Police'
 'Business Entity Type 1' 'Postal' 'Industry: type 4' 'Agriculture'
 'Restaurant' 'Culture' 'Hotel' 'Industry: type 7' 'Trade: type 3'
 'Industry: type 3' 'Bank' 'Industry: type 9' 'Insurance' 'Trade: type 6'
 'Industry: type 2' 'Transport: type 1' 'Industry: type 12' 'Mobile'
 'Trade: type 1' 'Industry: type 5' 'Industry: type 10' 'Legal Services'
 'Advertising' 'Trade: type 5' 'Cleaning' 'Industry: type 13'
 'Trade: type 4' 'Telecom' 'Industry: type 8' 'Realtor' 'Industry: type 6']
```

Finding and fixing XNA and XAP values

In [17]:

```
# Check 'XNA' or 'XAP' values in previous_application dataset
xna_xap_counts_previous = {}
for column in previous_application.columns:
    xna_xap_counts_previous[column] = previous_application[column].isin(['XNA', 'XA

# Check 'XNA' or 'XAP' values in application_data dataset
xna_xap_counts_application = {}
for column in application_data.columns:
    xna_xap_counts_application[column] = application_data[column].isin(['XNA', 'XAP

# Display the counts
# Display the counts
print("Counts of 'XNA' or 'XAP' values in Previous Application Data:")
print(xna_xap_counts_previous)

print("\nCounts of 'XNA' or 'XAP' values in Application Data:")
print(xna_xap_counts_application)
```

```
Counts of 'XNA' or 'XAP' values in Previous Application Data:
{'SK_ID_CURR': 0, 'NAME_CONTRACT_TYPE': 346, 'AMT_ANNUITY': 0, 'AMT_APPLICATION': 0,
'AMT_CREDIT': 0, 'AMT_DOWN_PAYMENT': 0, 'AMT_GOODS_PRICE': 0, 'WEEKDAY_APPR_PROCESS_
START': 0, 'HOUR_APPR_PROCESS_START': 0, 'RATE_DOWN_PAYMENT': 0, 'NAME_CASH_LOAN_PUR
POSE': 1600579, 'NAME_CONTRACT_STATUS': 0, 'DAYS_DECISION': 0, 'NAME_PAYMENT_TYPE':
627384, 'CODE_REJECT_REASON': 1358337, 'NAME_TYPE_SUITE': 0, 'NAME_CLIENT_TYPE': 194
1, 'NAME_GOODS_CATEGORY': 950809, 'NAME_PORTFOLIO': 372230, 'NAME_PRODUCT_TYPE': 106
3666, 'CHANNEL_TYPE': 0, 'NAME_SELLER_INDUSTRY': 855720, 'CNT_PAYMENT': 0, 'NAME_YIE
LD_GROUP': 517215, 'PRODUCT_COMBINATION': 0, 'DAYS_FIRST_DRAWING': 0, 'DAYS_FIRST_DU
E': 0, 'DAYS_LAST_DUE_1ST_VERSION': 0, 'DAYS_LAST_DUE': 0, 'DAYS_TERMINATION': 0, 'N
FLAG_INSURED_ON_APPROVAL': 0}

Counts of 'XNA' or 'XAP' values in Application Data:
{'SK_ID_CURR': 0, 'TARGET': 0, 'NAME_CONTRACT_TYPE': 0, 'CODE_GENDER': 0, 'FLAG_OWN_
CAR': 0, 'FLAG_OWN_REALTY': 0, 'CNT_CHILDREN': 0, 'AMT_INCOME_TOTAL': 0, 'AMT_CREDI
T': 0, 'AMT_ANNUITY': 0, 'AMT_GOODS_PRICE': 0, 'NAME_TYPE_SUITE': 0, 'NAME_INCOME_TY
PE': 0, 'NAME_EDUCATION_TYPE': 0, 'NAME_FAMILY_STATUS': 0, 'NAME_HOUSING_TYPE': 0,
'REGION_POPULATION_RELATIVE': 0, 'DAYS_BIRTH': 0, 'DAYS_EMPLOYED': 0, 'DAYS_REGISTRA
TION': 0, 'DAYS_ID_PUBLISH': 0, 'OWN_CAR_AGE': 0, 'OCCUPATION_TYPE': 0, 'CNT_FAM_MEM
BERS': 0, 'WEEKDAY_APPR_PROCESS_START': 0, 'HOUR_APPR_PROCESS_START': 0, 'REG_REGION
_NOT_LIVE_REGION': 0, 'REG_REGION_NOT_WORK_REGION': 0, 'LIVE_REGION_NOT_WORK_REGIO
N': 0, 'REG_CITY_NOT_LIVE_CITY': 0, 'REG_CITY_NOT_WORK_CITY': 0, 'LIVE_CITY_NOT_WORK
_CITY': 0, 'ORGANIZATION_TYPE': 0, 'EXT_SOURCE_1': 0, 'EXT_SOURCE_2': 0, 'EXT_SOURCE
_3': 0, 'APARTMENTS_AVG': 0, 'BASEMENTAREA_AVG': 0, 'YEARS_BEGINEXPLUATATION_AVG':
0, 'YEARS_BUILD_AVG': 0, 'COMMONAREA_AVG': 0, 'ELEVATORS_AVG': 0, 'ENTRANCES_AVG':
0, 'FLOORSMAX_AVG': 0, 'FLOORSMIN_AVG': 0, 'LANDAREA_AVG': 0, 'LIVINGAPARTMENTS_AV
G': 0, 'LIVINGAREA_AVG': 0, 'NONLIVINGAPARTMENTS_AVG': 0, 'NONLIVINGAREA_AVG': 0, 'A
PARTMENTS_MODE': 0, 'BASEMENTAREA_MODE': 0, 'YEARS_BEGINEXPLUATATION_MODE': 0, 'YEAR
S_BUILD_MODE': 0, 'COMMONAREA_MODE': 0, 'ELEVATORS_MODE': 0, 'ENTRANCES_MODE': 0, 'F
LOORSMAX_MODE': 0, 'FLOORSMIN_MODE': 0, 'LANDAREA_MODE': 0, 'LIVINGAPARTMENTS_MODE':
0, 'LIVINGAREA_MODE': 0, 'NONLIVINGAPARTMENTS_MODE': 0, 'NONLIVINGAREA_MODE': 0, 'AP
ARTMENTS_MEDI': 0, 'BASEMENTAREA_MEDI': 0, 'YEARS_BEGINEXPLUATATION_MEDI': 0, 'YEARS
_BUILD_MEDI': 0, 'COMMONAREA_MEDI': 0, 'ELEVATORS_MEDI': 0, 'ENTRANCES_MEDI': 0, 'FL
OORSMAX_MEDI': 0, 'FLOORSMIN_MEDI': 0, 'LANDAREA_MEDI': 0, 'LIVINGAPARTMENTS_MEDI':
0, 'LIVINGAREA_MEDI': 0, 'NONLIVINGAPARTMENTS_MEDI': 0, 'NONLIVINGAREA_MEDI': 0, 'FO
NDKAPREMONT_MODE': 0, 'HOUSETYPE_MODE': 0, 'TOTALAREA_MODE': 0, 'WALLSMATERIAL_MOD
E': 0, 'EMERGENCYSTATE_MODE': 0, 'OBS_30_CNT_SOCIAL_CIRCLE': 0, 'DEF_30_CNT_SOCIAL_C
IRCLE': 0, 'OBS_60_CNT_SOCIAL_CIRCLE': 0, 'DEF_60_CNT_SOCIAL_CIRCLE': 0, 'DAYS_LAST_
PHONE_CHANGE': 0, 'AMT_REQ_CREDIT_BUREAU_HOUR': 0, 'AMT_REQ_CREDIT_BUREAU_DAY': 0,
'AMT_REQ_CREDIT_BUREAU_WEEK': 0, 'AMT_REQ_CREDIT_BUREAU_MON': 0, 'AMT_REQ_CREDIT_BUR
EAU_QRT': 0, 'AMT_REQ_CREDIT_BUREAU_YEAR': 0}
```

Handling XNA or XAP values in previous_application

In [18]:
```
# Replace 'XNA' or 'XAP' with NaN ()
previous_application.replace(['XNA', 'XAP'], np.nan, inplace=True)

# Handle missing values dropping columns with more than 30% missing values)
threshold = 0.3
previous_application = previous_application.dropna(thresh=len(previous_application)
```

In [19]:
```
# Check 'XNA' or 'XAP' values along with NaN in Previous Application Data
xna_xap_counts = {}
```

```
for column in previous_application.columns:
    xna_count = previous_application[column].eq('XNA').sum()
    xap_count = previous_application[column].eq('XAP').sum()
    nan_count = previous_application[column].isna().sum()
    xna_xap_counts[column] = {'XNA': xna_count, 'XAP': xap_count, 'NaN': nan_count}

# Display the counts
print("Counts of 'XNA' or 'XAP' values in Previous Application Data after handling
print(xna_xap_counts)
```

```
Counts of 'XNA' or 'XAP' values in Previous Application Data after handling NaN:
{'SK_ID_CURR': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'NAME_CONTRACT_TYPE': {'XNA': 0, 'XA
P': 0, 'NaN': 346}, 'AMT_ANNUITY': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'AMT_APPLICATIO
N': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'AMT_CREDIT': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'A
MT_DOWN_PAYMENT': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'AMT_GOODS_PRICE': {'XNA': 0, 'XA
P': 0, 'NaN': 0}, 'WEEKDAY_APPR_PROCESS_START': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'HOU
R_APPR_PROCESS_START': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'RATE_DOWN_PAYMENT': {'XNA':
0, 'XAP': 0, 'NaN': 0}, 'NAME_CONTRACT_STATUS': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'DAY
S_DECISION': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'NAME_TYPE_SUITE': {'XNA': 0, 'XAP': 0,
'NaN': 0}, 'NAME_CLIENT_TYPE': {'XNA': 0, 'XAP': 0, 'NaN': 1941}, 'NAME_PORTFOLIO':
{'XNA': 0, 'XAP': 0, 'NaN': 372230}, 'CHANNEL_TYPE': {'XNA': 0, 'XAP': 0, 'NaN': 0},
'CNT_PAYMENT': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'PRODUCT_COMBINATION': {'XNA': 0, 'XA
P': 0, 'NaN': 0}, 'DAYS_FIRST_DRAWING': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'DAYS_FIRST_
DUE': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'DAYS_LAST_DUE_1ST_VERSION': {'XNA': 0, 'XAP':
0, 'NaN': 0}, 'DAYS_LAST_DUE': {'XNA': 0, 'XAP': 0, 'NaN': 0}, 'DAYS_TERMINATION':
{'XNA': 0, 'XAP': 0, 'NaN': 0}, 'NFLAG_INSURED_ON_APPROVAL': {'XNA': 0, 'XAP': 0, 'N
aN': 0}}
```

Merge the data after Data Cleaning

In [20]:

```
# Merge datasets
merged_data = pd.merge(application_data, previous_application, on='SK_ID_CURR', how

# Display the merged dataset
print("Merged Data:")
# Display the first few rows of the merged dataset in a table
merged_data.head()
```

```
Merged Data:
```

Out[20]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE_x	CODE_GENDER	FLAG_OWN_CAR	FLAG
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100003	0	Cash loans	F	N	
3	100003	0	Cash loans	F	N	
4	100004	0	Revolving loans	M	Y	

5 rows × 117 columns

Convert negative values to absolute values in the merged dataset

In [21]:

```
# Identify numeric columns
numeric_columns = merged_data.select_dtypes(include=['number']).columns

# Convert negative values to absolute values in numeric columns
merged_data[numeric_columns] = merged_data[numeric_columns].abs()

# Display the first few rows of the updated merged dataset
print("Updated Merged Data with Absolute Values:")
print(merged_data.head())
```

```
Updated Merged Data with Absolute Values:
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE_x CODE_GENDER FLAG_OWN_CAR  \
0      100002       1           Cash loans           M            N
1      100003       0           Cash loans           F            N
2      100003       0           Cash loans           F            N
3      100003       0           Cash loans           F            N
4      100004       0      Revolving loans           M            Y

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT_x  \
0               Y             0          202500.0      406597.5
1               N             0          270000.0     1293502.5
2               N             0          270000.0     1293502.5
3               N             0          270000.0     1293502.5
4               Y             0           67500.0      135000.0

   AMT_ANNUITY_x  ...  NAME_PORTFOLIO             CHANNEL_TYPE CNT_PAYMENT  \
0        24700.5  ...             POS                    Stone        24.0
1        35698.5  ...            Cash  Credit and cash offices        12.0
2        35698.5  ...             POS                    Stone         6.0
3        35698.5  ...             POS             Country-wide        12.0
4         6750.0  ...             POS         Regional / Local         4.0

          PRODUCT_COMBINATION DAYS_FIRST_DRAWING DAYS_FIRST_DUE  \
0      POS other with interest           365243.0          565.0
1            Cash X-Sell: low           365243.0          716.0
2   POS industry with interest           365243.0          797.0
3  POS household with interest           365243.0         2310.0
4  POS mobile without interest           365243.0          784.0

   DAYS_LAST_DUE_1ST_VERSION  DAYS_LAST_DUE  DAYS_TERMINATION  \
0                      125.0           25.0              17.0
1                      386.0          536.0             527.0
2                      647.0          647.0             639.0
3                     1980.0         1980.0            1976.0
4                      694.0          724.0             714.0

   NFLAG_INSURED_ON_APPROVAL
0                        0.0
1                        1.0
2                        0.0
3                        1.0
4                        0.0

[5 rows x 117 columns]
```

In [22]:

```python
# Find null values in the merged dataset
null_values = merged_data.isnull().sum()

# Display the count of null values for each column
print("Null Values in Merged Data:")
print(null_values)
```

```
Null Values in Merged Data:
SK_ID_CURR                    0
TARGET                        0
NAME_CONTRACT_TYPE_x          0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
                             ..
DAYS_FIRST_DUE                0
DAYS_LAST_DUE_1ST_VERSION     0
DAYS_LAST_DUE                 0
DAYS_TERMINATION              0
NFLAG_INSURED_ON_APPROVAL     0
Length: 117, dtype: int64
```

Modified merged_data

In [23]:
```
print("Modified Merged Data with Absolute Values:")
merged_data.head()
```

```
Modified Merged Data with Absolute Values:
```

Out[23]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE_x	CODE_GENDER	FLAG_OWN_CAR	FLAG
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100003	0	Cash loans	F	N	
3	100003	0	Cash loans	F	N	
4	100004	0	Revolving loans	M	Y	

5 rows × 117 columns

Statistical information

In [24]:
```
# Display summary statistics for numeric columns
summary_stats = merged_data.describe()

# Display the summary statistics
print("Summary Statistics for Merged Data:")
print(summary_stats)
```

```
Summary Statistics for Merged Data:
         SK_ID_CURR        TARGET  CNT_CHILDREN  AMT_INCOME_TOTAL  \
count  1.413701e+06  1.413701e+06  1.413701e+06      1.413701e+06
mean   2.784813e+05  8.655296e-02  4.048933e-01      1.733160e+05
std    1.028118e+05  2.811789e-01  7.173454e-01      1.985734e+05
min    1.000020e+05  0.000000e+00  0.000000e+00      2.565000e+04
25%    1.893640e+05  0.000000e+00  0.000000e+00      1.125000e+05
50%    2.789920e+05  0.000000e+00  0.000000e+00      1.575000e+05
75%    3.675560e+05  0.000000e+00  1.000000e+00      2.070000e+05
max    4.562550e+05  1.000000e+00  1.900000e+01      1.170000e+08

       AMT_CREDIT_x  AMT_ANNUITY_x  AMT_GOODS_PRICE_x  \
count  1.413701e+06   1.413701e+06       1.413701e+06
mean   5.875537e+05   2.701688e+04       5.276522e+05
std    3.849173e+05   1.395072e+04       3.531028e+05
min    4.500000e+04   1.615500e+03       4.050000e+04
25%    2.700000e+05   1.682100e+04       2.385000e+05
50%    5.084955e+05   2.492550e+04       4.500000e+05
75%    8.079840e+05   3.454200e+04       6.795000e+05
max    4.050000e+06   2.250000e+05       4.050000e+06

       REGION_POPULATION_RELATIVE    DAYS_BIRTH  DAYS_EMPLOYED  ...  \
count                1.413701e+06  1.413701e+06   1.413701e+06  ...
mean                 2.074985e-02  1.632105e+04   7.266347e+04  ...
std                  1.334702e-02  4.344557e+03   1.433374e+05  ...
min                  2.900000e-04  7.489000e+03   0.000000e+00  ...
25%                  1.003200e-02  1.273900e+04   1.042000e+03  ...
50%                  1.885000e-02  1.604400e+04   2.401000e+03  ...
75%                  2.866300e-02  1.998000e+04   6.313000e+03  ...
max                  7.250800e-02  2.520100e+04   3.652430e+05  ...

       HOUR_APPR_PROCESS_START_y  RATE_DOWN_PAYMENT  DAYS_DECISION  \
count               1.413701e+06       1.413701e+06   1.413701e+06
mean                1.247893e+01       6.502725e-02   8.803670e+02
std                 3.331474e+00       7.524069e-02   7.835402e+02
min                 0.000000e+00       0.000000e+00   1.000000e+00
25%                 1.000000e+01       5.160508e-02   2.710000e+02
50%                 1.200000e+01       5.160508e-02   5.820000e+02
75%                 1.500000e+01       5.160508e-02   1.313000e+03
max                 2.300000e+01       1.000000e+00   2.922000e+03

        CNT_PAYMENT  DAYS_FIRST_DRAWING  DAYS_FIRST_DUE  \
count  1.413701e+06        1.413701e+06    1.413701e+06
mean   1.517141e+01        2.064933e+05    9.413824e+03
std    1.299505e+01        1.810146e+05    5.583225e+04
min    0.000000e+00        0.000000e+00    0.000000e+00
25%    1.000000e+01        0.000000e+00    0.000000e+00
50%    1.200000e+01        3.652430e+05    3.450000e+02
75%    1.800000e+01        3.652430e+05    1.146000e+03
max    8.400000e+01        3.652430e+05    3.652430e+05

       DAYS_LAST_DUE_1ST_VERSION  DAYS_LAST_DUE  DAYS_TERMINATION  \
count               1.413701e+06   1.413701e+06      1.413701e+06
mean                2.090898e+04   4.718203e+04      5.057674e+04
std                 8.383098e+04   1.217984e+05      1.254963e+05
min                 0.000000e+00   0.000000e+00      0.000000e+00
```

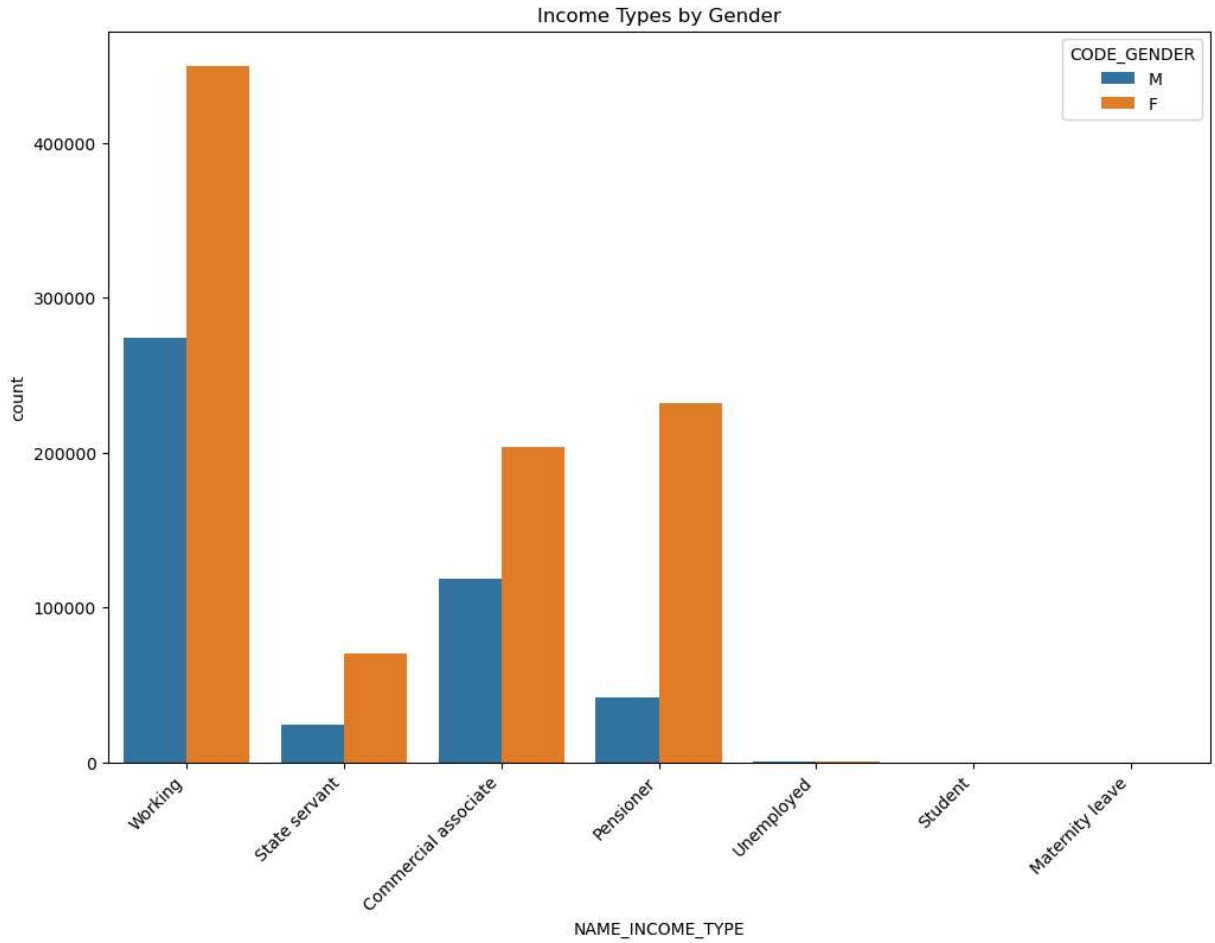
```
25%                 0.000000e+00   0.000000e+00      0.000000e+00
50%                 1.630000e+02   3.030000e+02      2.950000e+02
75%                 1.010000e+03   1.542000e+03      1.570000e+03
max                 3.652430e+05   3.652430e+05      3.652430e+05

       NFLAG_INSURED_ON_APPROVAL
count               1.413701e+06
mean                1.993661e-01
std                 3.995239e-01
min                 0.000000e+00
25%                 0.000000e+00
50%                 0.000000e+00
75%                 0.000000e+00
max                 1.000000e+00

[8 rows x 93 columns]
```

In [25]:
```
merged_data.shape
```

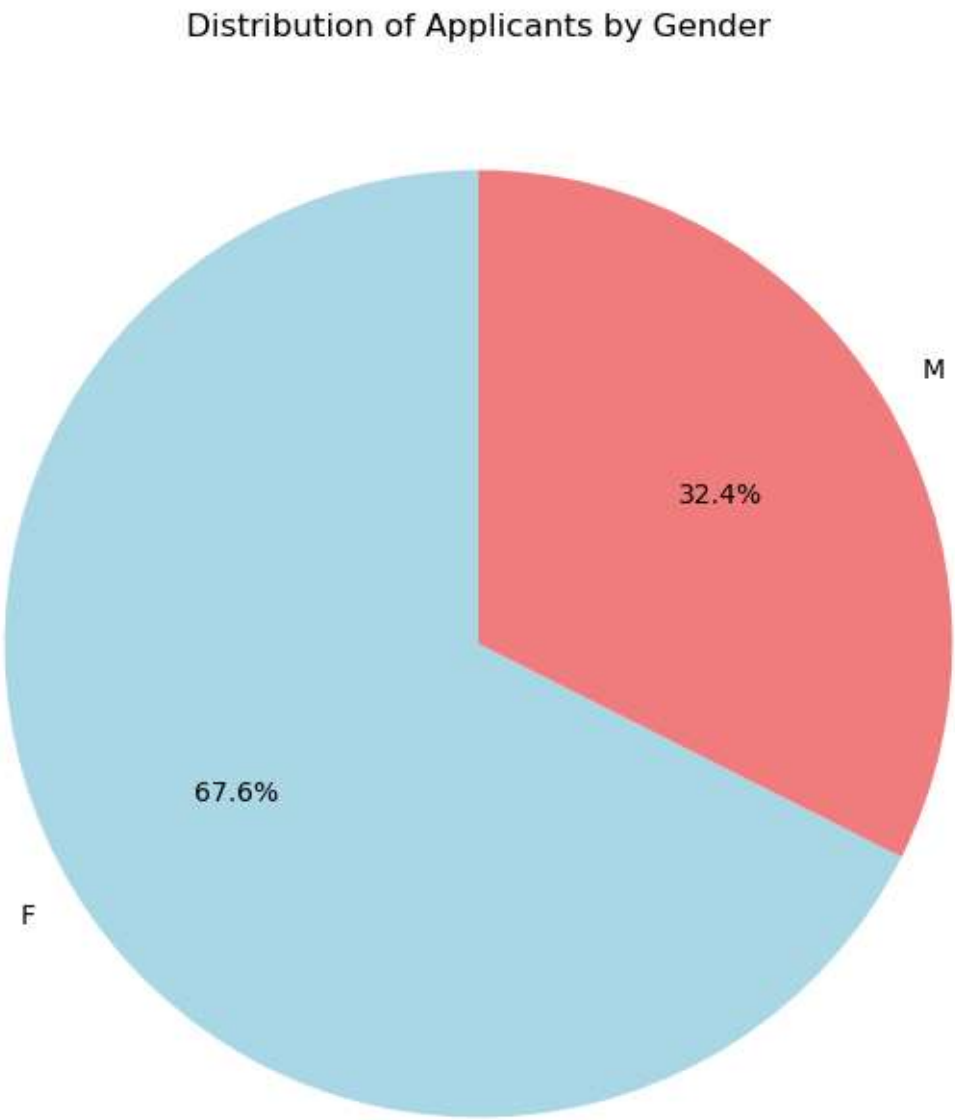
Out[25]:
```
(1413701, 117)
```

Univariate analysis

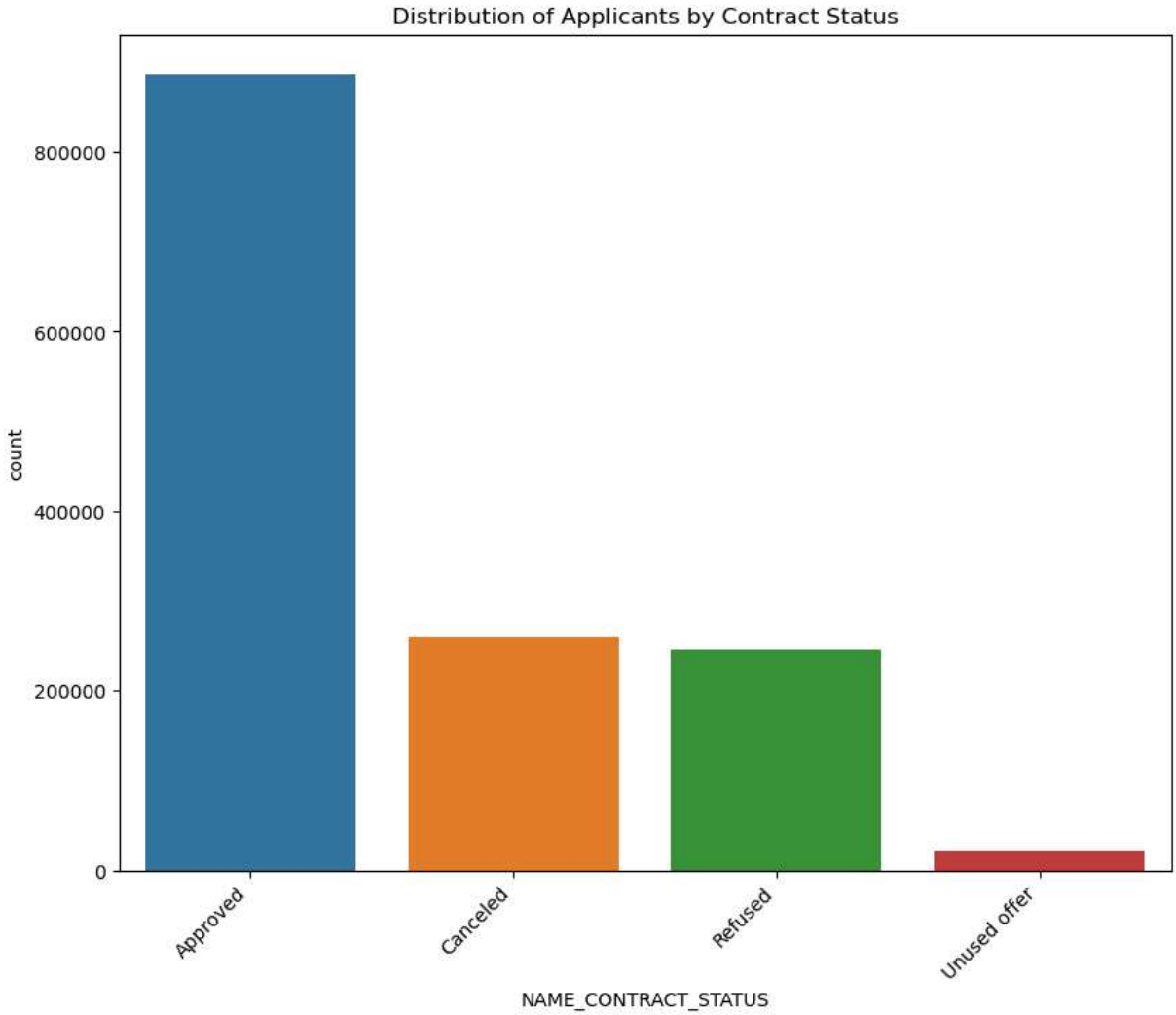
In [26]:
```
# Countplot for income types by gender
plt.figure(figsize=(12, 8))
sns.countplot(x='NAME_INCOME_TYPE', hue='CODE_GENDER', data=merged_data)
plt.title('Income Types by Gender')
plt.xticks(rotation=45, ha='right')
plt.show()
```



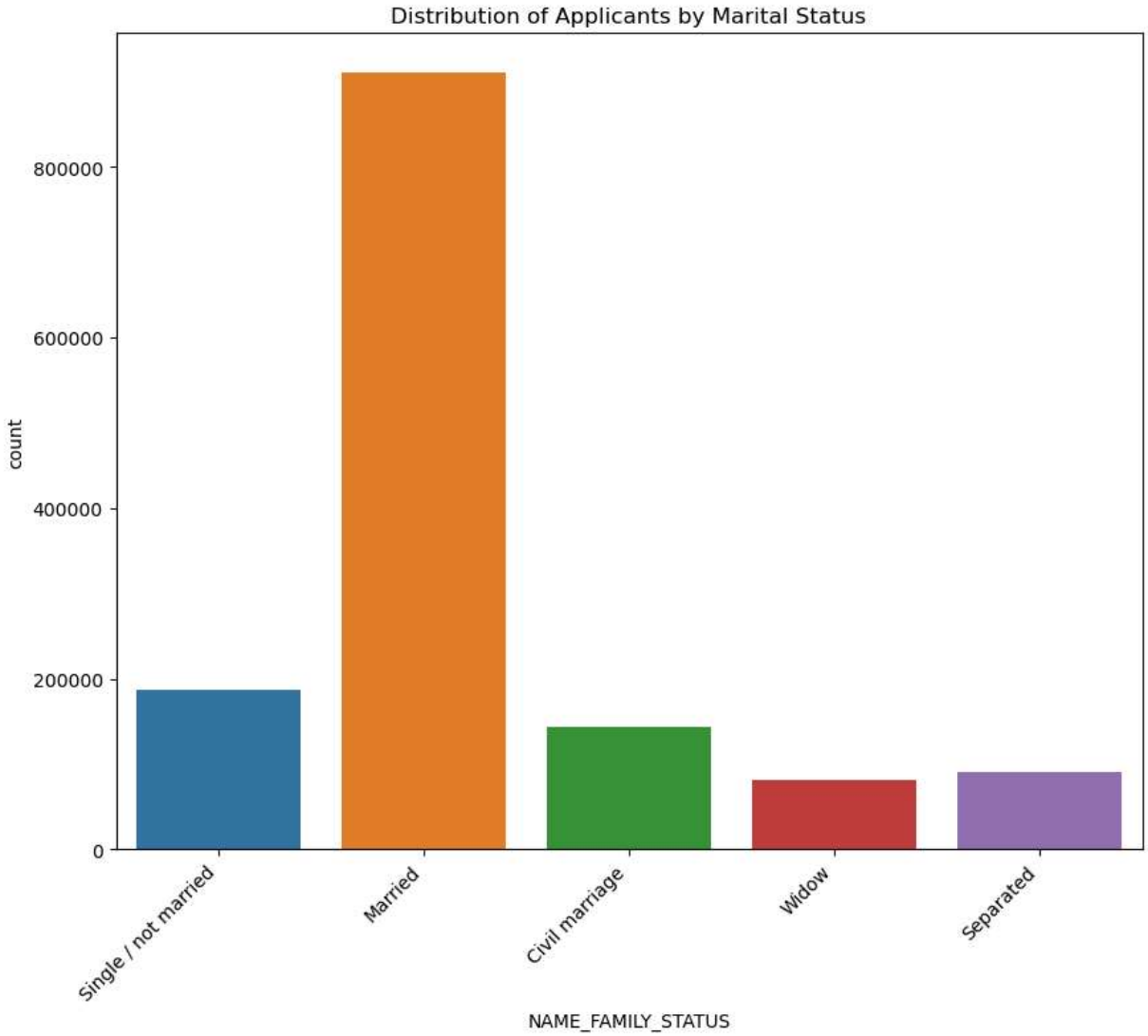
In [27]:
```
# Pie chart for gender distribution
gender_counts = merged_data['CODE_GENDER'].value_counts()
labels = gender_counts.index
sizes = gender_counts.values

plt.figure(figsize=(8, 8))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90, colors=['lightblue'
plt.title('Distribution of Applicants by Gender')
plt.show()
```



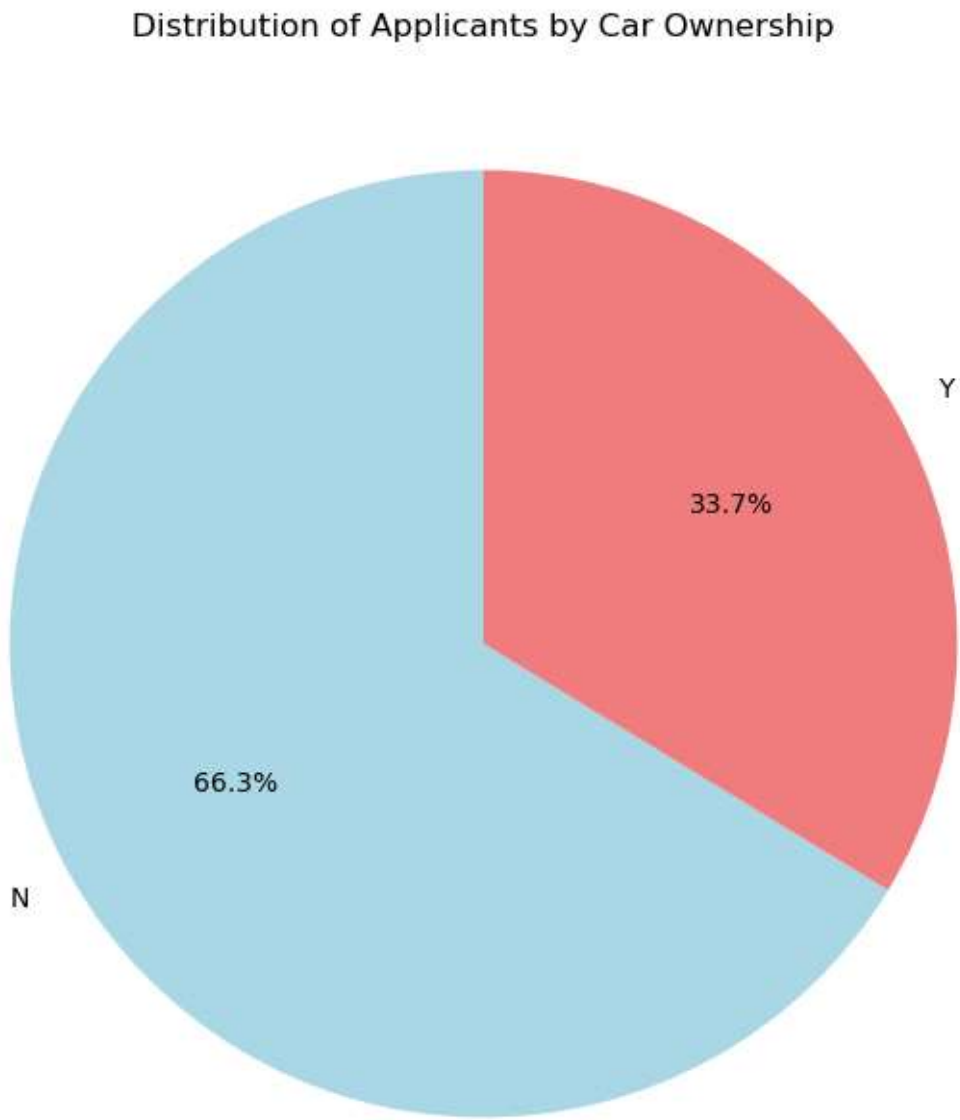
In [28]:
```
# Countplot for contract status distribution
plt.figure(figsize=(10, 8))
sns.countplot(x='NAME_CONTRACT_STATUS', data=merged_data)
plt.title('Distribution of Applicants by Contract Status')
plt.xticks(rotation=45, ha='right')
plt.show()
```



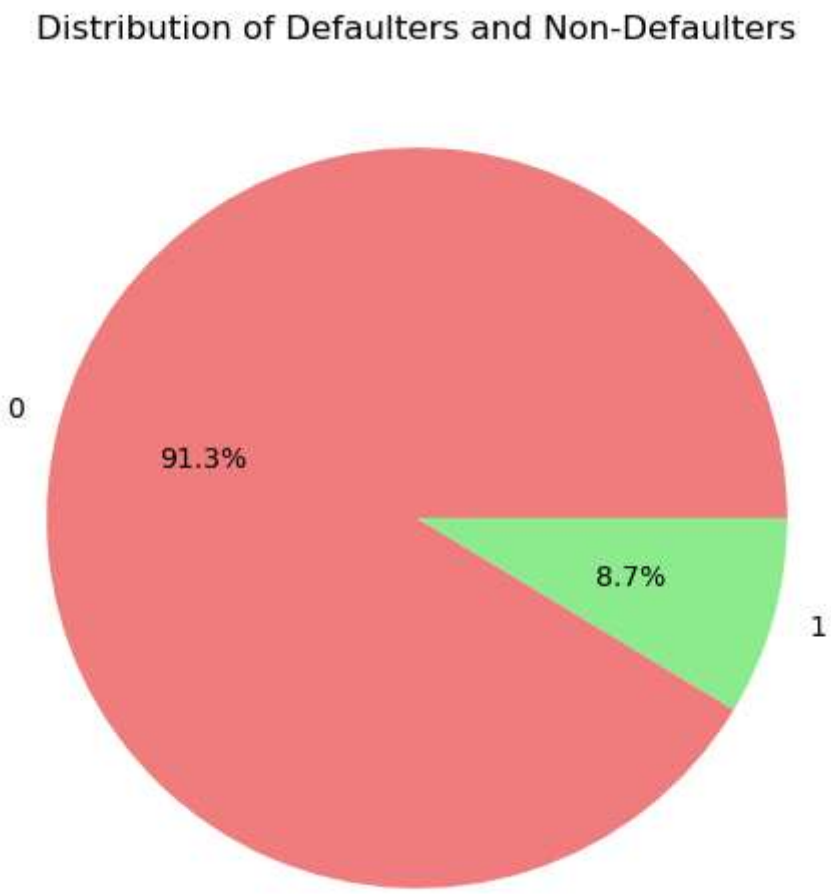
In [29]:
```
# Countplot for marital status distribution
plt.figure(figsize=(10, 8))
sns.countplot(x='NAME_FAMILY_STATUS', data=merged_data)
plt.title('Distribution of Applicants by Marital Status')
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better visibility
plt.show()
```



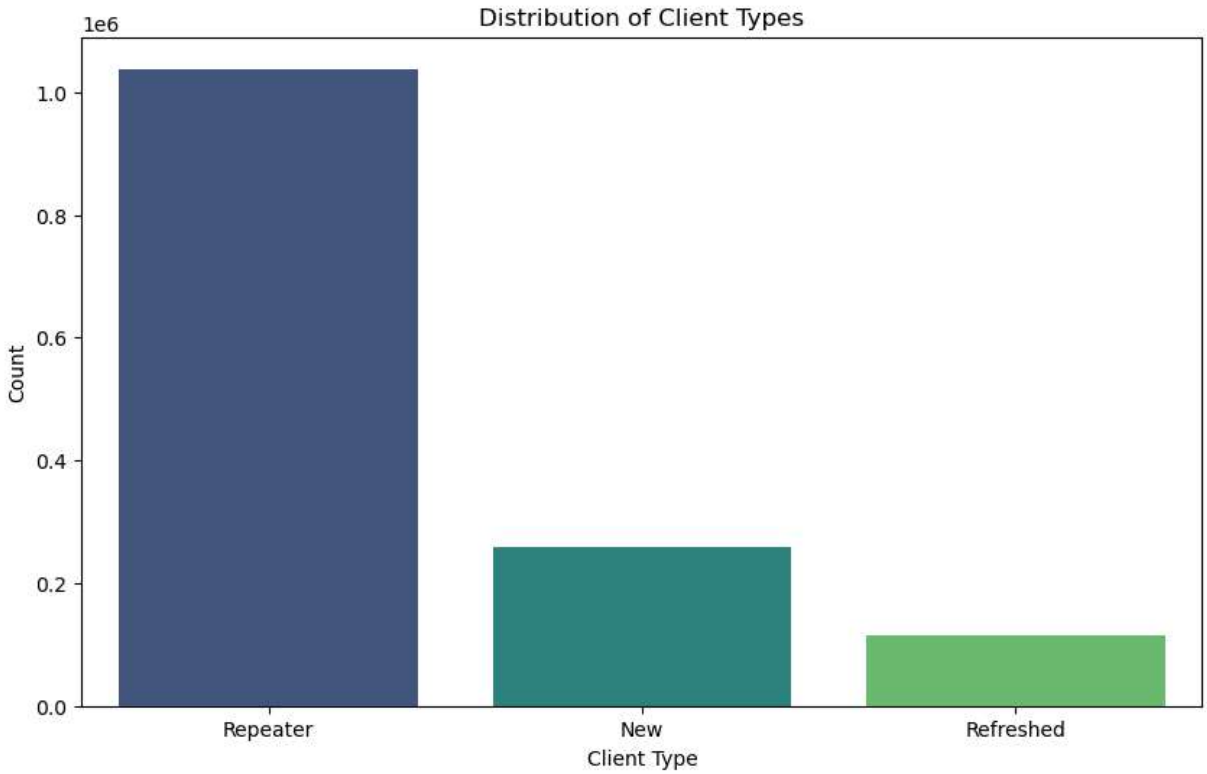
In [30]:
```
# Pie chart for car ownership distribution
car_ownership_counts = merged_data['FLAG_OWN_CAR'].value_counts()
labels = car_ownership_counts.index
sizes = car_ownership_counts.values

plt.figure(figsize=(8, 8))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90, colors=['lightblue'
plt.title('Distribution of Applicants by Car Ownership')
plt.show()
```



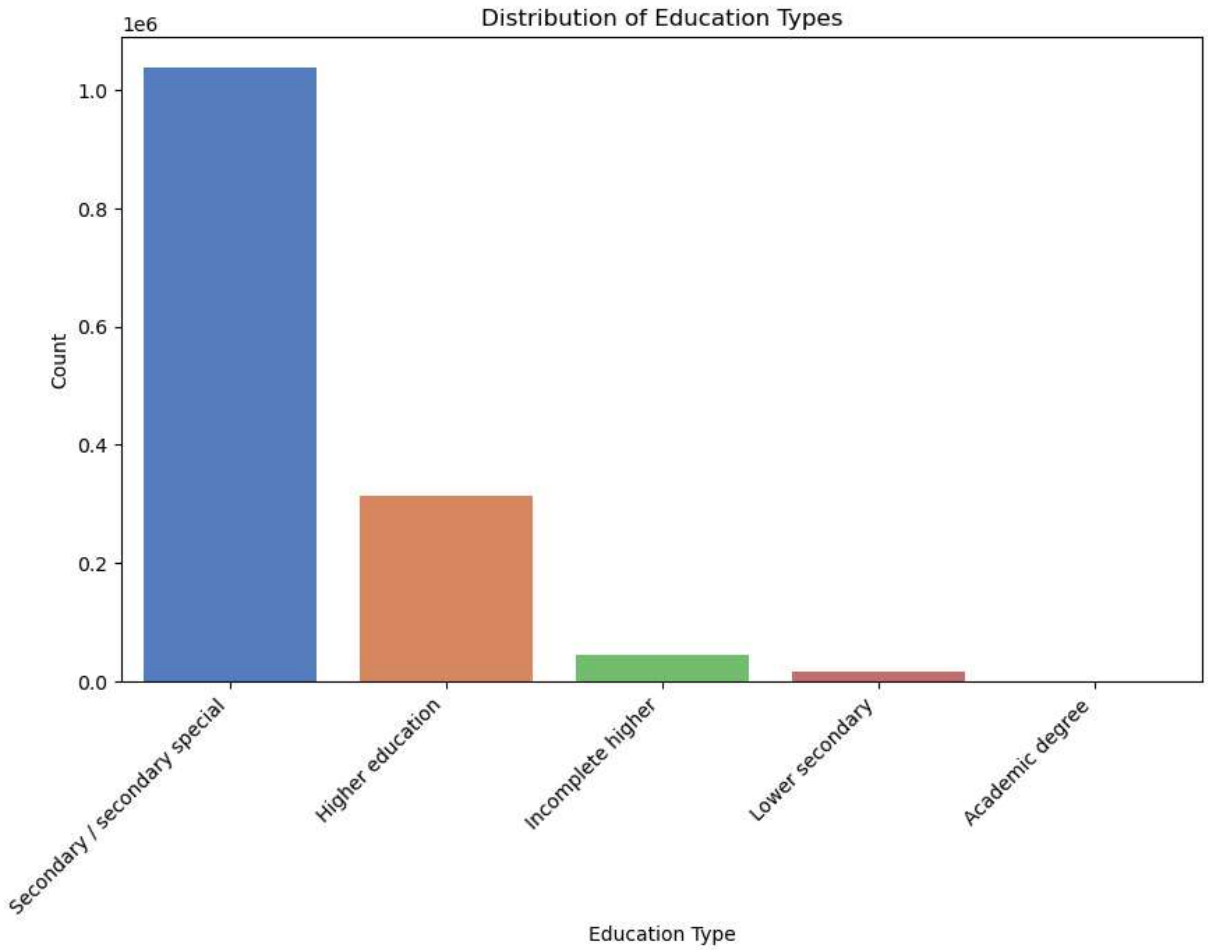
In [31]:
```
# Count the number of defaulters and non-defaulters
target_counts = merged_data['TARGET'].value_counts()

# Plotting a pie chart
plt.figure(figsize=(6, 6))
plt.pie(target_counts, labels=target_counts.index, autopct='%1.1f%%', colors=['ligh
plt.title('Distribution of Defaulters and Non-Defaulters')
plt.show()
```



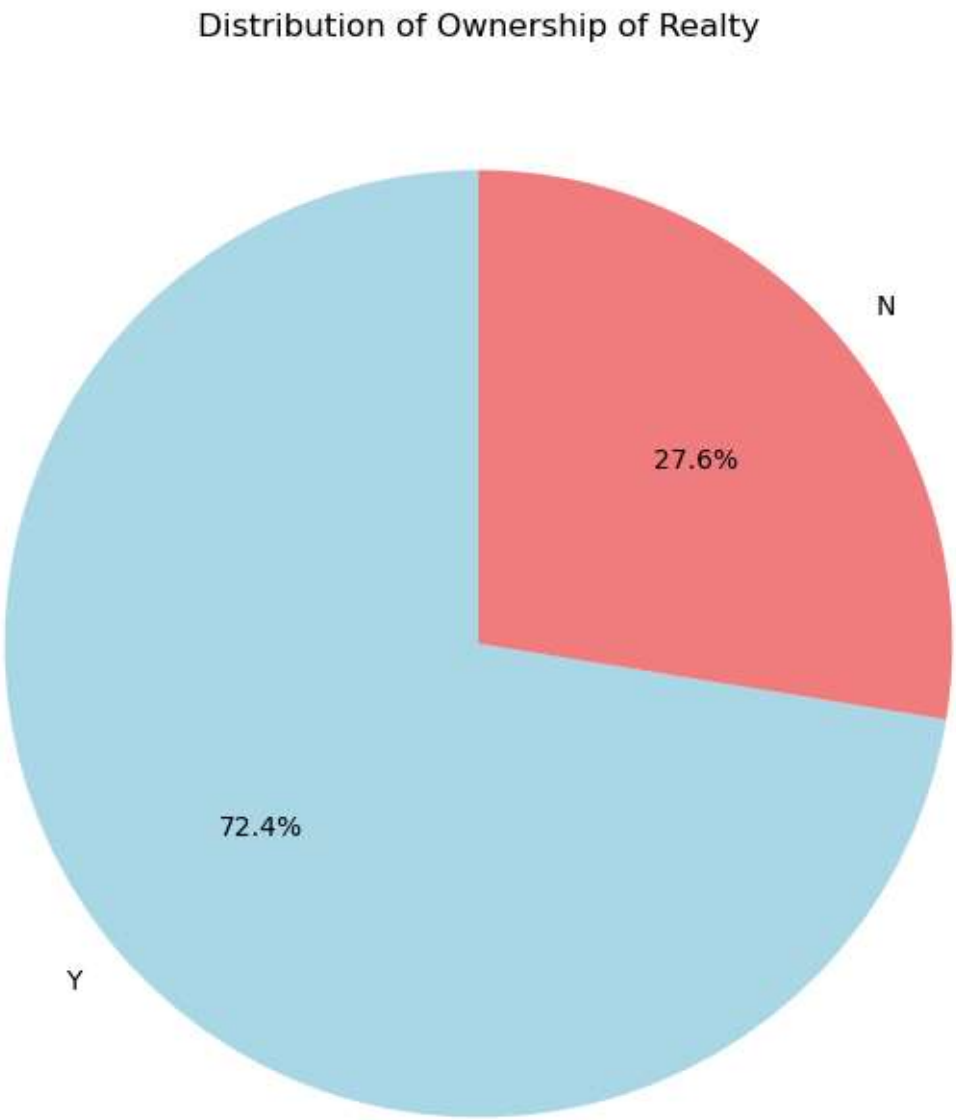
In [32]:
```
# Count the number of each client type
client_type_counts = merged_data['NAME_CLIENT_TYPE'].value_counts()

# Plotting a bar chart
plt.figure(figsize=(10, 6))
sns.barplot(x=client_type_counts.index, y=client_type_counts, palette='viridis')
plt.title('Distribution of Client Types')
plt.xlabel('Client Type')
plt.ylabel('Count')
plt.show()
```



In [33]:
```
# Count the number of each education type
education_type_counts = merged_data['NAME_EDUCATION_TYPE'].value_counts()

# Plotting a bar chart
plt.figure(figsize=(10, 6))
sns.barplot(x=education_type_counts.index, y=education_type_counts, palette='muted'
plt.title('Distribution of Education Types')
plt.xlabel('Education Type')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better visibility
plt.show()
```



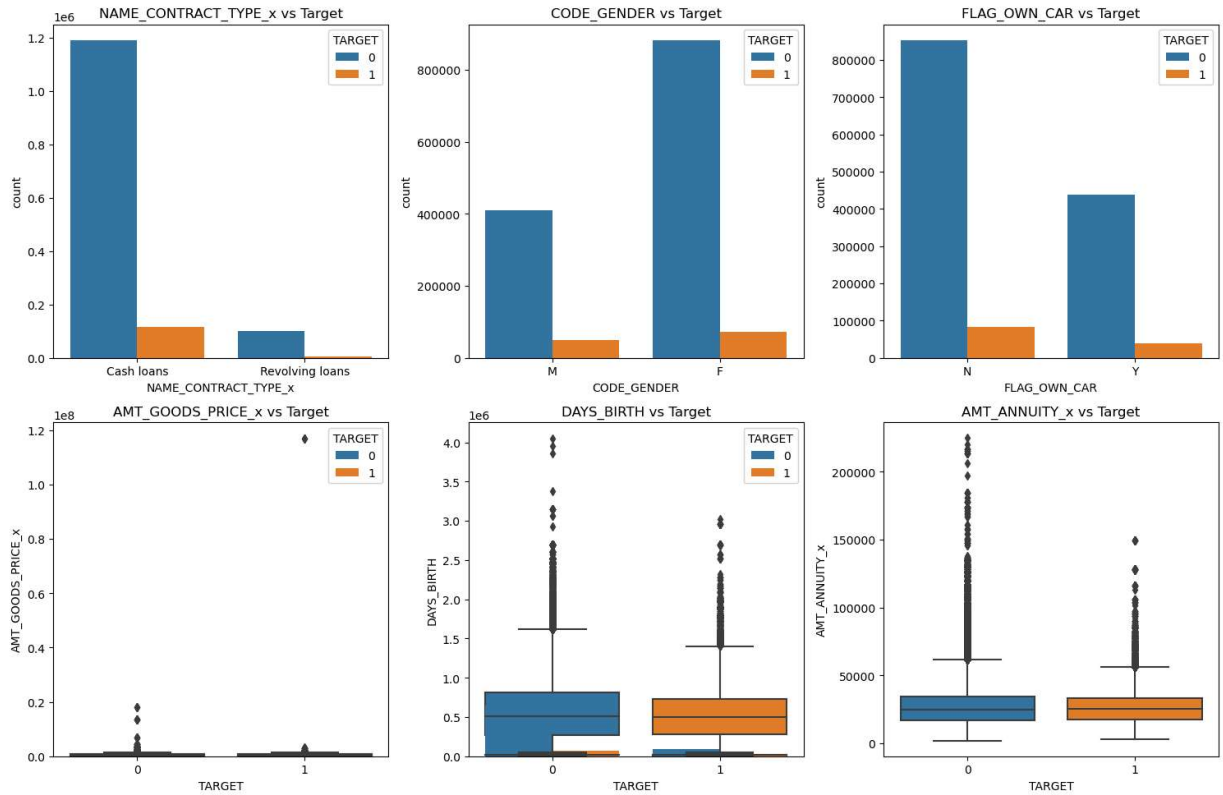
In [34]:
```
# Pie chart for ownership of realty
realty_counts = merged_data['FLAG_OWN_REALTY'].value_counts()
labels = realty_counts.index
sizes = realty_counts.values

plt.figure(figsize=(8, 8))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90, colors=['lightblue'
plt.title('Distribution of Ownership of Realty')
plt.show()
```



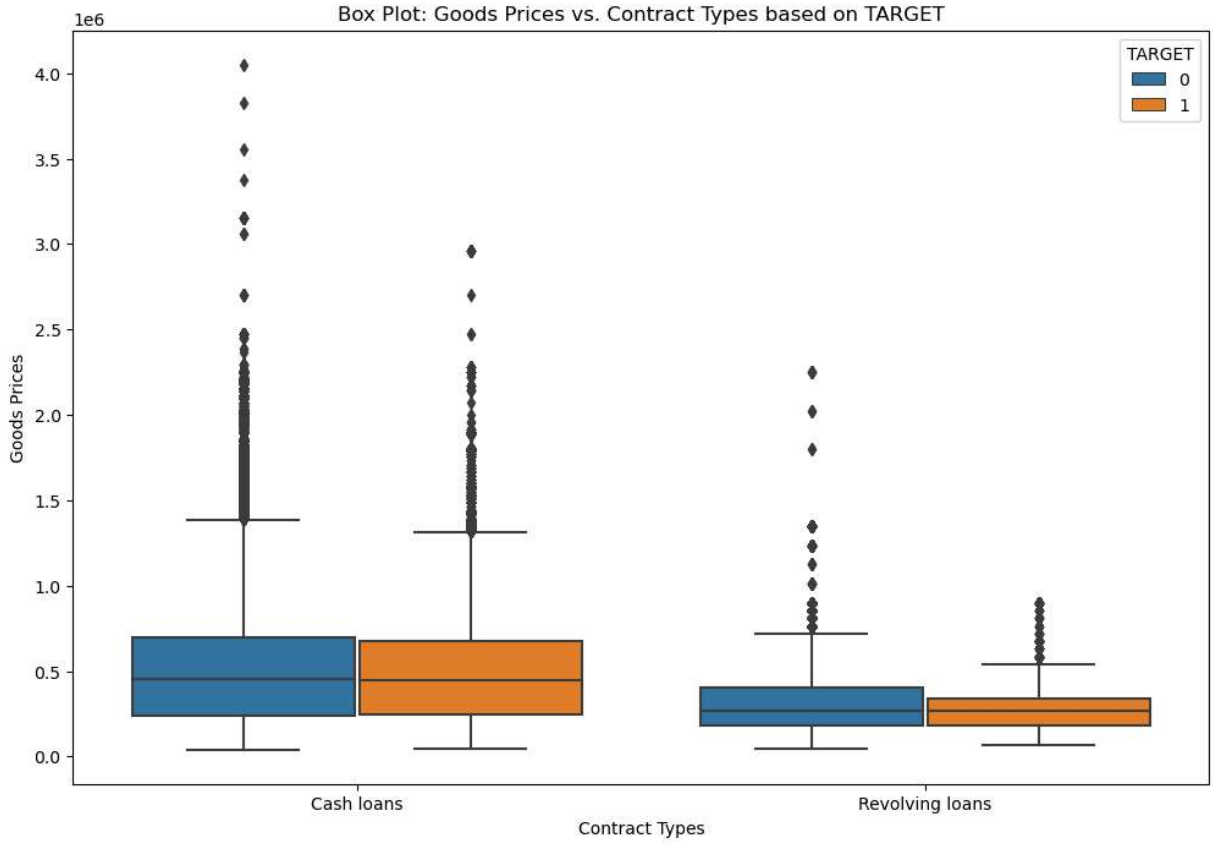
BiVariate Analysis

In [35]:
```
# Categorical variables
categorical_variables = ['NAME_CONTRACT_TYPE_x', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FL

# Numerical variables
numerical_variables = ['AMT_INCOME_TOTAL', 'AMT_CREDIT_x', 'AMT_ANNUITY_x', 'AMT_GO

# Set up subplots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 10))

# Bivariate analysis for categorical variables using bar plots
for i, variable in enumerate(categorical_variables):
    sns.countplot(x=variable, hue='TARGET', data=merged_data, ax=axes[i//3, i%3])
    axes[i//3, i%3].set_title(f'{variable} vs Target')
```

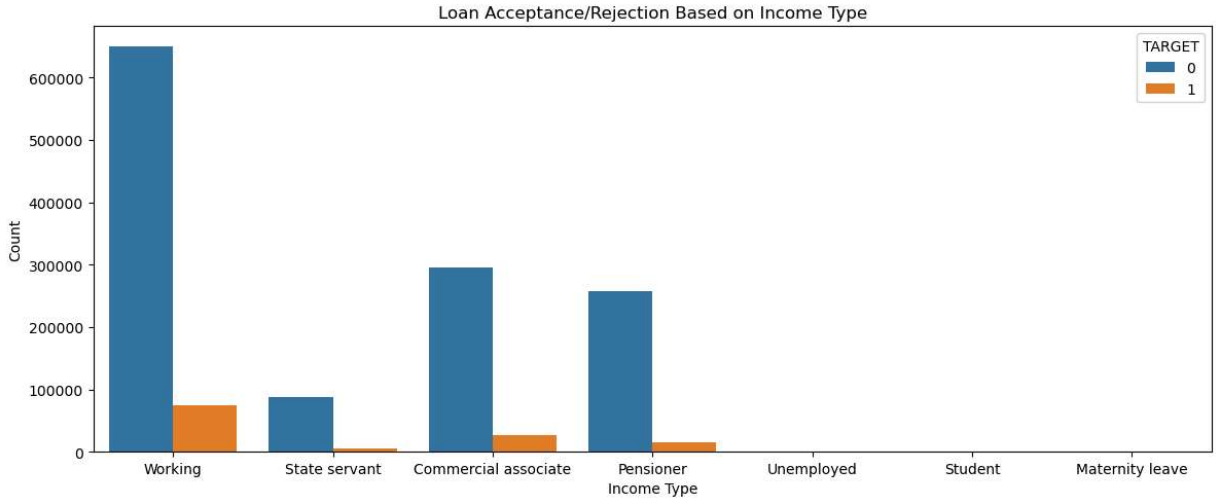
```
# Bivariate analysis for numerical variables using box plots
for i, variable in enumerate(numerical_variables):
    sns.boxplot(x='TARGET', y=variable, data=merged_data, ax=axes[1, i%3])
    axes[1, i%3].set_title(f'{variable} vs Target')

# Adjust layout
plt.tight_layout()

# Show the plots
plt.show()
```

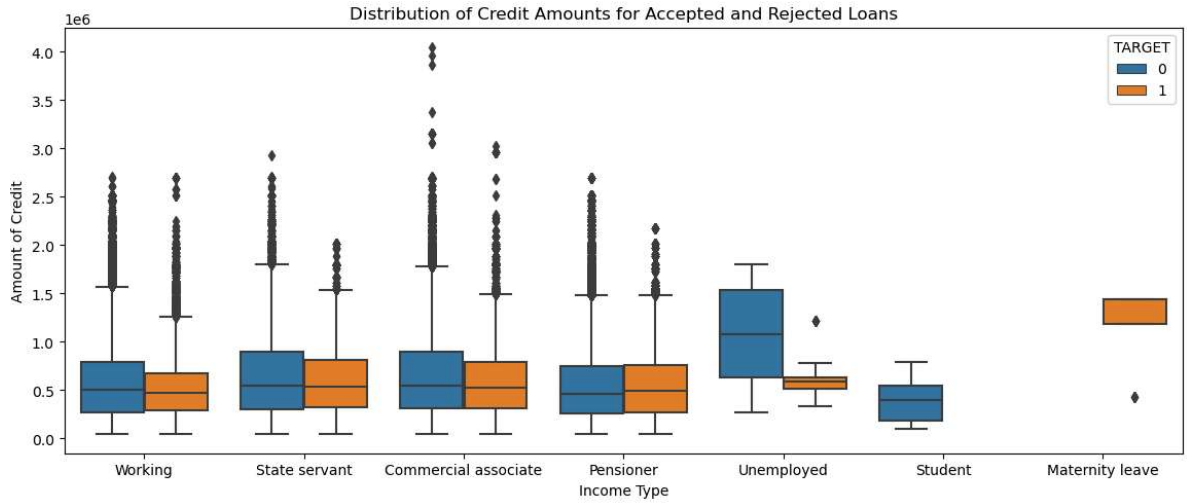


In [36]:
```
#Box plot for goods prices vs. contract types with hue 'TARGET'
plt.figure(figsize=(12, 8))
sns.boxplot(x='NAME_CONTRACT_TYPE_x', y='AMT_GOODS_PRICE_x', hue='TARGET', data=mer
plt.title('Box Plot: Goods Prices vs. Contract Types based on TARGET')
plt.xlabel('Contract Types')
plt.ylabel('Goods Prices')
plt.legend(title='TARGET')
plt.show()
```

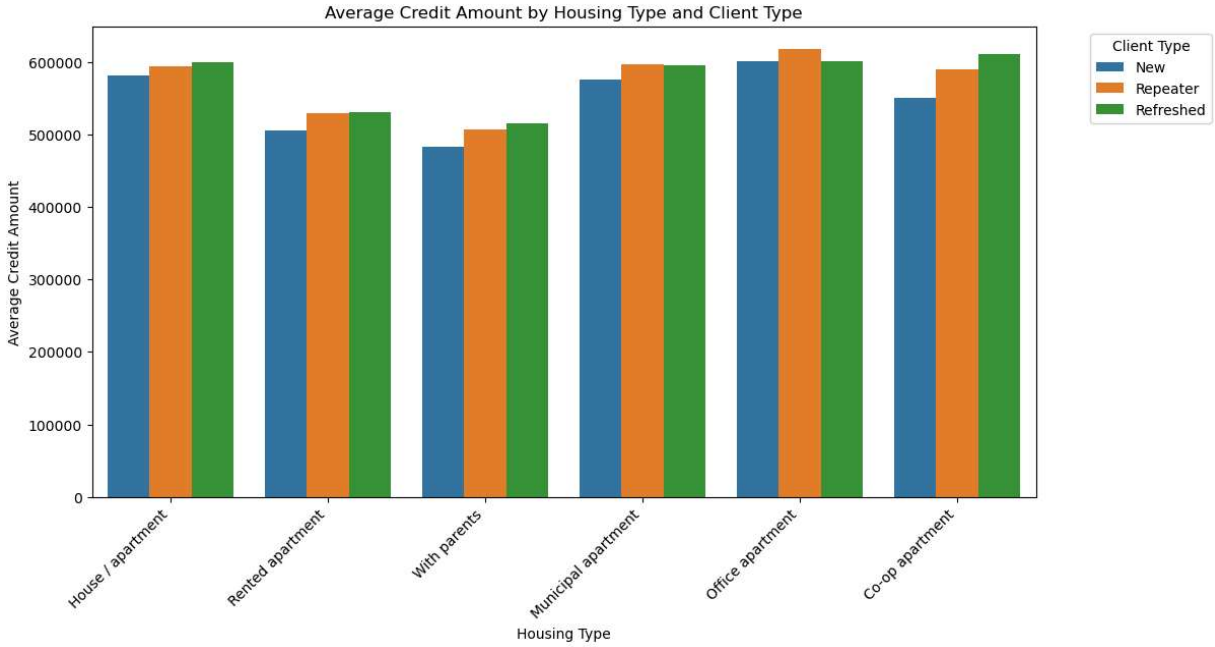


In [37]:
```
# Set up the figure with subplots
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 10))

# Plot the count of accepted and rejected loans
sns.countplot(x='NAME_INCOME_TYPE', hue='TARGET', data=merged_data, ax=ax1)
ax1.set_xlabel('Income Type')
ax1.set_ylabel('Count')
ax1.set_title('Loan Acceptance/Rejection Based on Income Type')

# Plot the distribution of amounts for accepted loans
sns.boxplot(x='NAME_INCOME_TYPE', y='AMT_CREDIT_x', hue='TARGET', data=merged_data,
ax2.set_xlabel('Income Type')
ax2.set_ylabel('Amount of Credit')
ax2.set_title('Distribution of Credit Amounts for Accepted and Rejected Loans')

# Show the plots
plt.tight_layout()
plt.show()
```

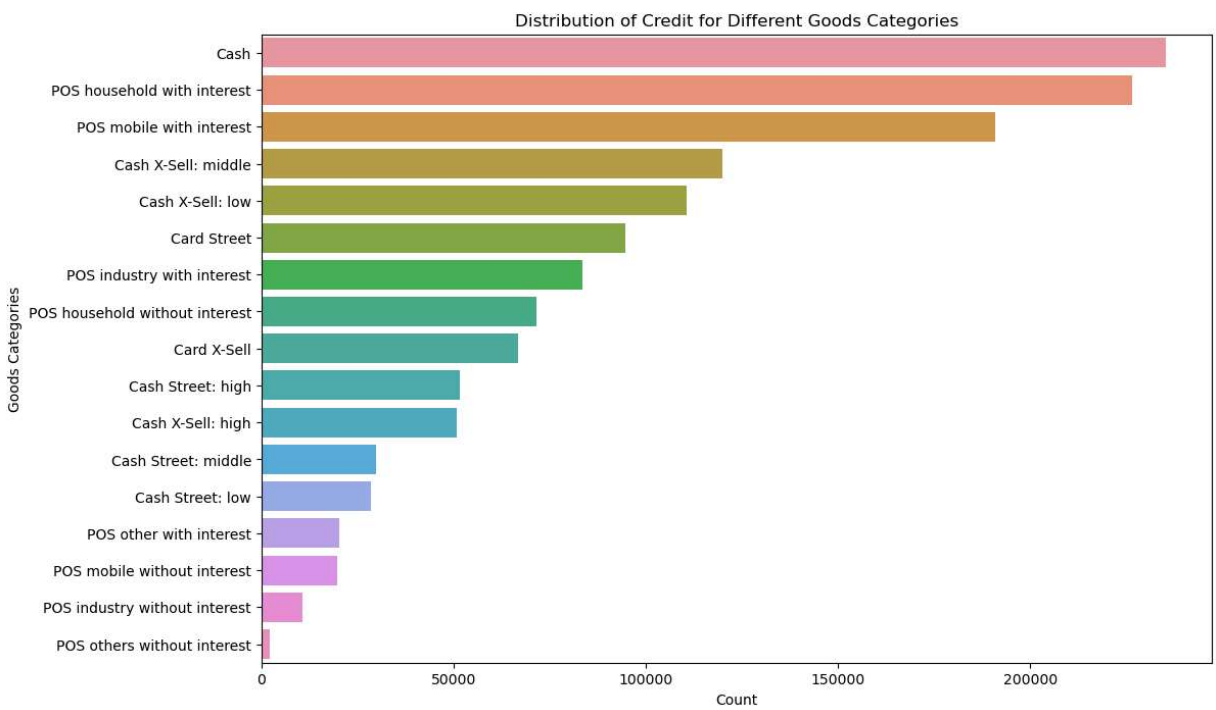




In [38]:
```
# Grouped bar chart for average credit amount by housing type and client type
plt.figure(figsize=(12, 6))
sns.barplot(x='NAME_HOUSING_TYPE', y='AMT_CREDIT_x', hue='NAME_CLIENT_TYPE', data=m
plt.title('Average Credit Amount by Housing Type and Client Type')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Housing Type')
plt.ylabel('Average Credit Amount')
plt.legend(title='Client Type', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

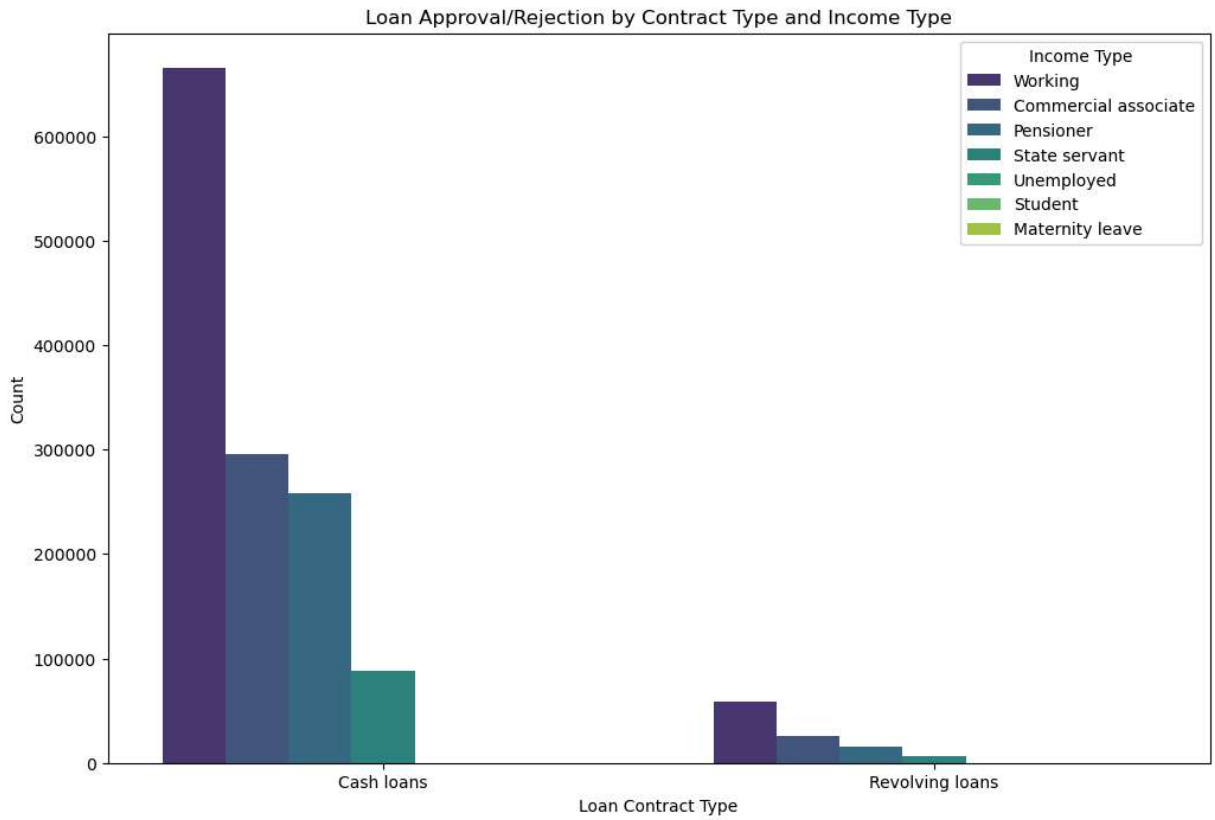


In [39]:
```
# Countplot for goods category distribution
plt.figure(figsize=(12, 8))
sns.countplot(y='PRODUCT_COMBINATION', data=merged_data, order=merged_data['PRODUCT
plt.title('Distribution of Credit for Different Goods Categories')
plt.xlabel('Count')
plt.ylabel('Goods Categories')
plt.show()
```

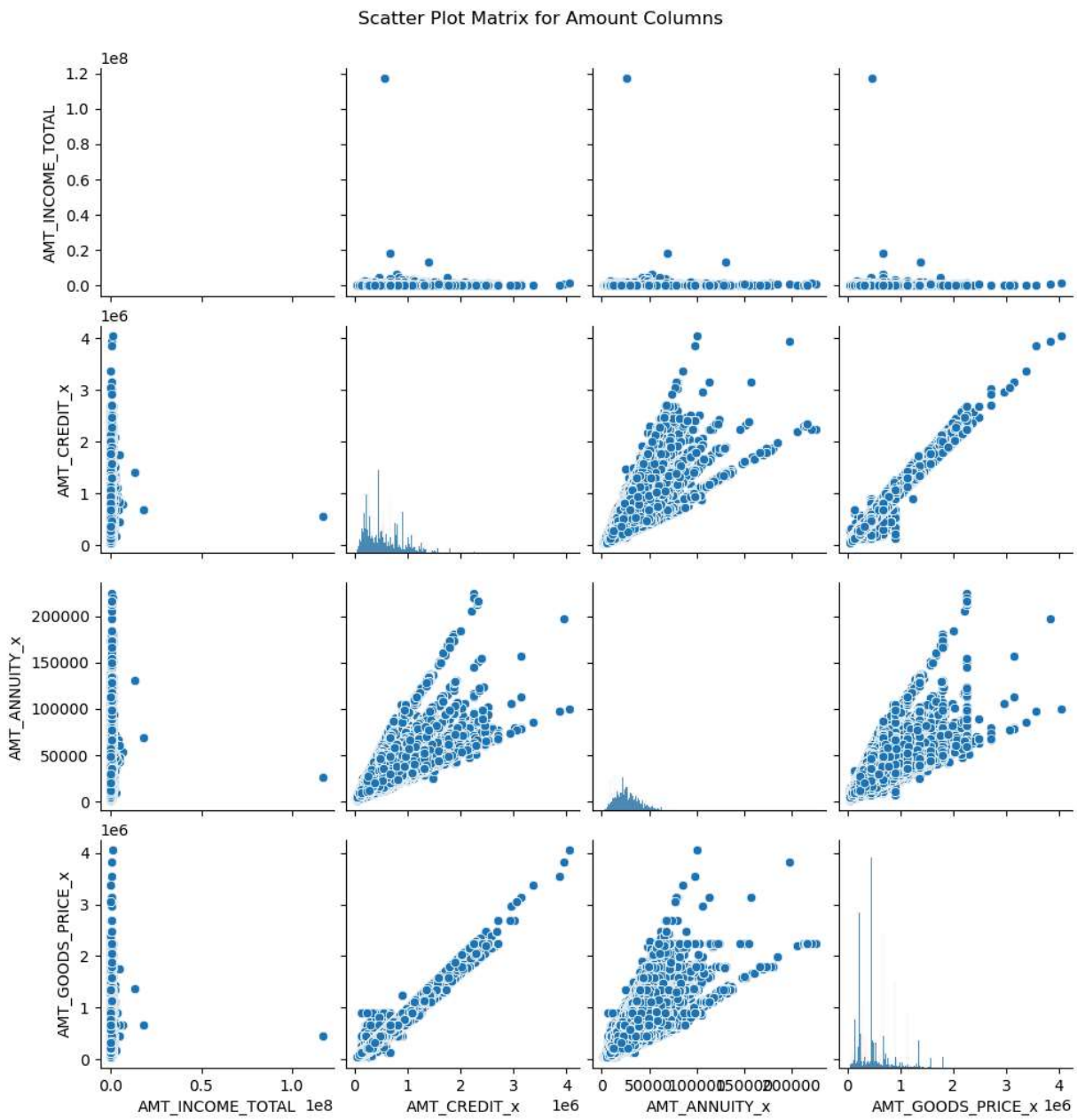


In [40]:
```
# Select relevant variables
selected_variables = ['NAME_CONTRACT_TYPE_x', 'NAME_INCOME_TYPE', 'TARGET']

# Subset the data
subset_data = merged_data[selected_variables]
```

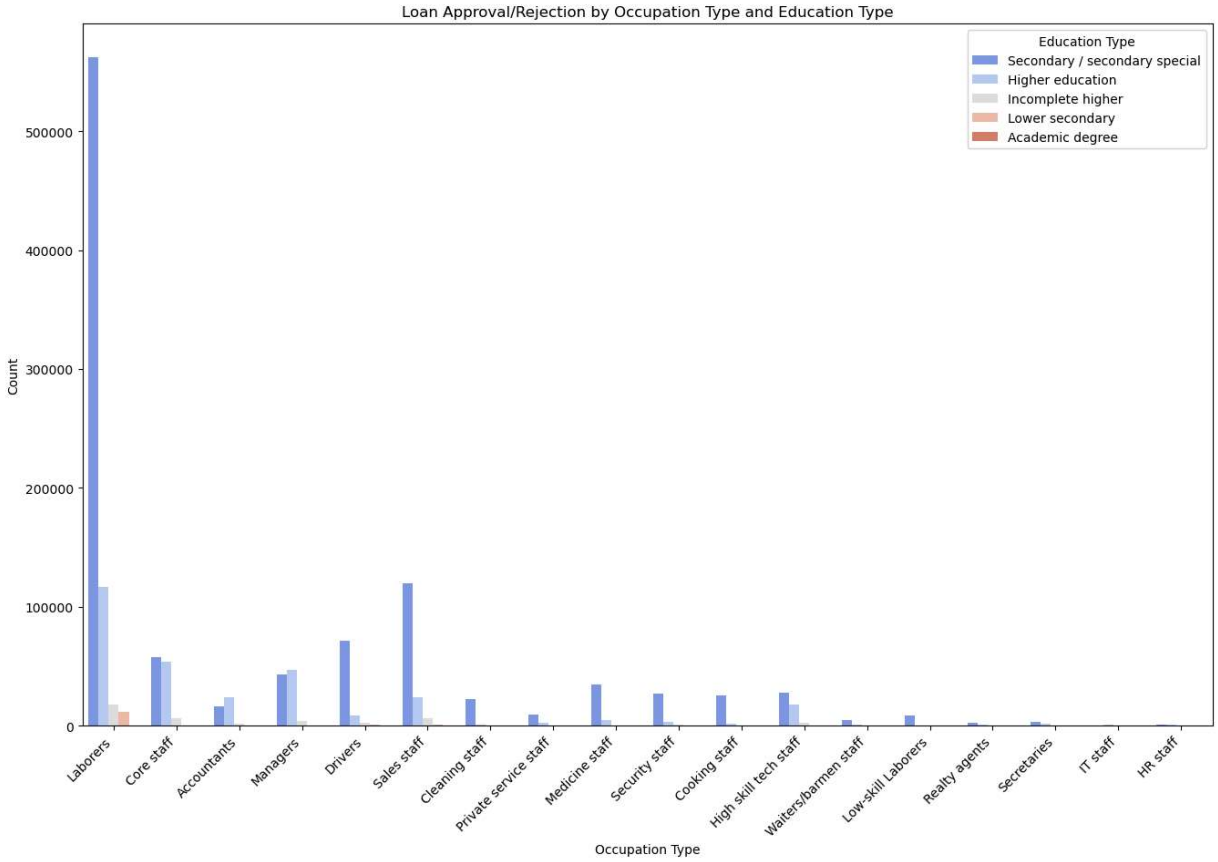
```
# Create a grouped bar chart
plt.figure(figsize=(12, 8))
sns.countplot(x='NAME_CONTRACT_TYPE_x', hue='NAME_INCOME_TYPE', data=subset_data, h
plt.title('Loan Approval/Rejection by Contract Type and Income Type')
plt.xlabel('Loan Contract Type')
plt.ylabel('Count')
plt.legend(title='Income Type')
plt.show()
```



In [41]:
```
# Columns to include in the scatter plot matrix
amount_columns = ['AMT_INCOME_TOTAL', 'AMT_CREDIT_x', 'AMT_ANNUITY_x', 'AMT_GOODS_P

# Scatter plot matrix
sns.pairplot(merged_data[amount_columns])
plt.suptitle('Scatter Plot Matrix for Amount Columns', y=1.02)
plt.show()
```

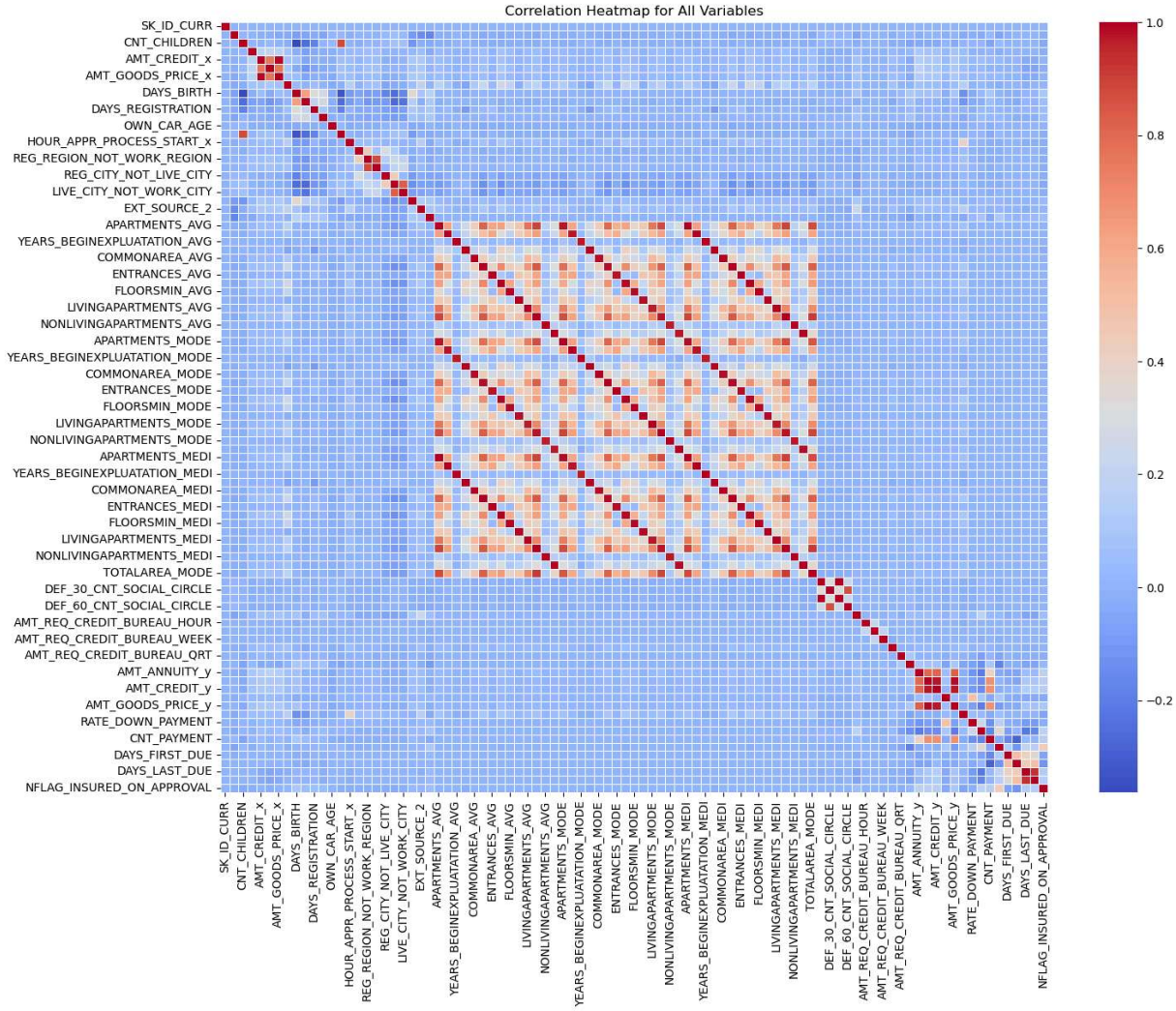


In [42]:
```
# Select relevant variables
selected_variables = ['OCCUPATION_TYPE', 'NAME_EDUCATION_TYPE', 'TARGET']

# Subset the data
subset_data = merged_data[selected_variables]

# Create a grouped bar chart
plt.figure(figsize=(16, 10))
sns.countplot(x='OCCUPATION_TYPE', hue='NAME_EDUCATION_TYPE', data=subset_data, hue
plt.title('Loan Approval/Rejection by Occupation Type and Education Type')
plt.xlabel('Occupation Type')
plt.ylabel('Count')
plt.legend(title='Education Type', bbox_to_anchor=(1, 1))
plt.xticks(rotation=45, ha='right')
plt.show()
```

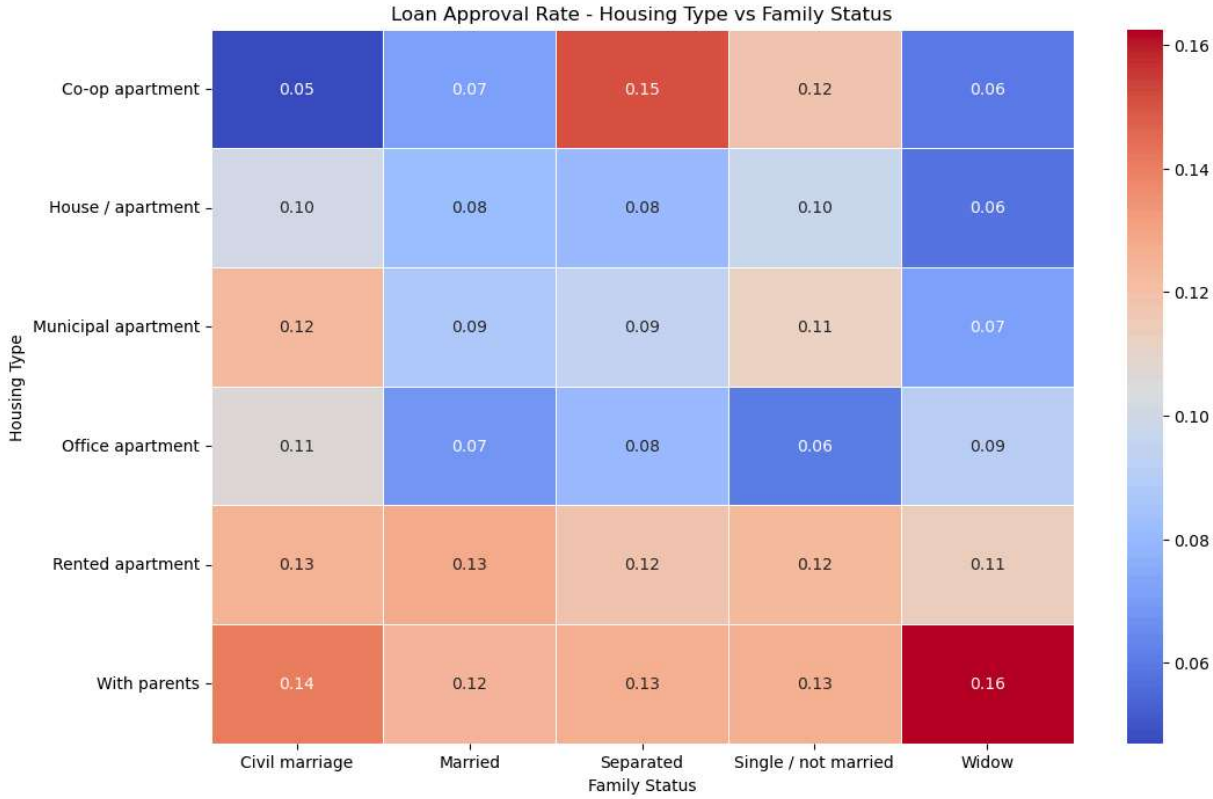


Multivariate Analysis: Correlation Heatmap

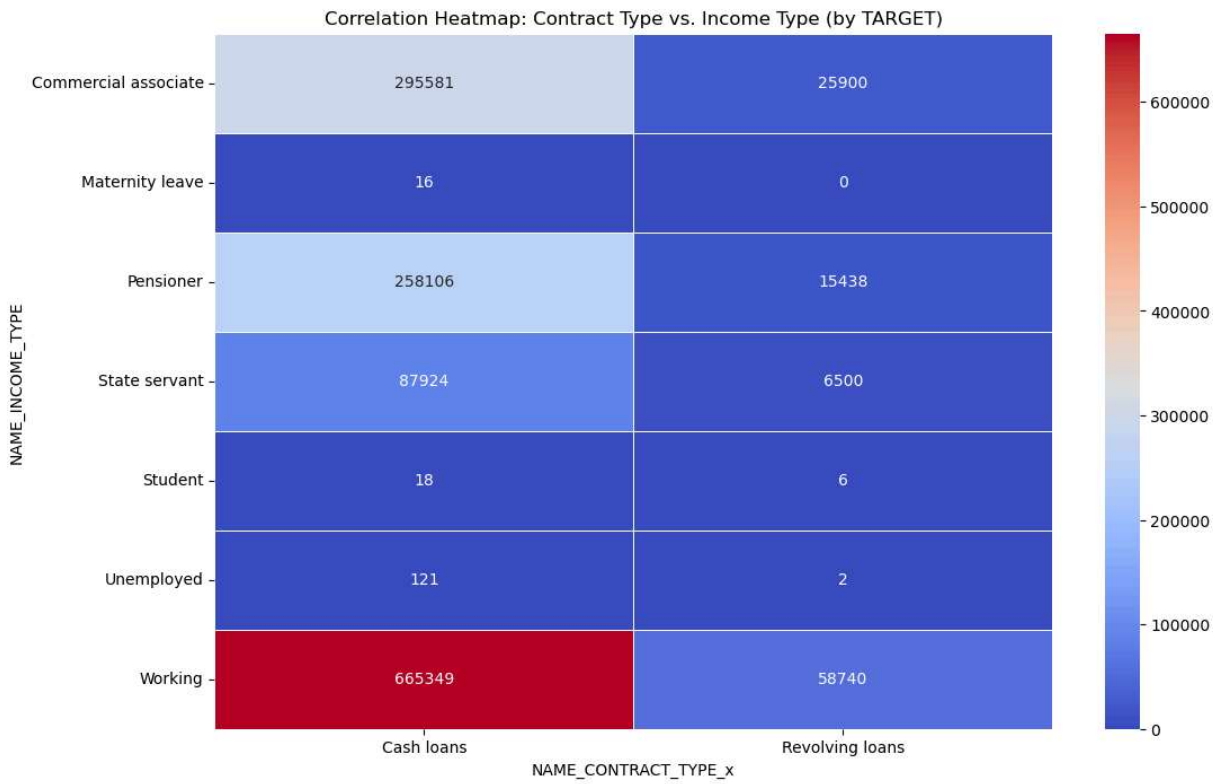
In [43]:
```
# Calculate the correlation matrix for the entire dataset
correlation_matrix_all = merged_data.corr()

# Create a heatmap
plt.figure(figsize=(16, 12))
sns.heatmap(correlation_matrix_all, cmap='coolwarm', linewidths=.5)
plt.title('Correlation Heatmap for All Variables')
plt.show()
```



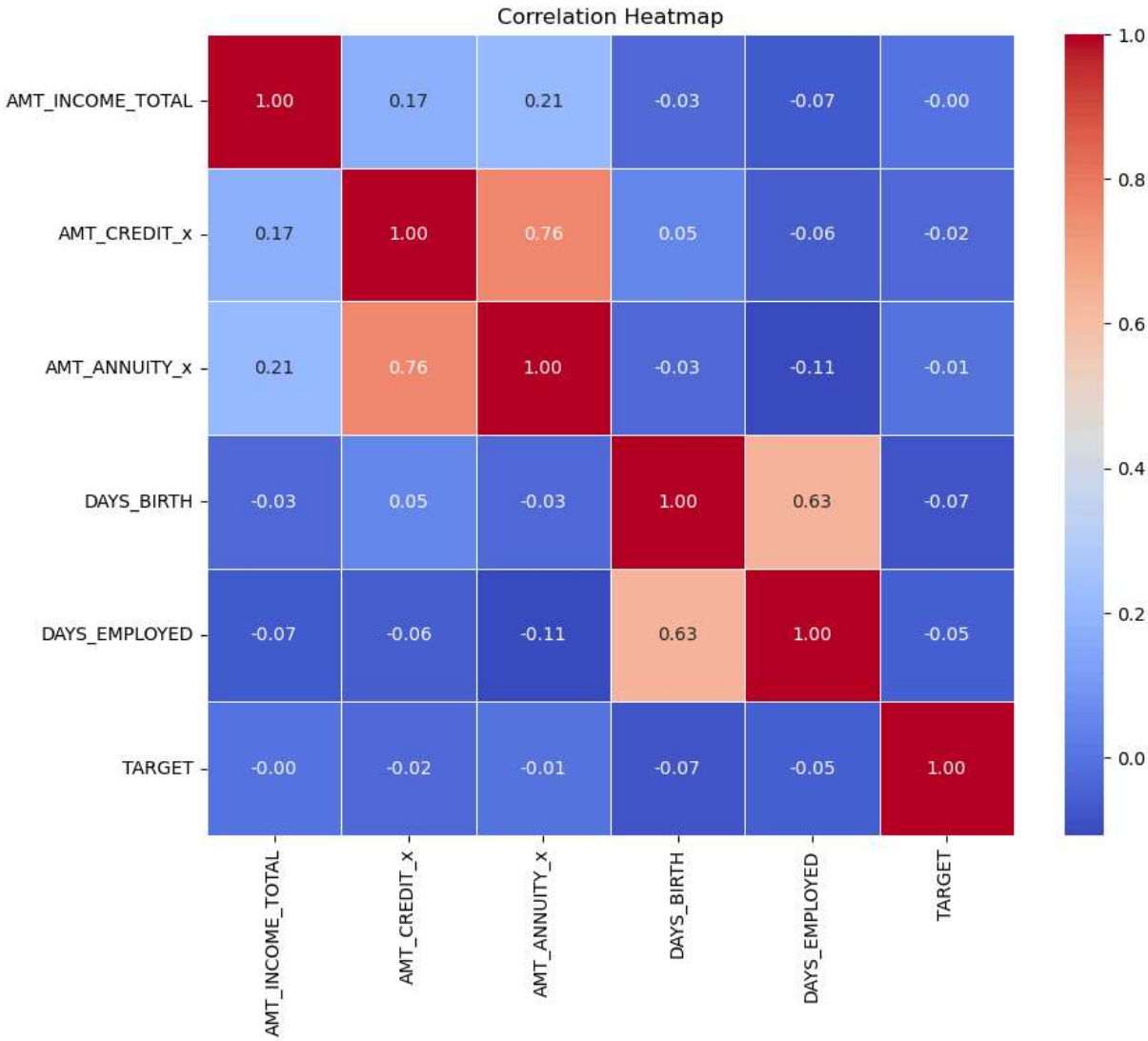
In [44]:
```
# Create a pivot table for better visualization
pivot_table = pd.pivot_table(merged_data, values='TARGET', index='NAME_HOUSING_TYPE

# Plot heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(pivot_table, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Loan Approval Rate - Housing Type vs Family Status')
plt.xlabel('Family Status')
plt.ylabel('Housing Type')
plt.show()
```



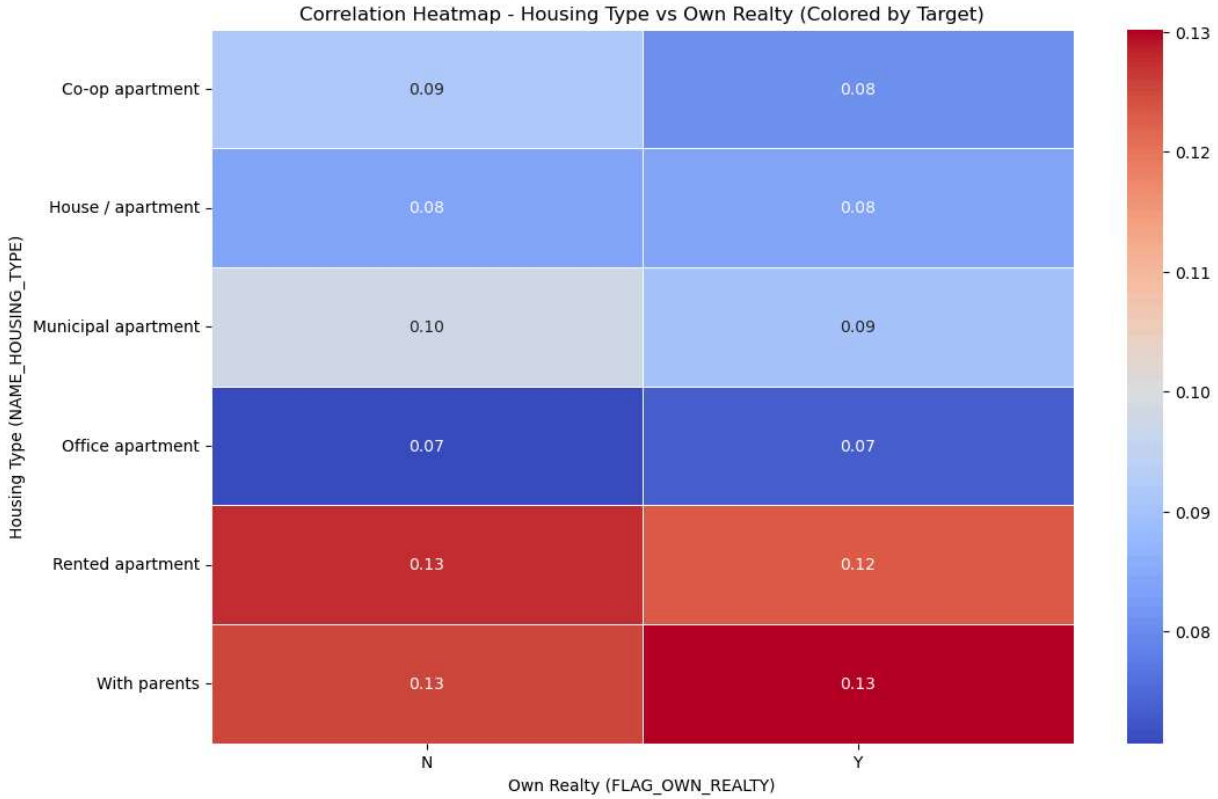
In [45]:
```
# Select relevant variables
selected_variables = ['NAME_CONTRACT_TYPE_x', 'NAME_INCOME_TYPE']

# Subset the data
subset_data = merged_data[selected_variables]

# Create a contingency table
contingency_table = pd.crosstab(index=subset_data['NAME_INCOME_TYPE'], columns=subs

# Plot heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(contingency_table, annot=True, cmap='coolwarm', fmt="d", linewidths=.5)
plt.title('Correlation Heatmap: Contract Type vs. Income Type (by TARGET)')
plt.show()
```



In [46]:
```
# Select columns for correlation analysis
selected_columns = ['AMT_INCOME_TOTAL', 'AMT_CREDIT_x', 'AMT_ANNUITY_x', 'DAYS_BIRT

# Subset the data
subset_data = merged_data[selected_columns]

# Calculate the correlation matrix
correlation_matrix = subset_data.corr()

# Create a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=
plt.title('Correlation Heatmap')
plt.show()
```



In [52]:
```
# Create a pivot table for better visualization
pivot_table = pd.pivot_table(merged_data, values='TARGET', index='NAME_HOUSING_TYPE

# Plot heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(pivot_table, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)

# Set plot labels and title
plt.title('Correlation Heatmap - Housing Type vs Own Realty (Colored by Target)')
plt.xlabel('Own Realty (FLAG_OWN_REALTY)')
plt.ylabel('Housing Type (NAME_HOUSING_TYPE)')

# Show the plot
plt.show()
```


Correlation Heatmap - Housing Type vs Own Realty (Colored by Target)
Housing Type (NAME_HOUSING_TYPE)
Co-op apartment
House / apartment
Municipal apartment
Office apartment
Rented apartment
With parents
0.09
0.08
0.08
0.08
0.10
0.09
0.07
0.07
0.13
0.12
0.13
0.13
N
Y
Own Realty (FLAG_OWN_REALTY)
0.13
0.12
0.11
0.10
0.09
0.08

In [ ]: