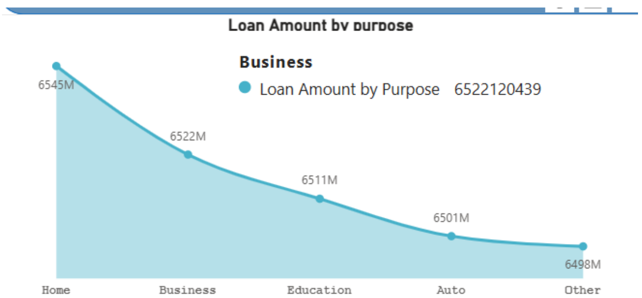
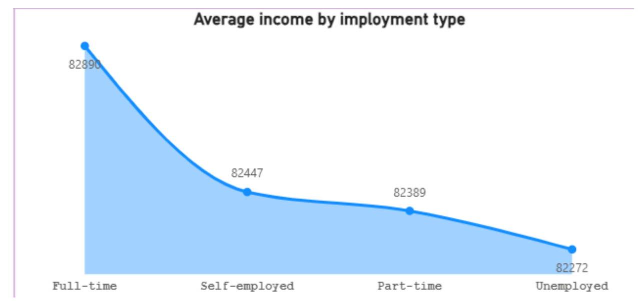
Loan Amount by Purpose (DAX Measure and Validation)



Loan Amount by Purpose = SUMX(FILTER('Loan_default',NOT(ISBLANK('Loan_default'[LoanAmount]))),'Loan_default'[LoanAmount])

I built a DAX measure using `SUMX` with `FILTER`, `NOT`, and `ISBLANK` to sum only non-blank loan amounts. The measure was stored in a dedicated Measures Table for better organization. A line chart was then created to show loan amounts by purpose (Home, Business, Education, Auto, Other). To ensure accuracy, I validated the results against a simple Power BI table and the original Excel pivot, both of which matched. This confirmed the calculation's reliability and provided a clear view of loan distribution across purposes.

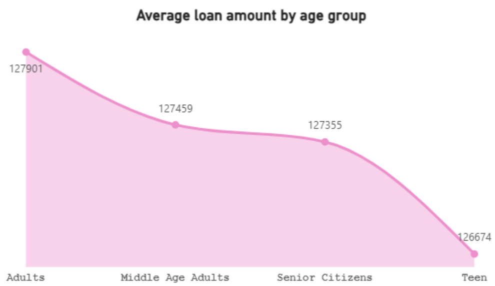
Average Income by Employment Type



Average Income by Employment type = CALCULATE(AVERAGE('Loan_default'[Income]),ALLEXCEPT('Loan_default','Loan_default'[EmploymentType]))

I built a DAX measure using `CALCULATE`, `AVERAGE`, and `ALLEXCEPT` to compute average income segmented by employment type, ensuring that only this filter influenced the calculation. The measure was visualized in a line chart to compare Full-time, Self-employed, Part-time, and Unemployed borrowers, making differences in income levels clear, with Full-time the highest and Unemployed the lowest. Using `ALLEXCEPT` kept the results consistent regardless of slicers or other visuals on the page. To confirm accuracy, I validated the outputs against Excel Pivot Tables and Power BI table visuals, with results matching perfectly. This step ensured reliable insights into how employment status affects borrower income.

Average Loan Amount by Age Group

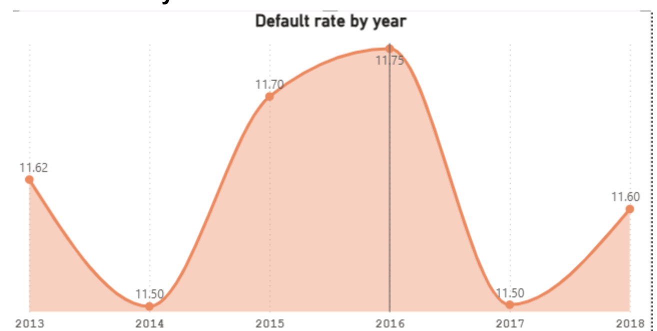



```
Age Groups =
 IF('Loan_default'[Age]<=19,"Teen",
    IF('Loan_default'[Age]<=39,"Adults",
        IF('Loan_default'[Age]<=59,"Middle Age Adults",
            "Senior Citizens")))
```

```
Average Loan by Age Group =
 AVERAGEX(VALUES('Loan_default'[Age Groups]),
 AVERAGE('Loan_default'[LoanAmount]))
```

To analyze borrowing patterns by age, I first created a new calculated column called *Age Groups* using nested `IF` statements, classifying borrowers into Teens, Adults, Middle Age Adults, and Senior Citizens. Next, I built a DAX measure with `AVERAGEX`, `VALUES`, and `AVERAGE` to compute the average loan amount for each distinct age group. This ensured that the calculation iterated across age categories and returned precise averages. The results were visualized in a line chart, clearly showing how loan amounts differed across the groups, with Adults borrowing the highest on average and Teens the lowest. This step provided valuable insights into how age demographics influence loan-taking behavior.

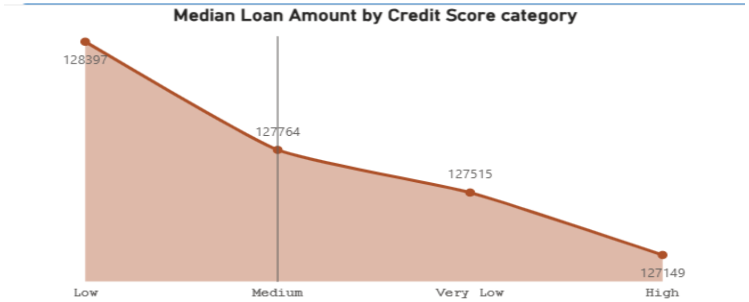
Default Rate by Year




```
Default Rate by Year =
 Var totalloans =

CALCULATE(COUNTROWS('Loan_default'),ALLEXCEPT('Loan_default',Loan_default[Year]))

Var default =
CALCULATE(COUNTROWS(FILTER('Loan_default','Loan_default'[Default]=TRUE())),ALLEX
CEPT('Loan_default',Loan_default[Year]))

RETURN
DIVIDE(default,totalloans)*100
```

To analyze repayment performance over time, I created a DAX measure that calculated the default rate by year, dividing the number of defaulted loans by the total loans issued in each year. The calculation was designed to consider only the year context, ensuring that no other filters influenced the results. I then visualized the output in a line chart, which highlighted fluctuations in default rates between 2013 and 2018. The results showed a peak in defaults during 2015–2016 and dips in 2014 and 2017, revealing clear patterns in borrower repayment behavior. This step provided valuable insights into portfolio risk trends and helped identify years where loan defaults were more significant.

Median Loan Amount by Credit Score Category

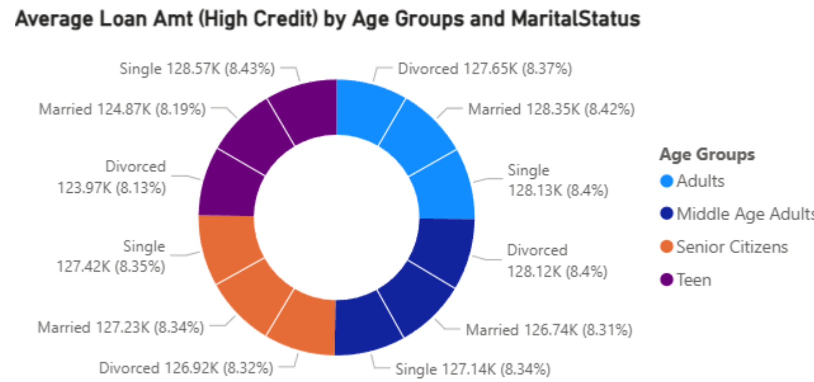


Median by Credit score bins =
MEDIANX('Loan_default','Loan_default'[LoanAmount])

Credit Score Bins =
IF(Loan_default[CreditScore]<=400,"Very Low",
IF('Loan_default'[CreditScore]<=450,"Low",
IF('Loan_default'[CreditScore]<=650,"Medium","High")))

To analyze borrowing behavior across different credit score ranges, I first created a calculated column called *Credit Score Bins* using nested IF statements, classifying borrowers into Very Low, Low, Medium, and High categories. Next, I built a DAX measure using MEDIANX to calculate the median loan amount within each score bin, ensuring the analysis reflected the central borrowing tendency rather than being skewed by extreme values. The results were visualized in a line chart, where the median loan amount was highest for borrowers in the Low credit score category and gradually decreased for Medium, Very Low, and High categories. The formatting was adjusted with smooth lines, markers, and custom colors for clarity. This visualization provided key insights into how creditworthiness relates to borrowing amounts, highlighting that riskier borrowers often take larger loans.

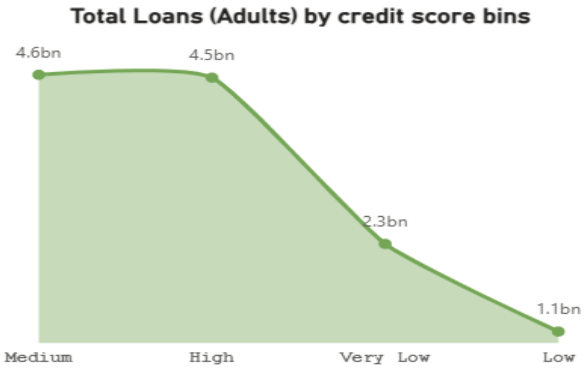
Average Loan Amount (High Credit) by Age Group & Marital Status



Average Loan Amt (High Credit) =
AVERAGEX(FILTER('Loan_default','Loan_default'[Credit Score Bins]="High"),'Loan_default'[LoanAmount])

To explore lending behavior among borrowers with strong credit profiles, I created a DAX measure to calculate the average loan amount specifically for the *High* credit score category. This measure was then visualized using a donut chart, segmented by marital status and age groups, to show how these demographics interact with loan sizes. The chart revealed that Single and Divorced borrowers in the Adult and Middle Age categories tend to have slightly higher average loan amounts compared to Married borrowers. Custom formatting, including color coding by age group and detailed labels showing both values and percentages, was applied to enhance readability. This visualization provided a multidimensional view of how marital status and age affect borrowing patterns within the high-credit borrower segment.

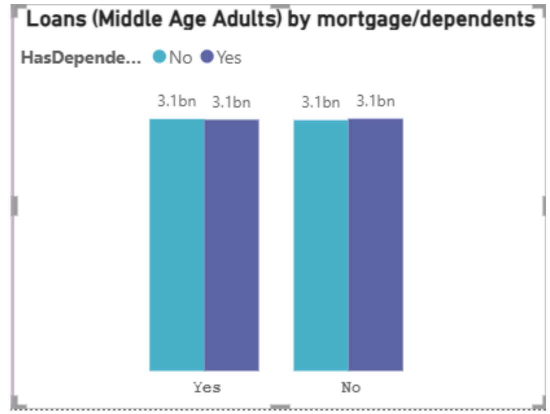
Total Loans (Adults) by Credit Score Bins



Total Loan (Credit Bins) =
CALCULATE(SUM('Loan_default'[LoanAmount]),'Loan_default'[Age Groups]="Adults",ALLEXCEPT('Loan_default','Loan_default'[Age],'Loan_default'[Age Groups],'Loan_default'[CreditScore],'Loan_default'[Credit Score Bins]))

To analyze loan distribution for adults across credit categories, I built a measure using `CALCULATE`, `SUM`, and `ALLEXCEPT` to compute the total loan amounts while keeping filters restricted to Age, Age Groups, Credit Score, and Credit Score Bins. This measure was then visualized in a line chart showing how loans were spread across credit score categories specifically for the Adult group. The chart highlighted that adults with Medium and High credit scores held the largest loan amounts, while those in the Low and Very Low categories had significantly lower totals. Finally, I validated these results by cross-checking with a table visual in Power BI and the original Excel dataset to ensure accuracy. This step ensured reliable insights into loan distribution patterns by credit quality for the adult population.

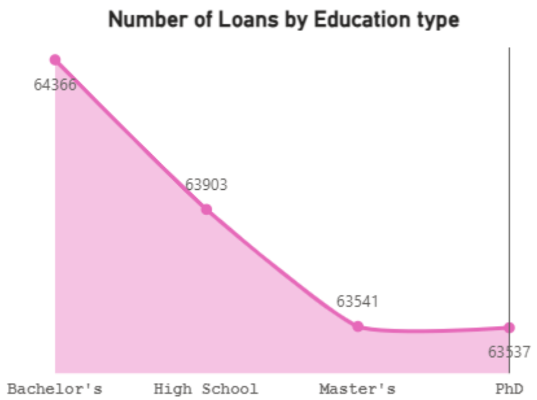
Loans (Middle Age Adults) by Mortgage/Dependents



Total Loan (Middle Age Adults) =
SUMX(FILTER('Loan_default','Loan_default'[Age Groups]="Middle Age Adults"),'Loan_default'[LoanAmount])

To analyze borrowing patterns among middle-aged adults, I created a DAX measure using the **SUMX** function, applying a filter to focus exclusively on this age group and summing their loan amounts. The results were then displayed in a **clustered column chart**, segmented by whether borrowers had dependents and whether they had an existing mortgage. This visualization provided a clear comparison, showing that loan amounts for middle-aged adults remained consistent across both categories, with each segment contributing around **3.1 billion** in loan value. By combining age group, dependents, and mortgage status, this analysis offered deeper insights into how family and housing responsibilities influence borrowing behavior.

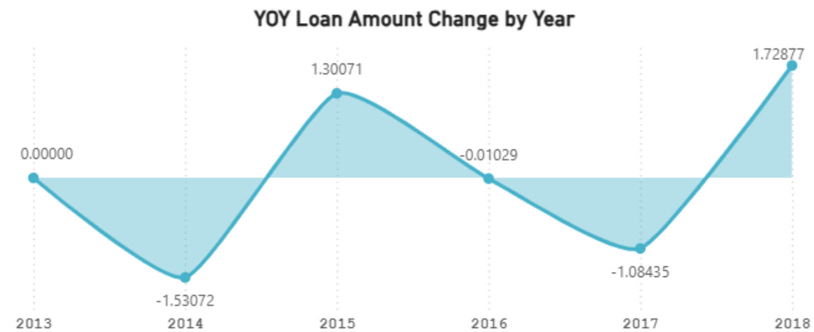
Number of Loans by Education Type



Loans by Education type =
COUNTROWS(FILTER('Loan_default',NOT(ISBLANK('Loan_default'[LoanID]))))

To assess how education level influences borrowing, I created a DAX measure that counts the number of valid loan records by ensuring only non-blank Loan IDs are included. This calculation was then visualized in a **line chart**, with education categories such as High School, Bachelor's, Master's, and PhD plotted on the x-axis. The chart highlighted that Bachelor's degree holders had the highest number of loans (64,366), while PhD holders showed the lowest (63,537). To ensure reliability, I validated these counts against both a table visual in Power BI and the original Excel dataset, confirming that the numbers aligned perfectly. This provided confidence in the accuracy of the measure and meaningful insights into how education level correlates with borrowing patterns.

YOY Loan Amount Change



YOY Loan Amount Change =
DIVIDE(

CALCULATE(SUM('Loan_default'[LoanAmount]),'Loan_default'[Year]=YEAR(MAX('Loan_default'[Loan_Date_DD_MM_YYYY]))) -

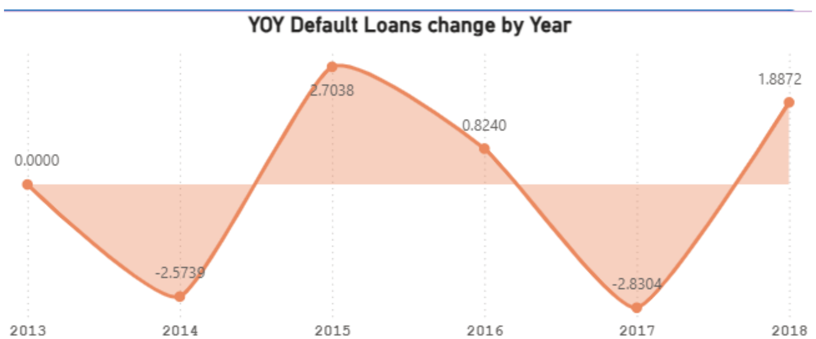
CALCULATE(SUM('Loan_default'[LoanAmount]),'Loan_default'[Year]=YEAR(MAX('Loan_default'[Loan_Date_DD_MM_YYYY]))-1)

,

CALCULATE(SUM('Loan_default'[LoanAmount]),'Loan_default'[Year]=YEAR(MAX('Loan_default'[Loan_Date_DD_MM_YYYY]))-1),0) * 100

To measure the year-on-year (YOY) change in loan amounts, a DAX formula was created using the **DIVIDE** function. The numerator was defined as the difference between the current year's loan amount and the previous year's loan amount, while the denominator captured the previous year's loan amount. This structure ensured accurate percentage growth or decline, with a safeguard against division by zero by returning zero when needed. Once the measure was created, it was visualized using a line chart with the year on the x-axis and YOY loan change on the y-axis. The results showed fluctuations across years, including declines in 2014 and 2017, and sharp growth in 2015 and 2018. By formatting the measure to display percentages with five decimal places, the analysis became more precise, clearly reflecting yearly variations in loan amounts and offering insights into lending trends over time.

YOY Default Loans Change



YOY Default Loans change =
DIVIDE(

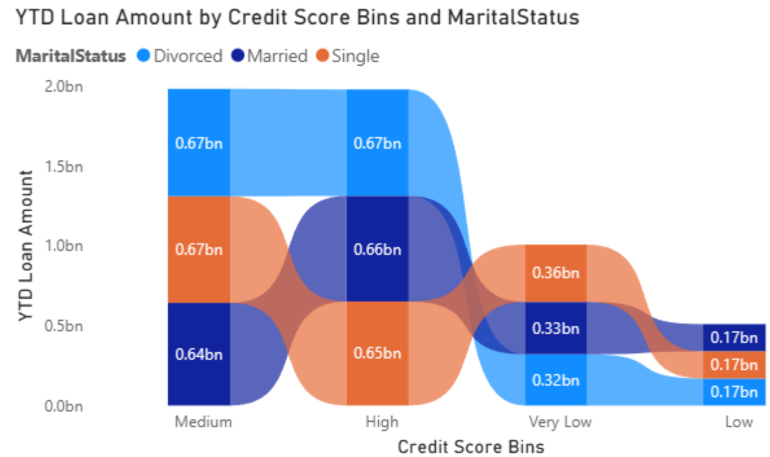
CALCULATE(COUNTROWS(FILTER('Loan_default','Loan_default'[Default]=TRUE())),'Loan_default'[Year]=YEAR(MAX('Loan_default'[Loan_Date_DD_MM_YYYY]))) -

CALCULATE(COUNTROWS(FILTER('Loan_default','Loan_default'[Default]=TRUE())),'Loan_default'[Year]=YEAR(MAX('Loan_default'[Loan_Date_DD_MM_YYYY]))-1)

,CALCULATE(COUNTROWS(FILTER('Loan_default','Loan_default'[Default]=TRUE())),'Loan_default'[Year]=YEAR(MAX('Loan_default'[Loan_Date_DD_MM_YYYY]))-1),0) * 100

To track changes in defaulted loans year over year, I built a DAX measure using `DIVIDE`, `CALCULATE`, `COUNTROWS`, and `FILTER`. The calculation compared the number of defaulted loans in the current year with the previous year and expressed the difference as a percentage. This allowed me to measure the increase or decrease in defaults relative to the prior year. I then visualized the results in a line chart, which highlighted key fluctuations—showing dips in 2014 and 2017, and sharp rises in 2015 and 2018. This insight provided a clear view of how loan defaults evolved over time.

YTD Loan Amount by Credit Score Bins and Marital Status

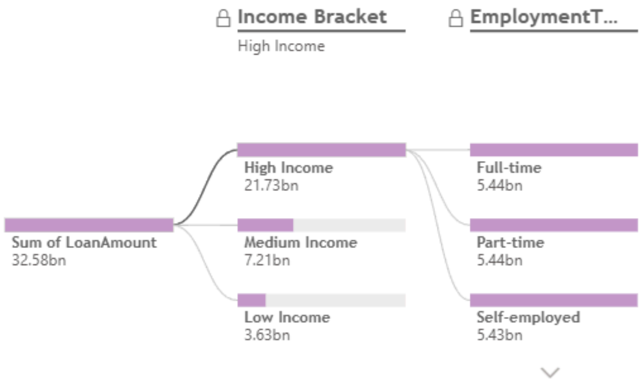


YTD Loan Amount =

CALCULATE(SUM('Loan_default'[LoanAmount]),DATESYTD('Loan_default'[Loan_Date_DD_MM_YYYY].[Date]),ALLEXCEPT('Loan_default',Loan_default[Credit Score Bins],Loan_default[MaritalStatus]))

The measure for calculating **YTD Loan Amount** uses the `CALCULATE` function with `SUM` over loan amounts, combined with `DATESYTD` to capture cumulative values from January 1st of the current year up to the latest available date. To ensure filtering applies only to **Credit Score Bins** and **Marital Status**, the `ALLEXCEPT` function is used, ignoring other filters. The resulting ribbon chart shows how loan amounts evolve across credit score categories while splitting them by marital status. From the visualization, **Medium and High credit scores dominate YTD loan amounts (around 0.64bn–0.67bn each per marital status group)**, while **Very Low and Low categories contribute significantly less (0.17bn–0.36bn)**. Marital status distribution is fairly even across bins, with no single group strongly dominating. This indicates that **borrowers with Medium and High credit scores are the primary contributors to overall loan volumes**, regardless of marital status.

Decomposition Tree: Loan Amount by Income Bracket & Employment Type




```
Income Bracket =
 SWITCH(
          TRUE(),
   'Loan_default'[Income]<30000,"Low Income",
          'Loan_default'[Income]>=30000 && 'Loan_default'[Income]<60000,"Medium Income",
          'Loan_default'[Income]>=60000, "High Income")
```

To analyze loan distribution by income levels, I created a calculated column called *Income Bracket* using the SWITCH function, which categorized borrowers into Low, Medium, and High Income groups based on their reported income. This classification was then used in a **Decomposition Tree** visual to break down the total loan amount first by income bracket and then further by employment type, such as Full-time, Part-time, and Self-employed. The results showed that the total loan amount stood at **32.58bn**, with High Income borrowers contributing the largest share (**21.73bn**), followed by Medium Income (**7.21bn**) and Low Income (**3.63bn**). Within the High Income category, the loan distribution was almost evenly split across employment types, with Full-time, Part-time, and Self-employed each accounting for around **5.44bn**. This visualization highlighted how income level and employment status together influence the scale of borrowing.