Lardieri Applied Statistical Modeling Midterm Project - Kiva Loans

Abstract

My interest is in the social sciences, and the use of data science for social good. From improving global health to city infrastructure, we can use data to help solve major societal issues. In my career, I'd like to contribute to these efforts.

I chose my project because it aligns with this goal. I'm interested in Kiva.org's cause because they empower so many individuals and communities around the world through crowdsourced loans, not donations. Anyone can go to the website, get familiar with someone's story and make a loan contribution.

Their website has a number of focus areas; women, single parents, conflict zones, water, and education to name a few. As a nonprofit, Kiva's mission is to connect people through lending to help alleviate poverty. Kiva supports 3 million borrowers in more than 80 countries, creating opportunities for individuals, their families, and their communities.

My project aims to take a deeper look at the Kiva loan data, to see if there are any underlying themes and behaviors that differ between regions and countries. Specifically, is there variation in category and amount of funding and to whom.

Method

The dataset is sourced and merged from 2 Kaggle datasets; loan detail from Kiva.org and regional multidimenisonal poverty index (MPI) detail. It was reshaped to have tag information per row (tags are additional information provided for borrowers, for example, "Elderly","Woman Owned Biz").

Variables $Partner.ID, Country, Region, WorldRegion, Sector, Activity, Use, Tags, Gender, Tags, Date, FundedLoanAmour$

Note that there is more data to be merged that will be relevant to analysis, loan theme by region, human development index, and population below the poverty line in the future. #Dataset 1: Kiva Loans The dataset contains the majority of the loan detail provided by Kiva.

```
##   partner_id funded_amount loan_amount         sector
## 1        247          2225        2225         Retail
## 2        334           250         250       Services
## 3        334           200         200    Agriculture
## 4        334           150         150 Transportation
## 5        334           250         250   Construction
## 6        334           250         250    Agriculture
##                  activity  country    region
## 1 Personal Products Sales Pakistan    Lahore
## 2                  Sewing    India Maynaguri
## 3                   Dairy    India Maynaguri
## 4          Transportation    India Maynaguri
## 5    Construction Supplies    India Maynaguri
## 6                 Farming    India  Dhupguri
##                                          borrower_genders
## 1 female,female,female,female,female,female,female,female
## 2                                                  female
## 3                                                  female
```

Figure 1: Data Science for Social Good.

```
## 4                                                      female
## 5                                                      female
## 6                                                      female
##                                                                                        use
## 1                                                        to buy hair oils to sell.
## 2                                                    to purchase a sewing machine.
## 3                          To purchase a dairy cow and start a milk products business .
## 4  To repair their old cycle-van and buy another one to rent out as a source of income
## 5 to purchase stones for starting a business supplying stones to building contractors.
## 6                                          to cultivate broad beans on her own land.
##   term_in_months       date month year
## 1             11 2014-01-01    01 2014
## 2             43 2014-01-01    01 2014
## 3             43 2014-01-01    01 2014
## 4             43 2014-01-01    01 2014
## 5             43 2014-01-01    01 2014
## 6             43 2014-01-01    01 2014
##                                      tags Female.count Male.count
## 1 #Parent, #Repeat Borrower, user_favorite            8          0
## 2             user_favorite, user_favorite            1          0
## 3             user_favorite, user_favorite            1          0
## 4             user_favorite, user_favorite            1          0
## 5             user_favorite, user_favorite            1          0
## 6             user_favorite, user_favorite            1          0
##   Woman.Biz M.F.loan F.loan M.loan F.only.loan M.only.loan fully.funded
## 1         0        0      1      0           1           0            1
## 2         0        0      1      0           1           0            1
```

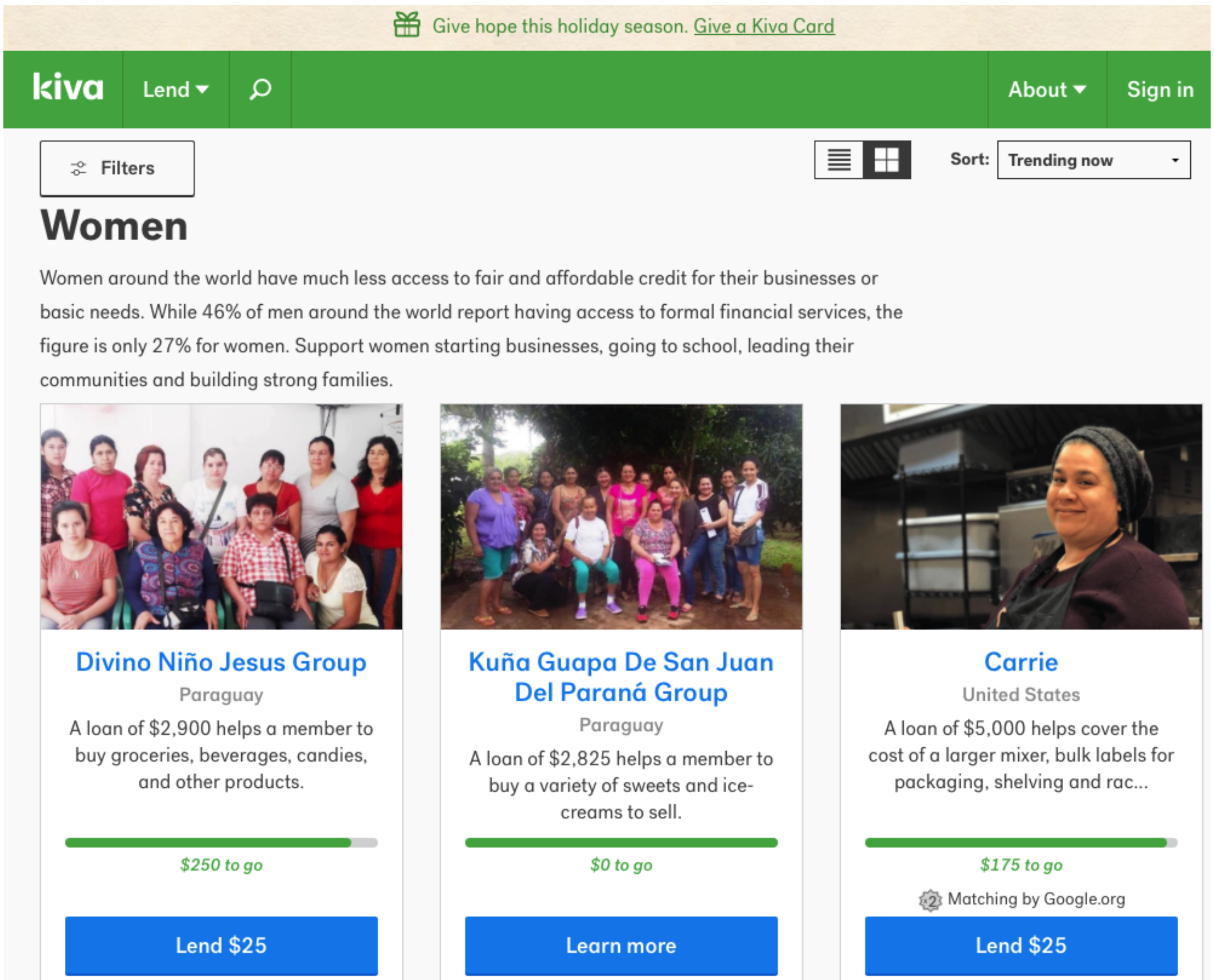


Figure 2: Kiva.org.

```
## 3         0        0      1      0           1           0             1
## 4         0        0      1      0           1           0             1
## 5         0        0      1      0           1           0             1
## 6         0        0      1      0           1           0             1
##   unfunded partial.funded Gender Gender.Var Water
## 1        0              0 female          1     0
## 2        0              0 female          1     0
## 3        0              0 female          1     0
## 4        0              0 female          1     0
## 5        0              0 female          1     0
## 6        0              0 female          1     0
```

Dataset 2: Multidimensional Poverty Index (MPI) and World Region Detail

This dataset contains World Region and MPI variables.

```
##       country     region world_region   MPI
## 1 Afghanistan Badakhshan   South Asia 0.387
## 2 Afghanistan    Badghis   South Asia 0.466
## 3 Afghanistan    Baghlan   South Asia 0.300
## 4 Afghanistan      Balkh   South Asia 0.301
## 5 Afghanistan     Bamyan   South Asia 0.325
## 6 Afghanistan   Daykundi   South Asia 0.313
```

Datasets Merged

This is one iteration of the dataset. I summarized loans and MPI separately by world region, region, and country for analysis.

```
## # A tibble: 6 x 4
## # Groups:   country [6]
##   country      MPI_country sumloan_amount sumfunded_amount
##   <chr>              <dbl>          <dbl>            <dbl>
## 1 Afghanistan       0.310          0.014            0.014
## 2 Burundi           0.412          2.28             2.17
## 3 Benin             0.320          0.05             0.05
## 4 Burkina Faso      0.548          2.7              2.64
## 5 Belize            0.0201         0.078            0.078
## 6 Brazil            0.0273         0.596            0.595
```

The Loans: Distribution of Fully Funded, Partially Funded, and Unfunded Loans

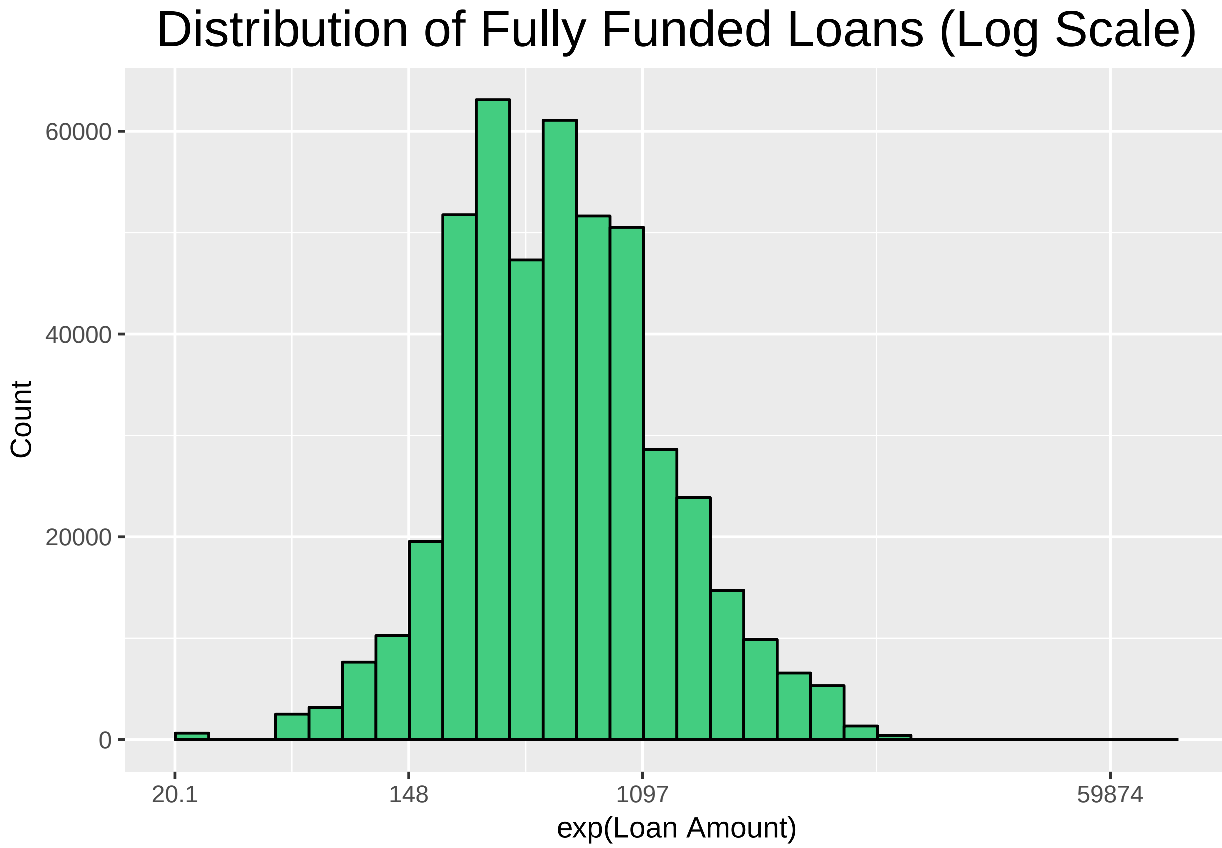
Not all loans receive full funding.

```
## [1] "No. of Fully Funded Loans = 423089"
```

```
## [1] "No. of Unfunded Loans = 2054"
```

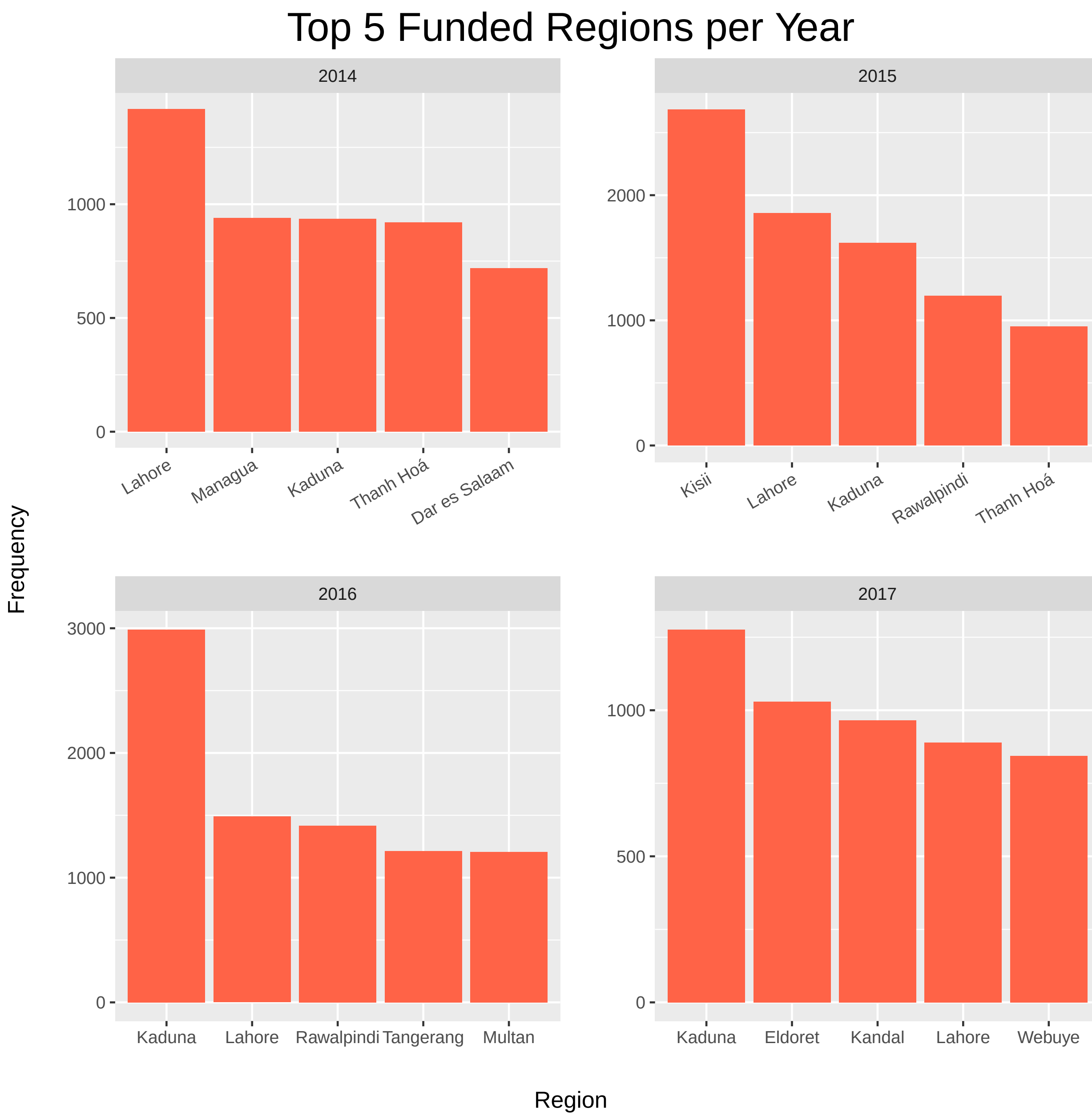
```
## [1] "No. of Partially Funded Loans = 37022"
```

```
## [1] "No. of Over Funded Loans = 2"
```



In the dataset, an unfunded loan is $FundedAmount$=$0, a partially funded loan is funded amount

From the bar plots, the top funded countries are consistently the Philippines and Kenya each year, Cambodia is also frequntly funded.



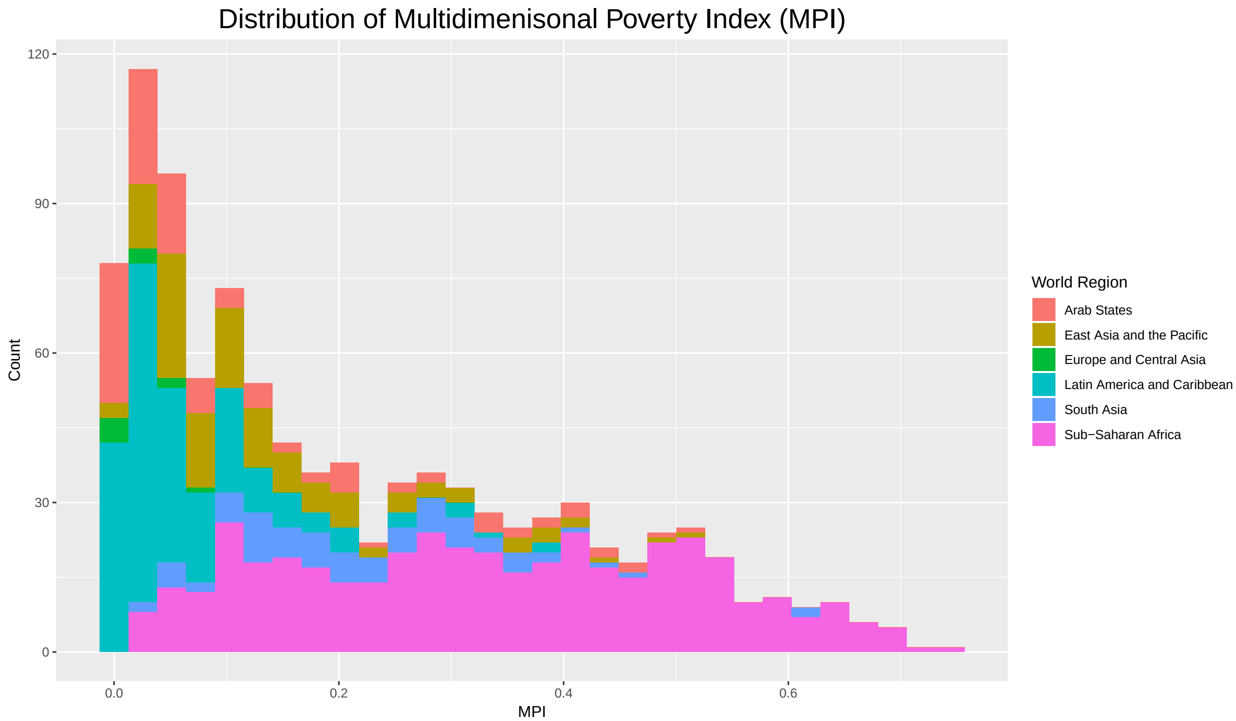
From the bar plot, there is a mix of top regions that are top funded per year.

Is there a relationship between frequently funded regions/countries and MPI?

Funded Loan Amount and Poverty Index (MPI)

Here we introduce MPI and the 6 World Regions. This includes only regions and countries with an MPI.

```
## [1] "Max MPI = 0.74"
## [1] "Min MPI = 0.00"
## [1] "Med MPI = 0.15"
## [1] "Mean MPI = 0.21"
```

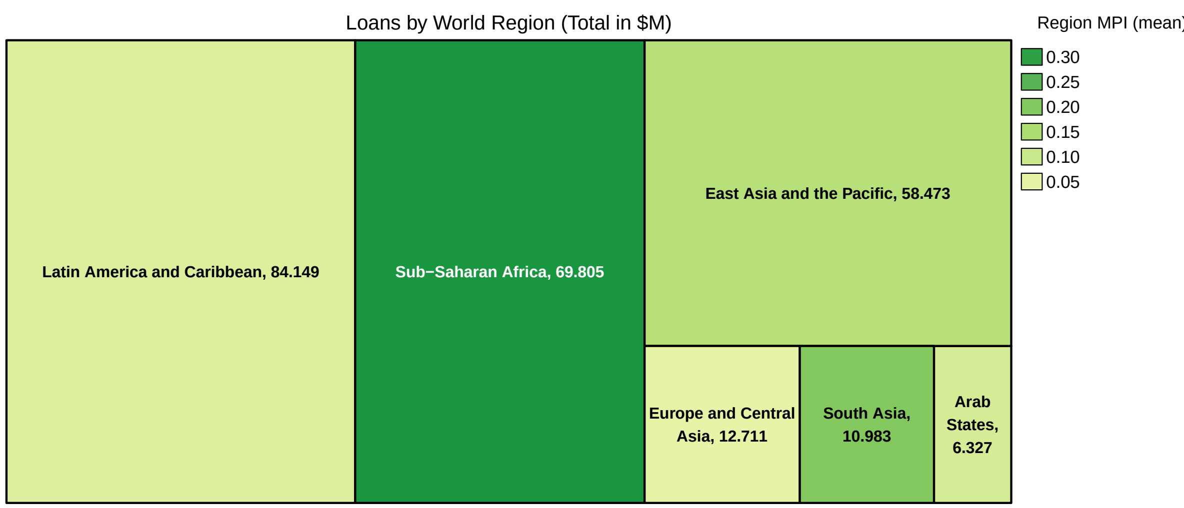


From distribution, the poorest world regions are Sub-Saharan Africa and South Asia. What proportion of loans are these $WorldRegions$ receiving?

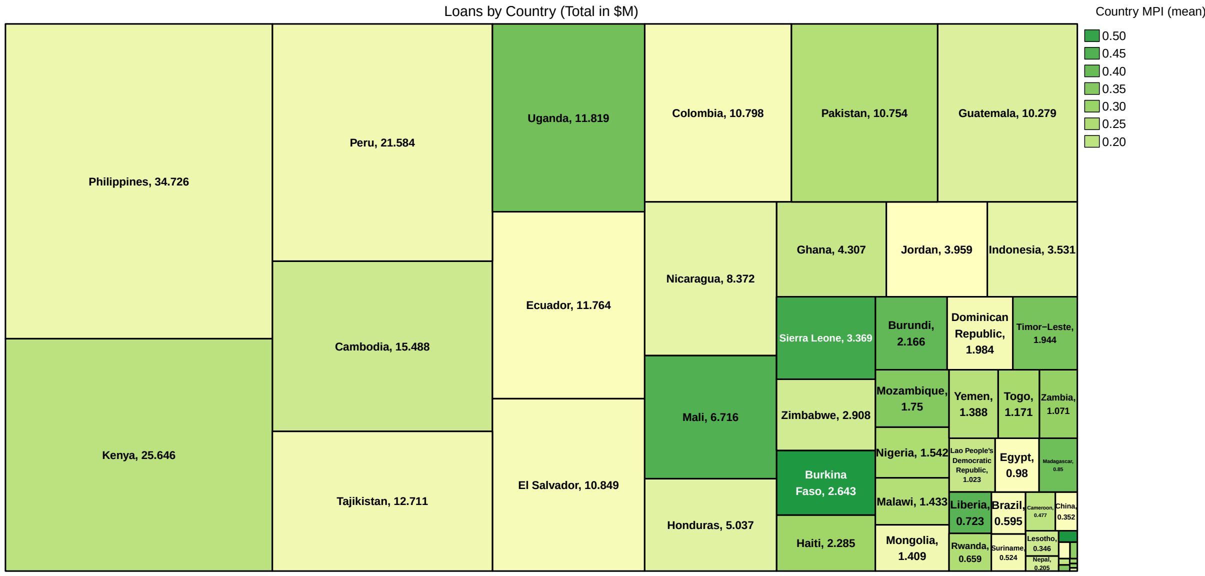
```
## [1] "No. of Total Regions = 928"
```

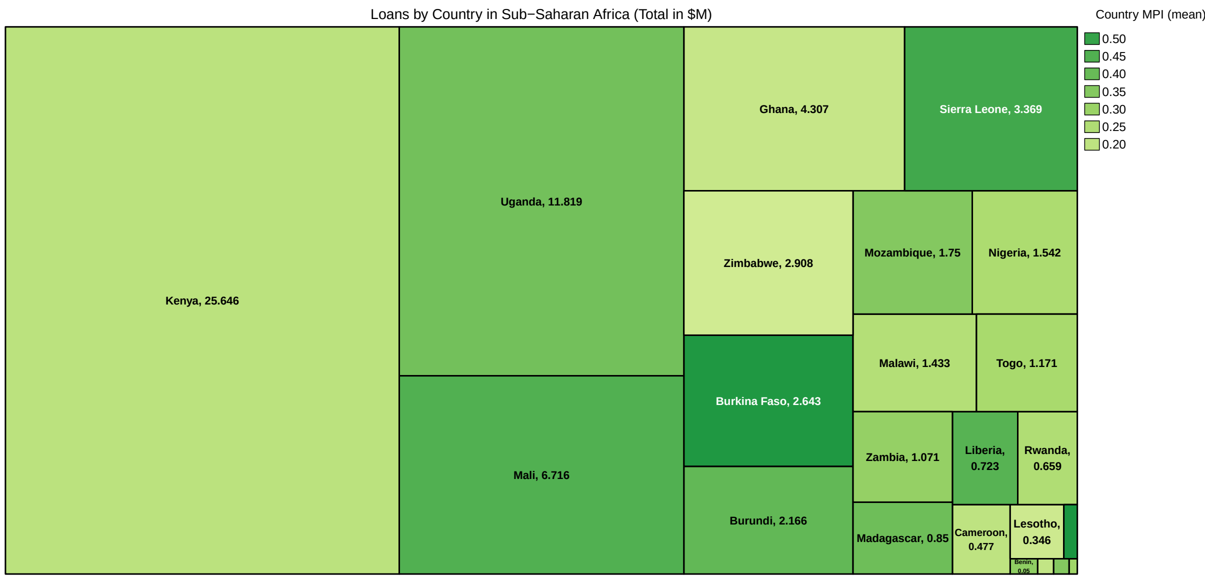
```
## [1] "No. of Total Countries = 102"
```

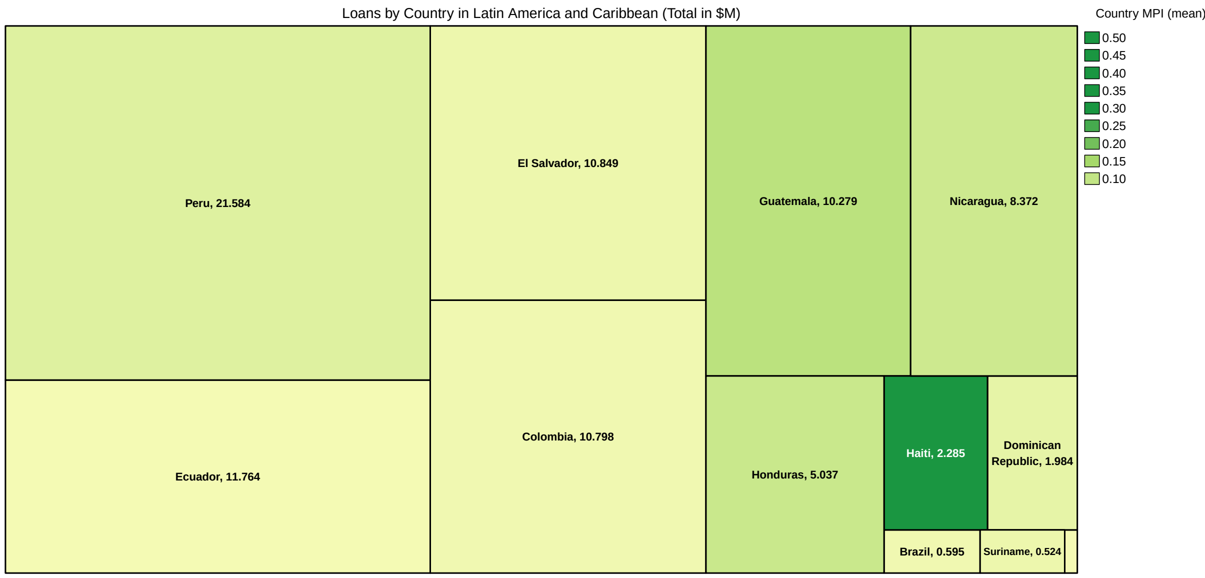
```
## [1] "No. of Total World Regions = 6"
```

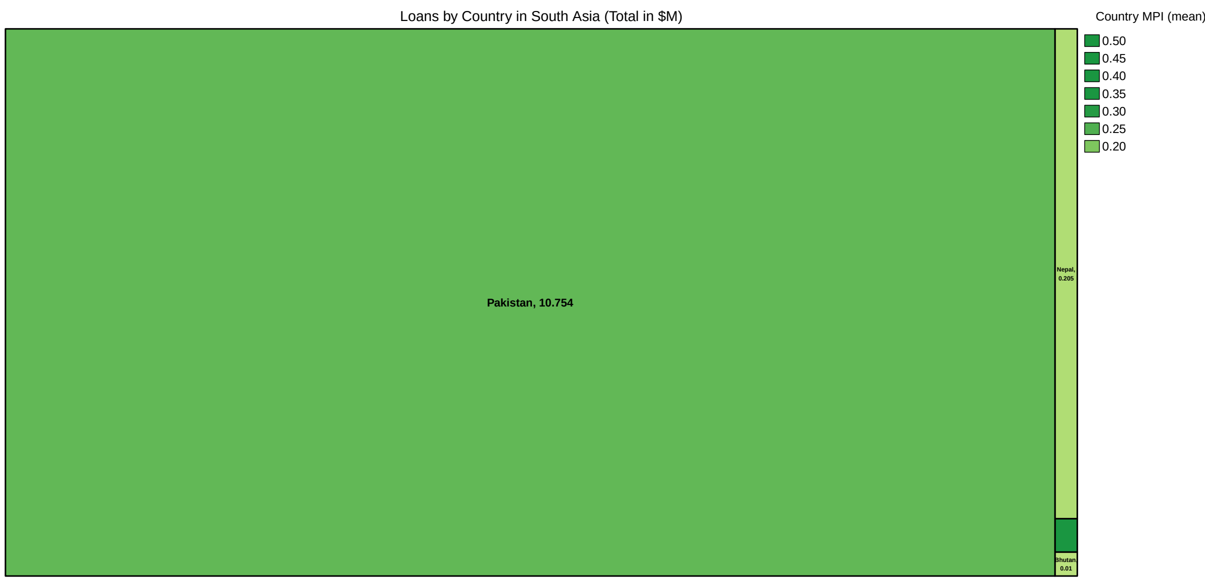


As we saw from the MPI distribution, Sub-Saharan Africa is the poorest $WorldRegion$. From the treemap, Sub-Saharan Africa has received a large portion of the total funded loans. While South Asia, high on the poverty index, receives the second smallest portion of funded loans. South Asia might be an area to focus on to identify loan trends.


Loans by Country (Total in $M)
Country MPI (mean)
0.50
0.45
0.40
0.35
0.30
0.25
0.20
Philippines, 34.726
Kenya, 25.646
Peru, 21.584
Cambodia, 15.488
Tajikistan, 12.711
Uganda, 11.819
Ecuador, 11.764
El Salvador, 10.849
Colombia, 10.798
Pakistan, 10.754
Guatemala, 10.279
Nicaragua, 8.372
Mali, 6.716
Honduras, 5.037
Ghana, 4.307
Jordan, 3.959
Indonesia, 3.531
Sierra Leone, 3.369
Zimbabwe, 2.908
Burkina Faso, 2.643
Haiti, 2.285
Burundi, 2.166
Dominican Republic, 1.984
Timor−Leste, 1.944
Mozambique, 1.75
Nigeria, 1.542
Malawi, 1.433
Mongolia, 1.409
Yemen, 1.388
Togo, 1.171
Zambia, 1.071
Lao People's Democratic Republic, 1.023
Egypt, 0.98
Madagascar, 0.85
Liberia, 0.723
Brazil, 0.595
Cameroon, 0.477
China, 0.352
Rwanda, 0.659
Suriname, 0.524
Lesotho, 0.346
Nepal, 0.205


Loans by Country in Sub−Saharan Africa (Total in $M)
Country MPI (mean)
0.50
0.45
0.40
0.35
0.30
0.25
0.20
Kenya, 25.646
Uganda, 11.819
Mali, 6.716
Ghana, 4.307
Sierra Leone, 3.369
Zimbabwe, 2.908
Burkina Faso, 2.643
Burundi, 2.166
Mozambique, 1.75
Nigeria, 1.542
Malawi, 1.433
Togo, 1.171
Zambia, 1.071
Liberia, 0.723
Rwanda, 0.659
Madagascar, 0.85
Cameroon, 0.477
Lesotho, 0.346
Benin, 0.05



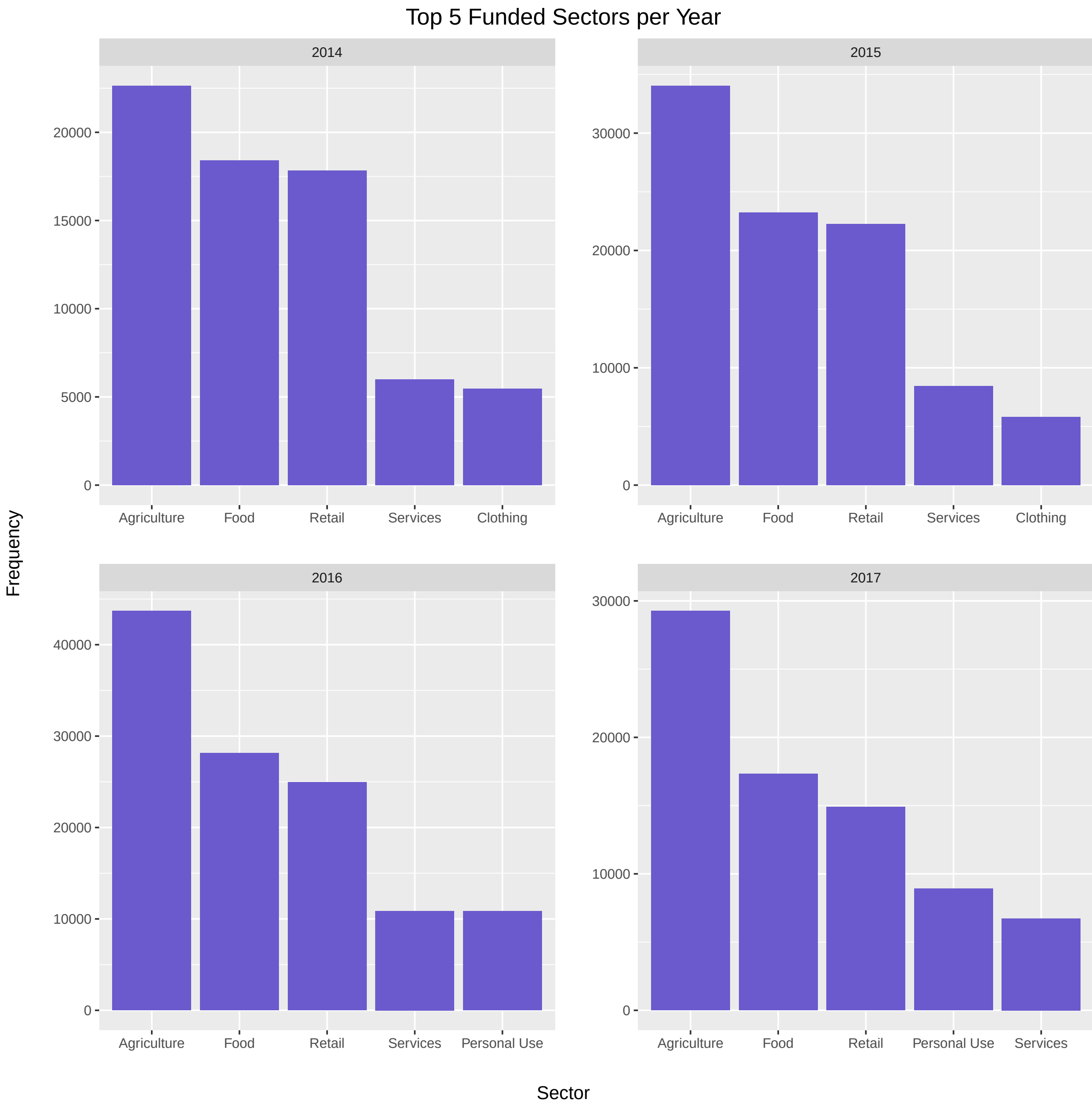


From these treemaps, some of the poorest countries are receiving a small portion of the total Kiva loans. Can see the darker green more prominent in the lower most corner.

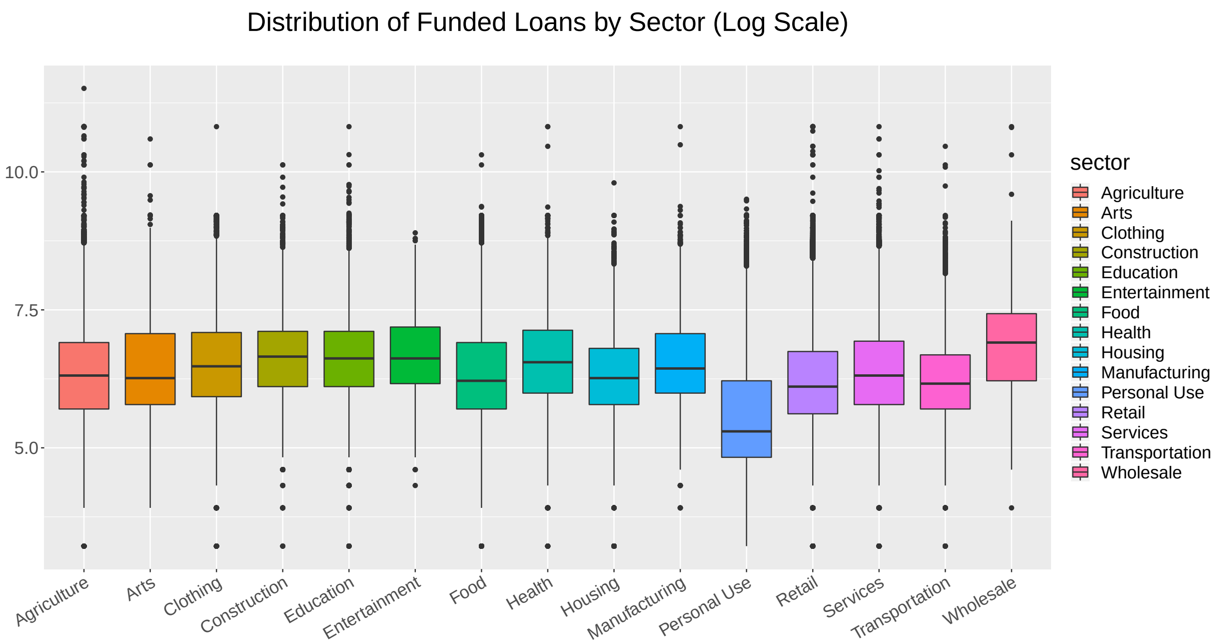
Burkina and South Sudan within Sub-Saharan Africa, Haiti within Latin America and Caribbean, and Afghanistan within South Asia are receiving a small portion of the funded amounts.

Again, these areas of focus for loan trends and what is driving these differences. One thing to consider are potential sector and activity differences between the regions/countries. Do the loan needs of the poorer countries cost less than the others? Can we use this to estimate poverty levels and needs for those countries?

Frequently Funded Sectors

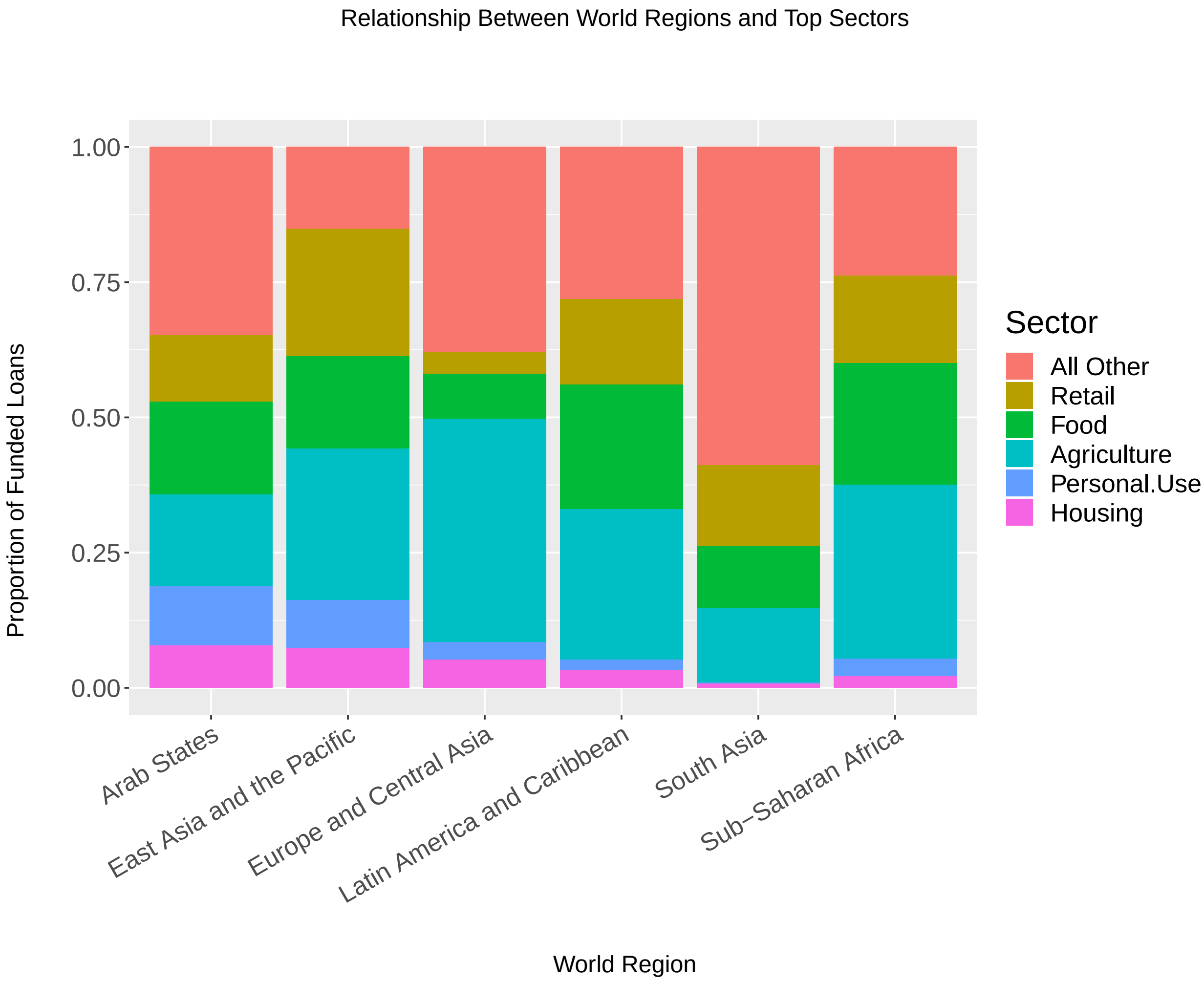


From the bar plots, the most frequently funded *sectors* are consistently Agriculture, Food, and Retail. What is the overall loan distribution among the sectors?



From the box plot, there is some variation in the loan amounts among the *sectors*. The Food, Housing, and Personal Use sectors have the lowest medians. This could correspond to what we saw from the treemaps. So, what is the funded loan breakdown for these top sectors for World Region and Country?

Proportion of Funded Loans for Sectors by World Region



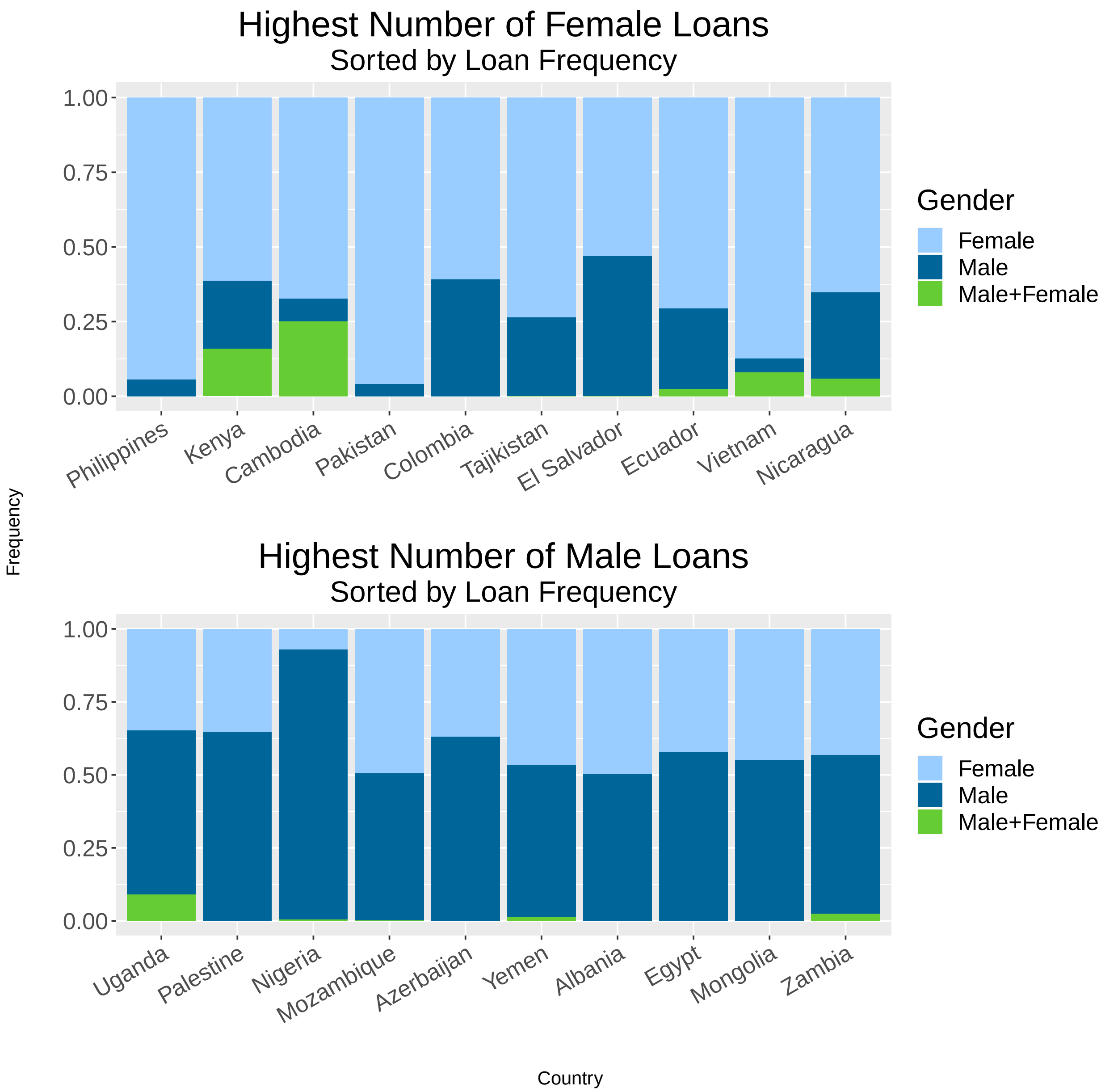
The chart indicates that Agricultural loans make up a good portion of the funded loan amounts. Recalling both the treemap by World Region and the sector boxplots, I would have expected a larger proportion of Personal Use and Housing within Sub-Saharan Africa and South Asia. (I will revisit this). Now we will take a look how *Gender* plays a role in the dataset.

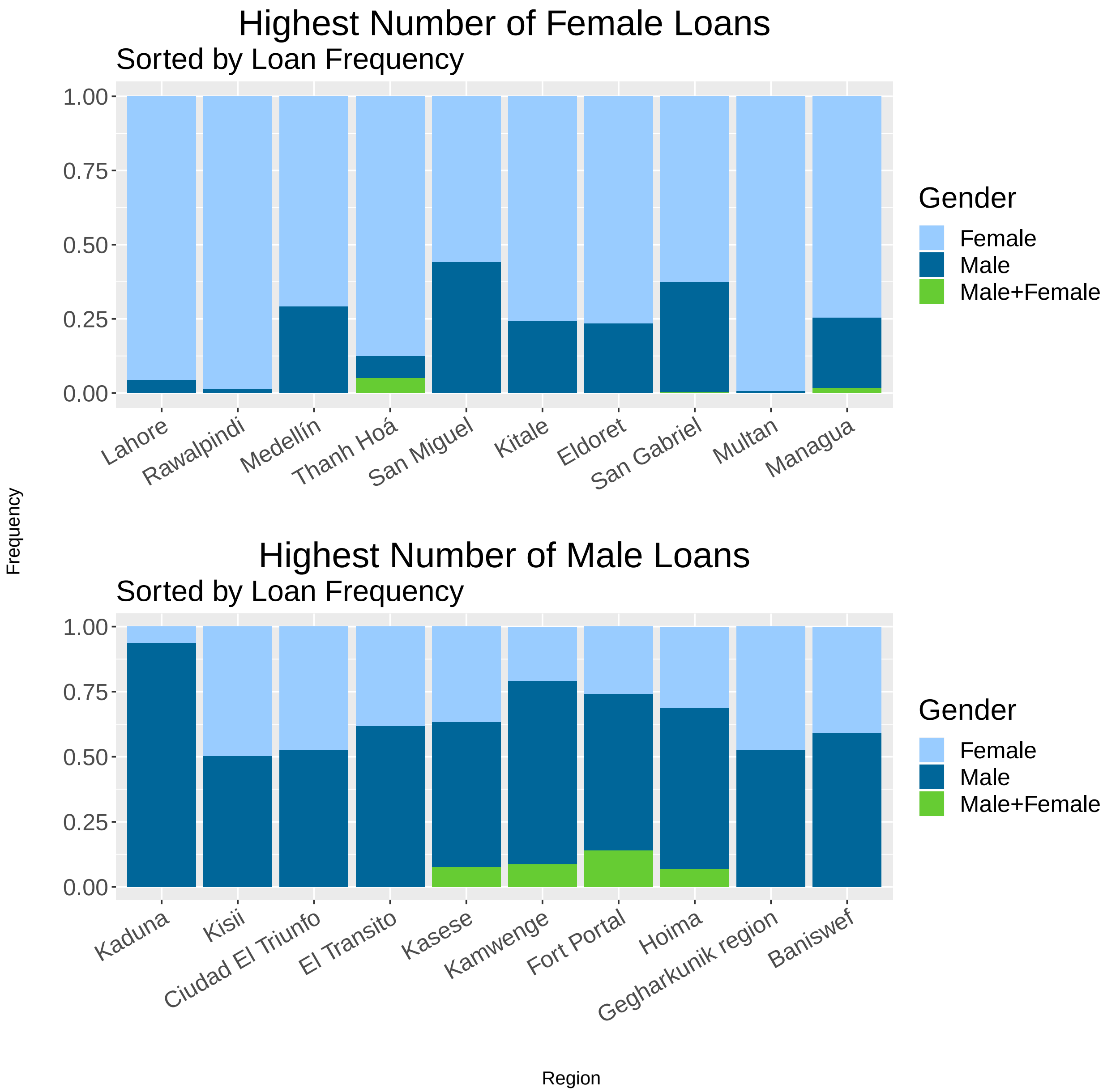
Loan Breakdown by Gender

Now that we have a sense for the loans

```
## [1] "No. of Total Loans = 462167"
## [1] "Female Only Loans = 70%"
## [1] "Male Only Loans = 23%"
## [1] "Female+Male Loans = 7%"
## [1] "Total Loans - Funded = 92%"
## [1] "Female Only Loans - Funded = 94%"
## [1] "Male Only Loans - Funded = 83%"
```

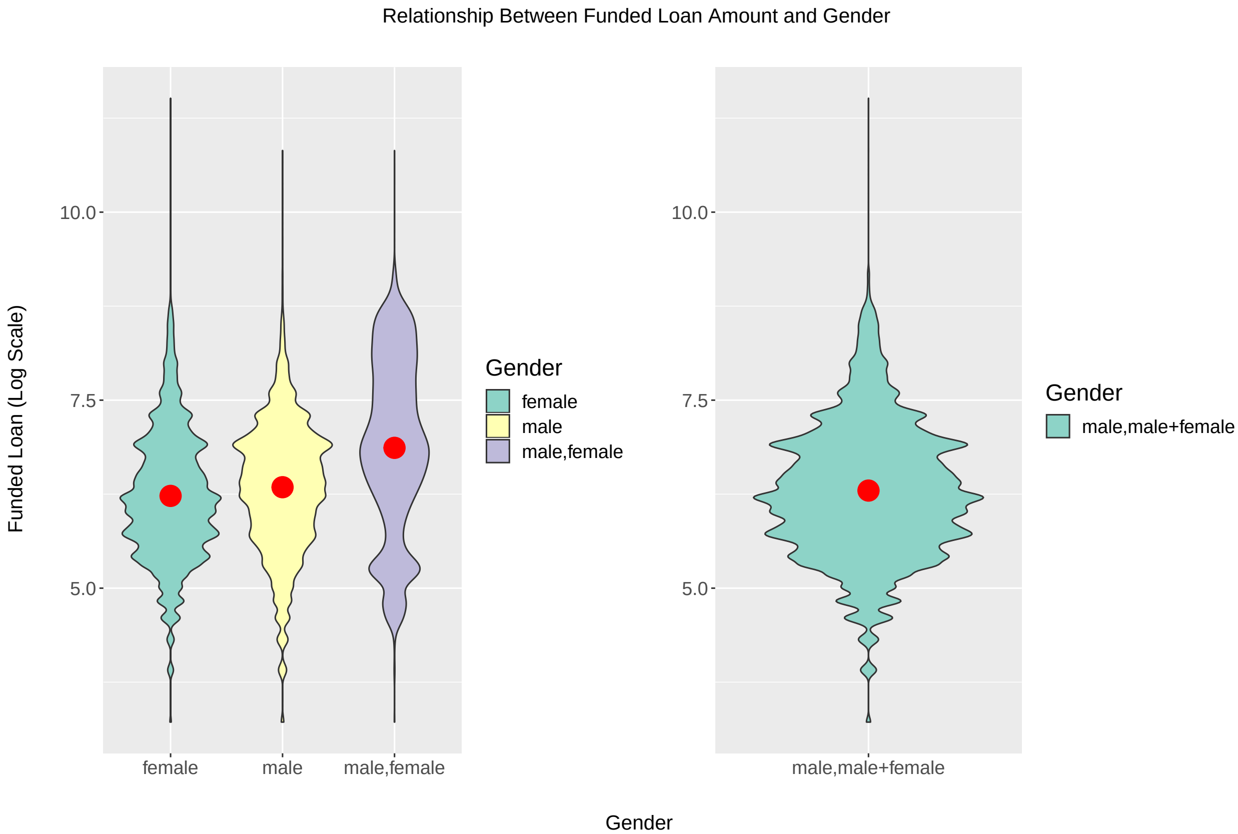
```
## [1] "Female+Male Loans - Funded = 92%"
```





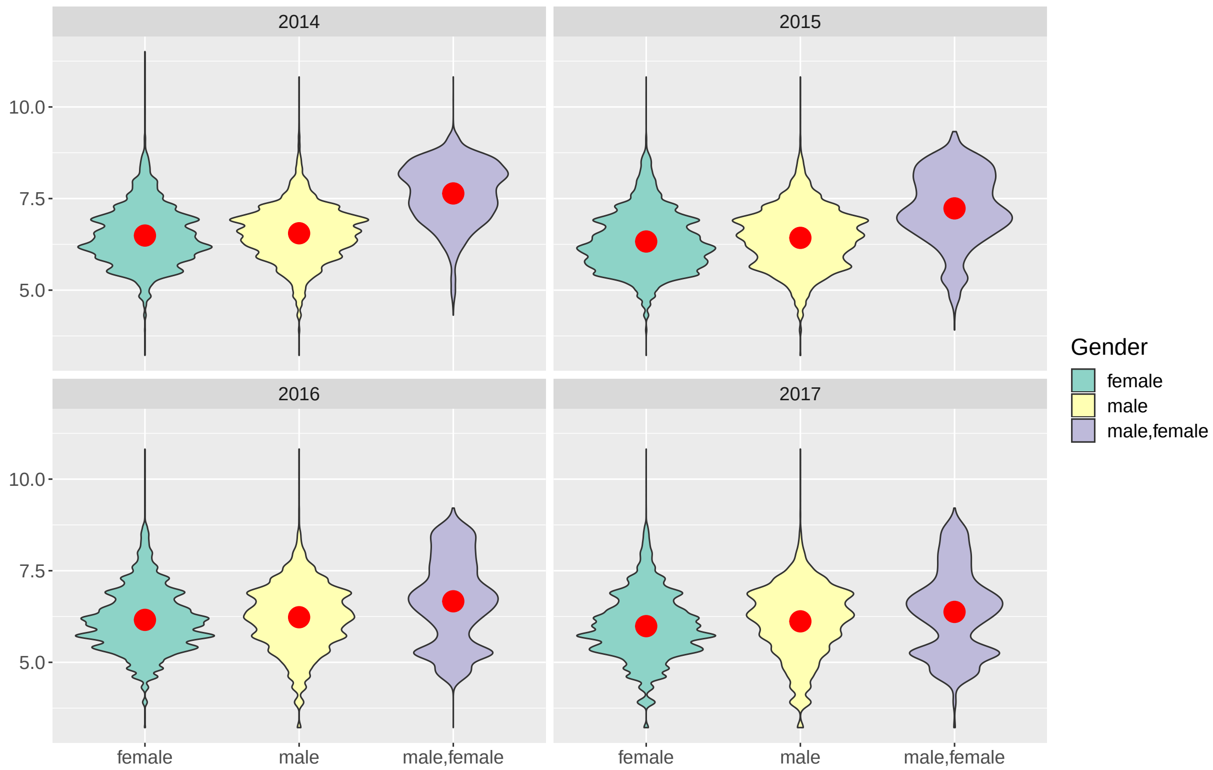
These charts provide good summaries for the *Gender* differences across countries and regions. There are clear differences among the countries and regions for who is taking out the loan.

Loan Breakdown by Gender



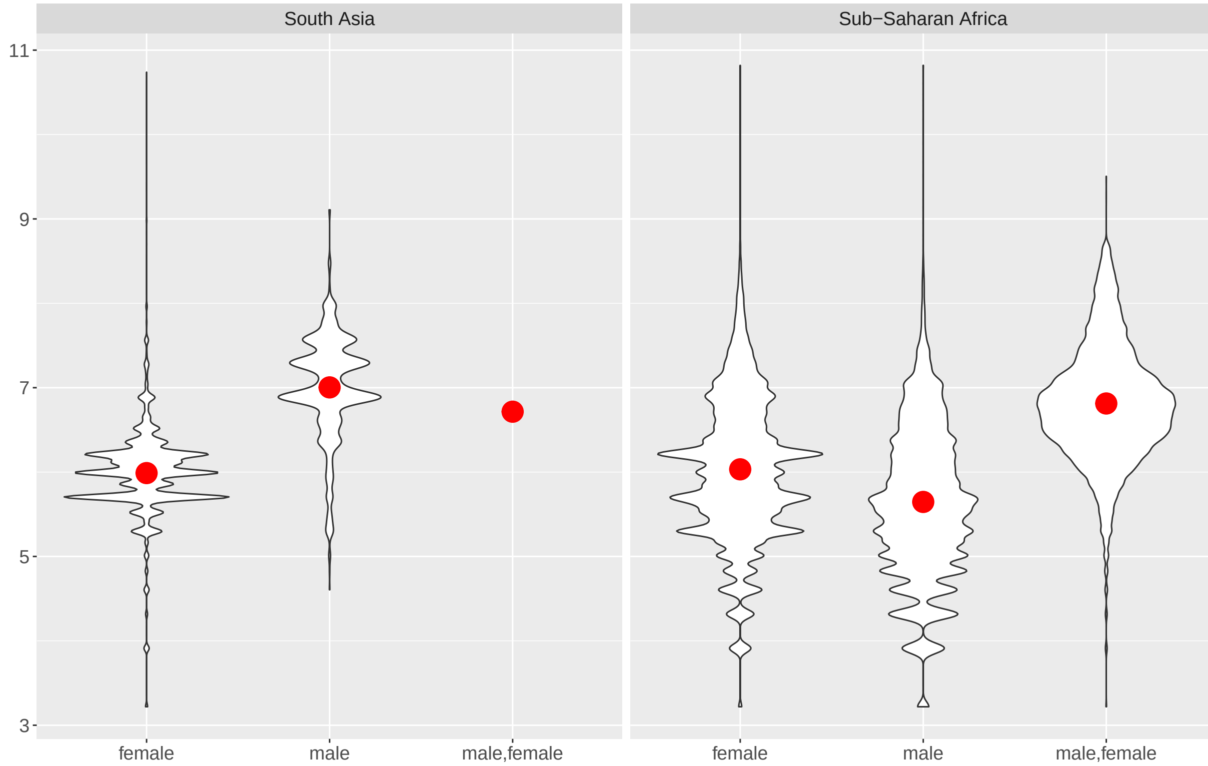
From the violin plots, there is a difference in the average funded loan amount (red dot) between females and males on an overall basis.

We may see even bigger differences by looking at the gender differences across World Regions and Countries and over time.

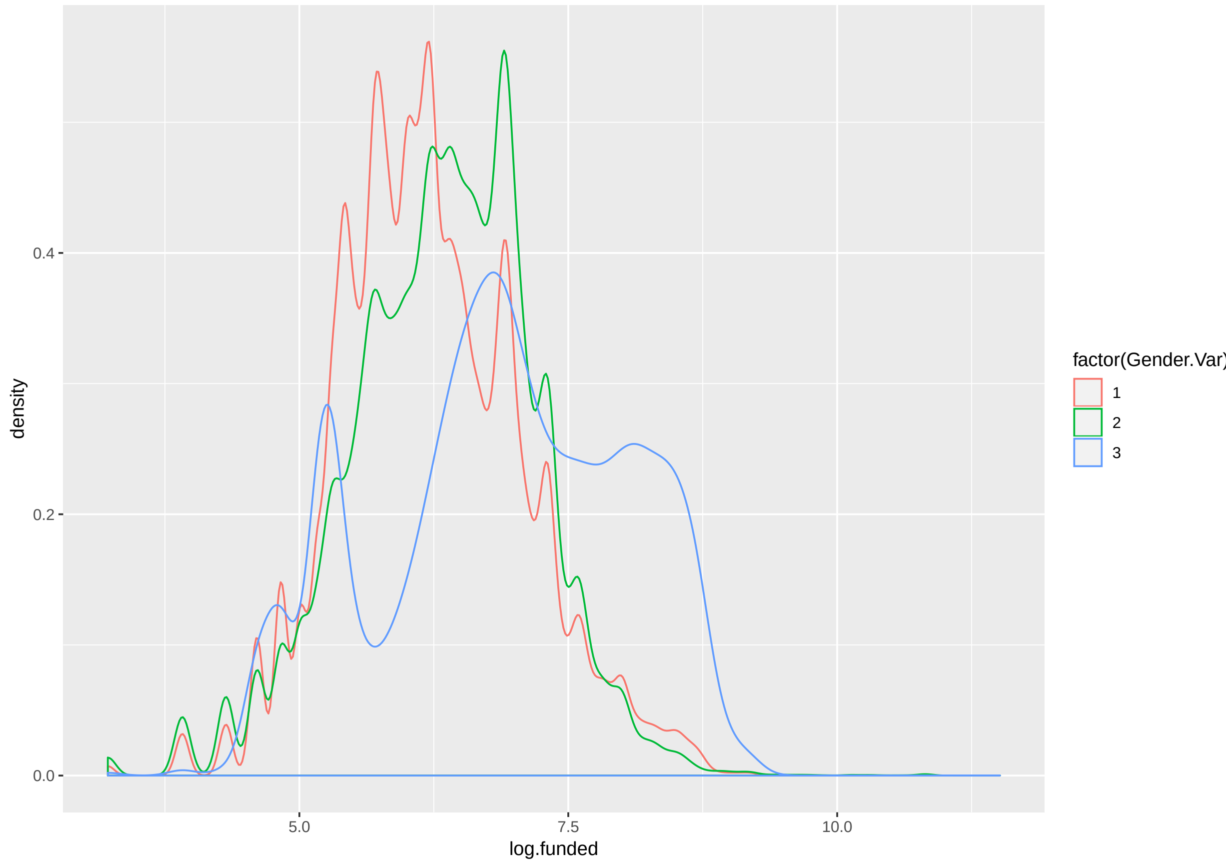


From the violin plots by year, the average loans overall seem to be decreasing, but also leveling between female, male, and male+female.

We may see something interesting across World Regions and Countries.



There was just one loan that had male,female variable for South Asia (in 2014). (We will revisit this in more detail in our modeling)



Multilevel Model

This is a work in progress. There are many different levels to this dataset.

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: log.funded ~ Gender.Var + sector + (1 + Gender.Var | country)
##    Data: fit1.data
##
## REML criterion at convergence: 924421
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -7.0133 -0.5798 -0.0108  0.6249  8.4946
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  country  (Intercept) 1.2636   1.1241
##           Gender.Var  0.1395   0.3734   -0.77
##  Residual             0.4356   0.6600
## Number of obs: 460113, groups:  country, 82
##
## Fixed effects:
##                       Estimate Std. Error  t value
## (Intercept)           6.790185   0.128360   52.899
## Gender.Var            0.130558   0.044362    2.943
```

```
## sectorArts            0.069592   0.007852    8.863
## sectorClothing        0.070697   0.004977   14.204
## sectorConstruction    0.079784   0.010421    7.656
## sectorEducation      -0.081100   0.004993  -16.241
## sectorEntertainment   0.167618   0.030477    5.500
## sectorFood            0.062365   0.003119   19.993
## sectorHealth         -0.126373   0.008485  -14.894
## sectorHousing        -0.206266   0.005106  -40.400
## sectorManufacturing   0.159284   0.010891   14.626
## sectorPersonal Use   -0.820076   0.005366 -152.837
## sectorRetail          0.067672   0.003238   20.897
## sectorServices        0.026327   0.004409    5.971
## sectorTransportation -0.043479   0.006771   -6.421
## sectorWholesale       0.381844   0.030321   12.594
```

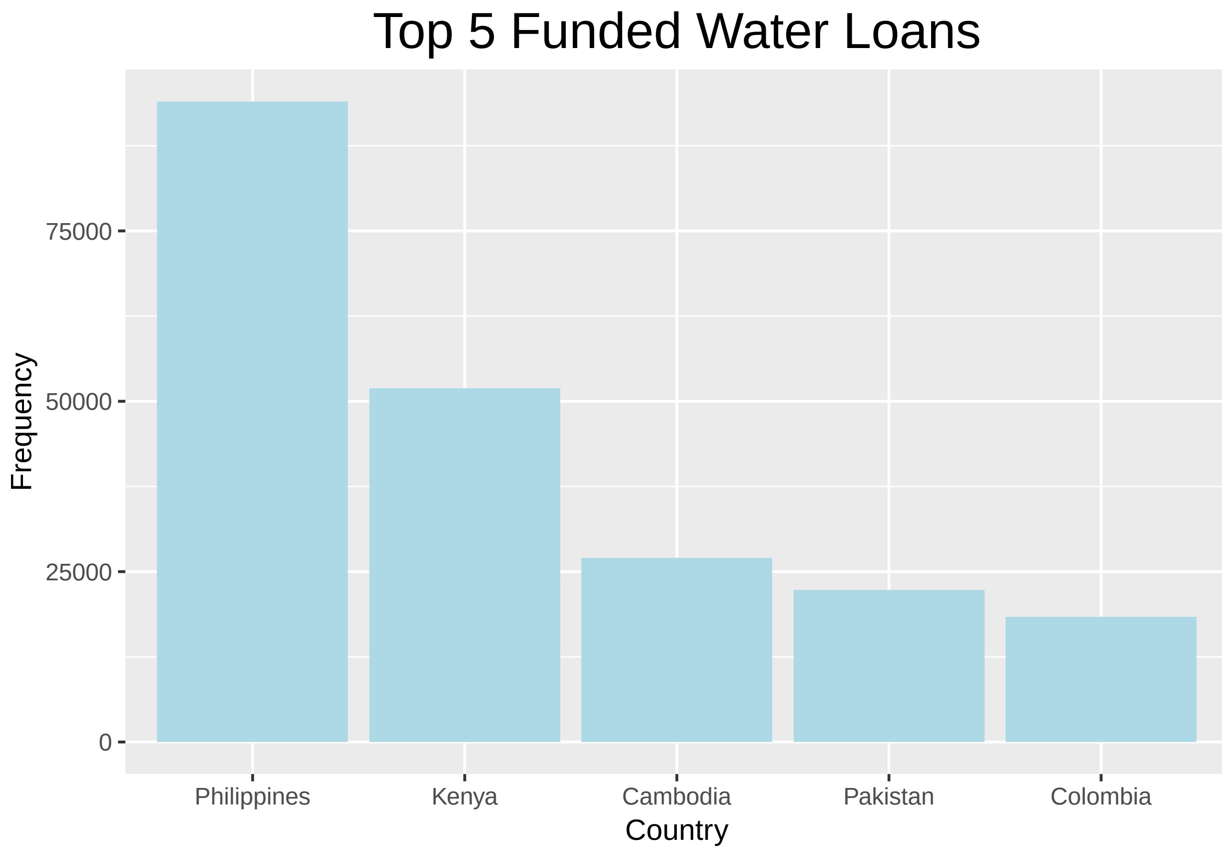
Conclusion/Next Steps

There is a lot to consider in this analysis. This project is ongoing and will be diving deeper into modeling next. It is important to understand the underlying themes and behaviors that differ between regions and countries. This data can help Kiva in supporting these areas.

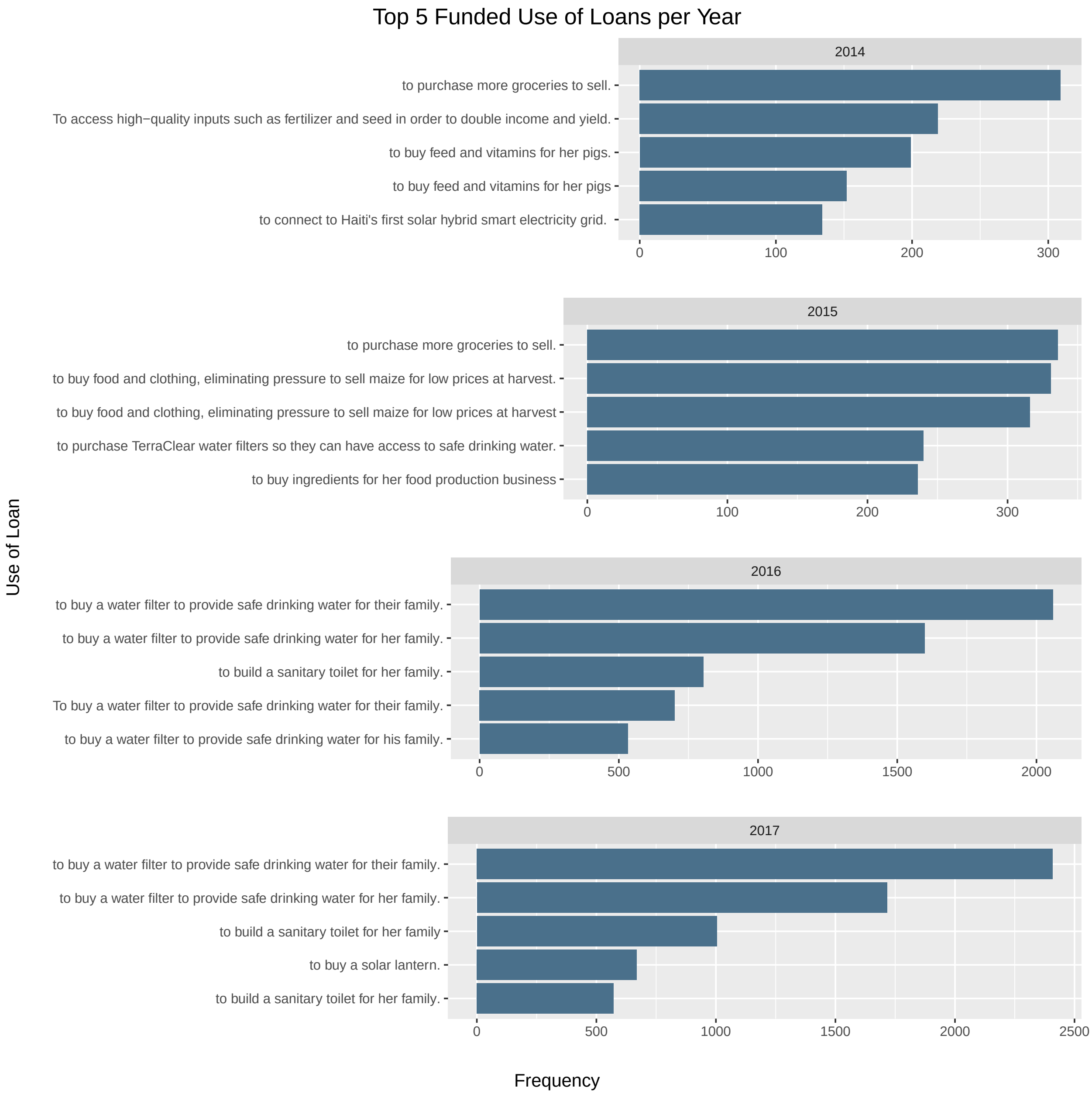
Appendix

Items to look at in the future:

Where is the use of water loan most prevelant?



How are loans being used?



From the bar plots, there is some variation in the use of the loan. For water uses, does this vary by region and become more prominent during dry seasons? If there is an expected dry season can we expect water loans to increase?

```
#- Most imporverished areas
#- What is being funded/partially funded/not funded and likelihood?
#- Female vs. male borrowers and whether having a male in the group affects loan behavior?
#- Repeat and type of borrowers
#EDA plot outcome on number of F and number of male and ratio of male count to female count to inform u
#Does a male impact on the loan.
#Number of females might not matter, but once adding in a male that could affect the loan amount.
#Linear regression model per country on amount of loan for gender
```