

# Dependence of risks on product logic

## (5. Audience structure, last year)

Problem statement:

**Hypothesis:** Locations with a low proportion of active women have a higher risk level.

**What to check:**

- Build a map of the proportion of active women in locations.
- Correlation between the proportion of active women and fraud metrics in a location.

To check whether there is a correlation between the proportion of active women and fraud metrics (we will consider fraud\_rate\_usd, vamp\_rate\_orders, chargeback\_rate\_usd/orders, decline\_rate\_orders, alert\_rate\_usd/orders, complaints\_rate\_usd/orders, and the percentage of unsubscribes immediately after subscriptions) in different countries, we first need to collect data on active women.

We will take data for the last year and review it on the Web, as it has the highest risk of fraud, within two product groups - A and B. We will consider those users who perform at least one activity consistently at least once a week to be active. Such generous limits for defining active users may inflate their actual number in some way, but it is important for us to study general trends, so we will accept this for now.

We calculate the main metrics as follows:

*Fraud\_rate\_usd: Calculate the sum of all payments where fraud = 1 divided by the sum of all payments.*

*Vamp\_rate\_orders: Calculate the number of orders from a.ov divided by the number of all orders in a.opdp.*

*Chargeback\_rate\_usd: Calculate the sum of all payments where chb = 1 divided by the sum of all payments.*

*Chargeback\_rate\_orders: Calculate the number of orders where chb = 1 divided by the number of all orders.*

*Decline\_rate\_orders: We calculate the number of orders where o\_status = 'decline' divided by the number of all orders (we do not calculate Decline\_rate\_usd because in all payments where o\_status = 'decline', g\_usd is always equal to 0, so decline\_rate\_usd = 0 is always true).*

*Alert\_rate\_usd: We calculate the sum of all payments where chb\_p\_dt IS NOT NULL divided by the sum of all payments.*

*Alert\_rate\_orders: We calculate the number of all payments where chb\_p\_dt IS NOT NULL divided by the number of all payments.*

*Complaints\_rate\_usd: We calculate the sum of all payments whose users are in the a.ccbd table, divided by the sum of all payments.*

*Complaints\_rate\_orders: We calculate the number of all payments whose users are in the a.ccbd table, divided by the number of all payments.*

*Unsubs\_rate\_usd: We calculate the sum of all subscription purchases that the user canceled within 24 hours after purchase, divided by the sum of all payments.*

*Unsubs\_rate\_orders: We calculate the number of all subscription purchases that the user canceled within 24 hours after purchase, divided by the number of all payments.*

*We take the unsubscription data from the p.uf table.*

We will limit the data for voters as follows:

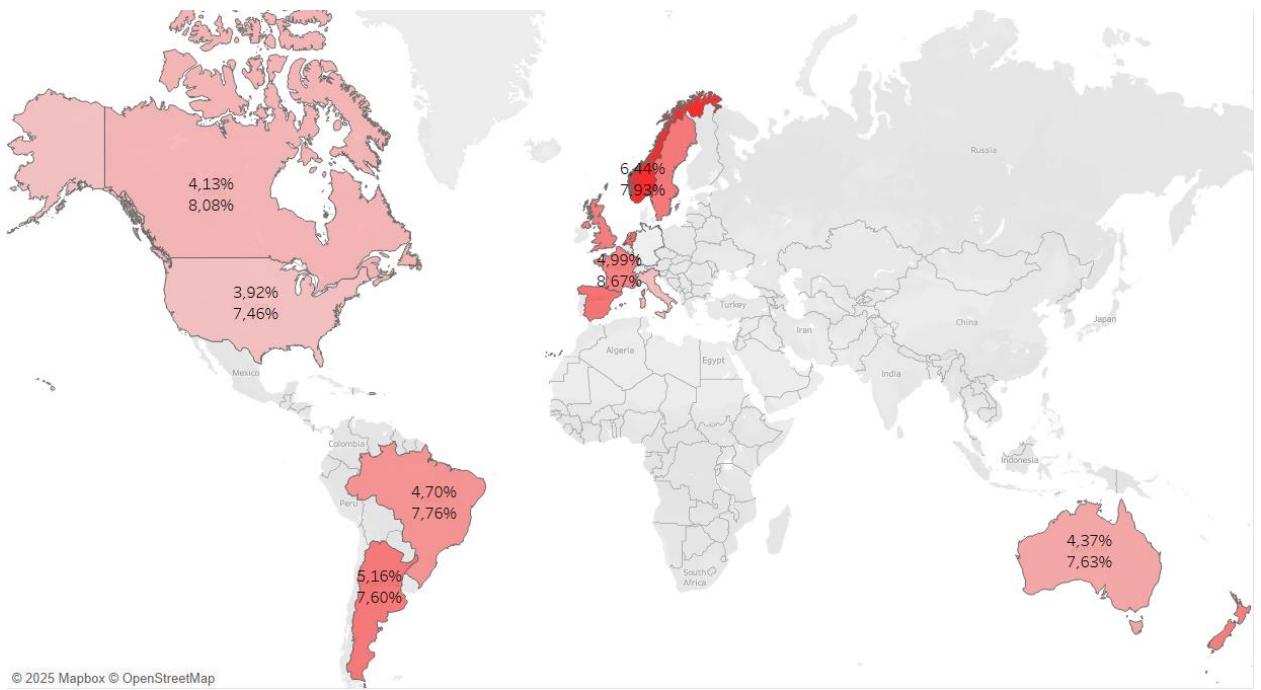
- 1) We will remove all test users
- 2) When analyzing countries, we will exclude those where the number of registered users does not exceed 10,000, because a smaller number does not allow us to objectively assess the proportion of active women in that location.

Having dealt with all the formalities, we move on to the research itself.

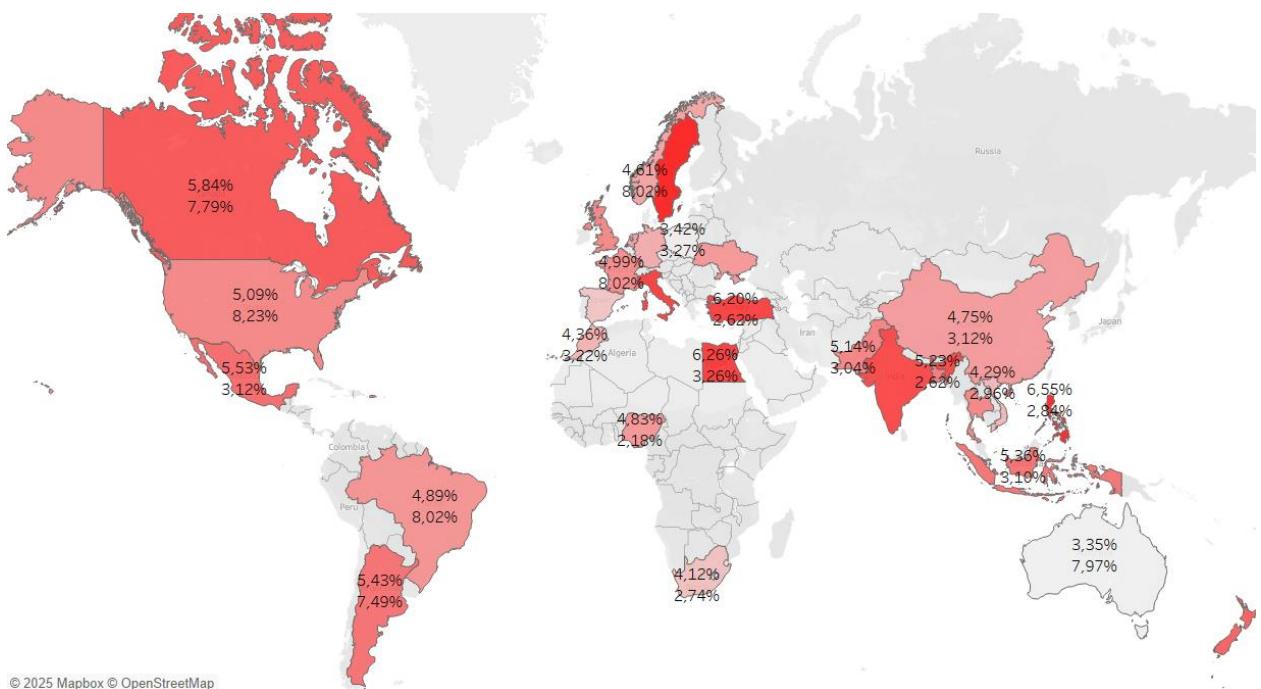
Fraud Rate	Vamp Rate (Orders)	Alert Rate (USD / Orders)	Chargeback Rate (USD / Orders)	Active Women Rate	Total Number of Users	Total Number of Orders	Active Women	Gross
2,5%	0,3%	3,5%	1,5%	2,5%	43,564,543	15,235,353	935,254	\$31 435 473
Alerts		Chargebacks		Fraud		Vamps		Complaints Declines Unsubscriptions (In 24 hours after subscription)
54,653		26,214		60,146		24,643		285,464 9,224,463 2,853,575
product_group_name (Multiple values)						Complaints Rate (USD / Orders) Declines Rate (Orders) Unsubs Rate (In 24 hours after subscription, USD / Orders)		
Type of Rate USD						2% 55,76% 25,6%		
app Web								

The average indicators for A (Web) and B (Web) (we will look at each product group separately below) show that over the year, our fraud rate is 2.5%, and the percentage of active women is 2.5% of all nearly 44 million users (for now, we will analyze the relationship between active\_women\_rate and fraud\_rate only, as these are our two main metrics; we will return to other indicators later). The indicators are close to each other, but it is not yet clear how they are related. To find out, I suggest referring to the following visualizations:

A (Web)



B (Web)



*Note: All the real values are hidden for the public share. Values on the screenshots are randomly generated for the presentation*

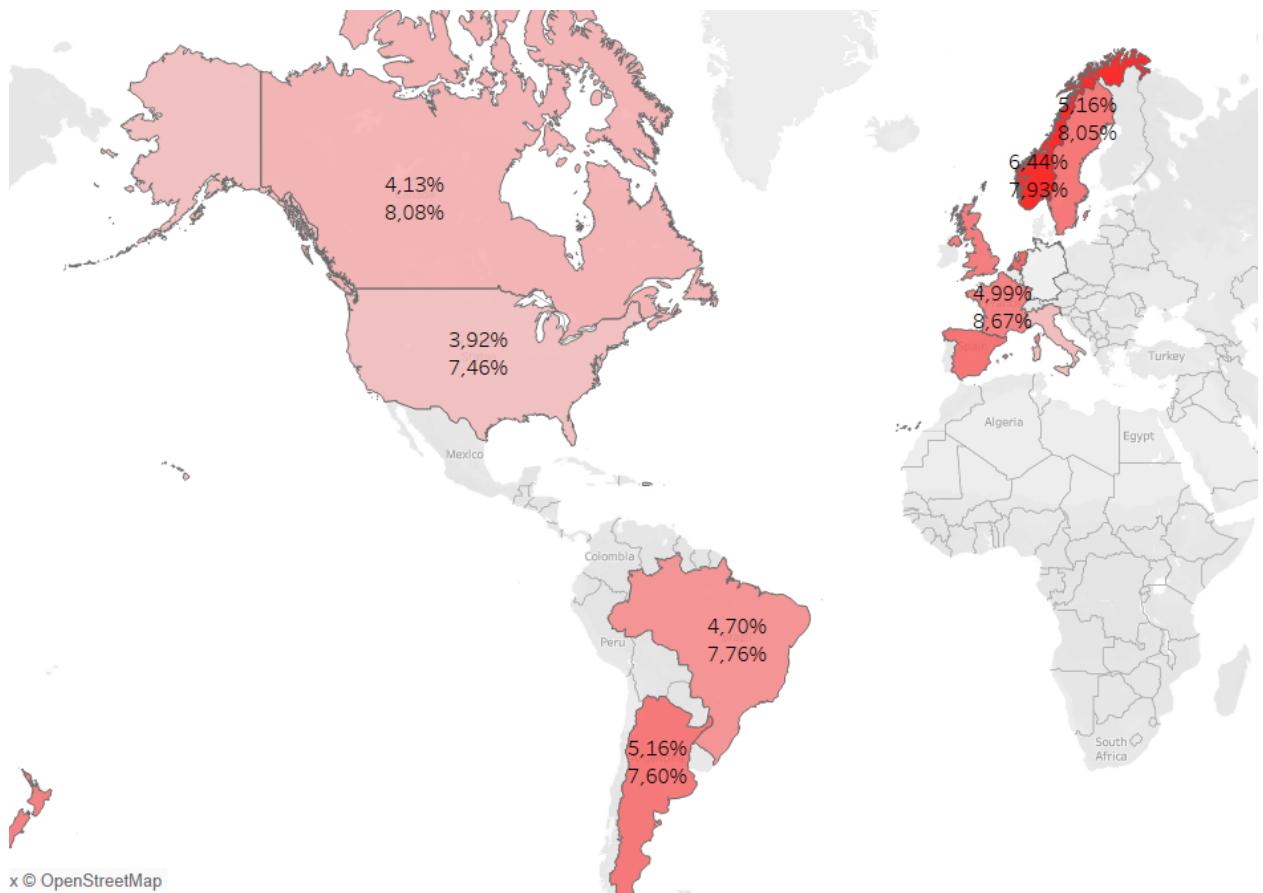
This map is actually what is required of us in the first sub-item of our task. On it, we see a map of countries colored in different shades of red depending on the level of active women there: the lower the level, the darker the country; the higher the level, the lighter the country (remember that countries with fewer than 10,000 users were not included in

the sample). The percentage value we see in the label is not the percentage of active women, oddly enough, but the level of fraud.

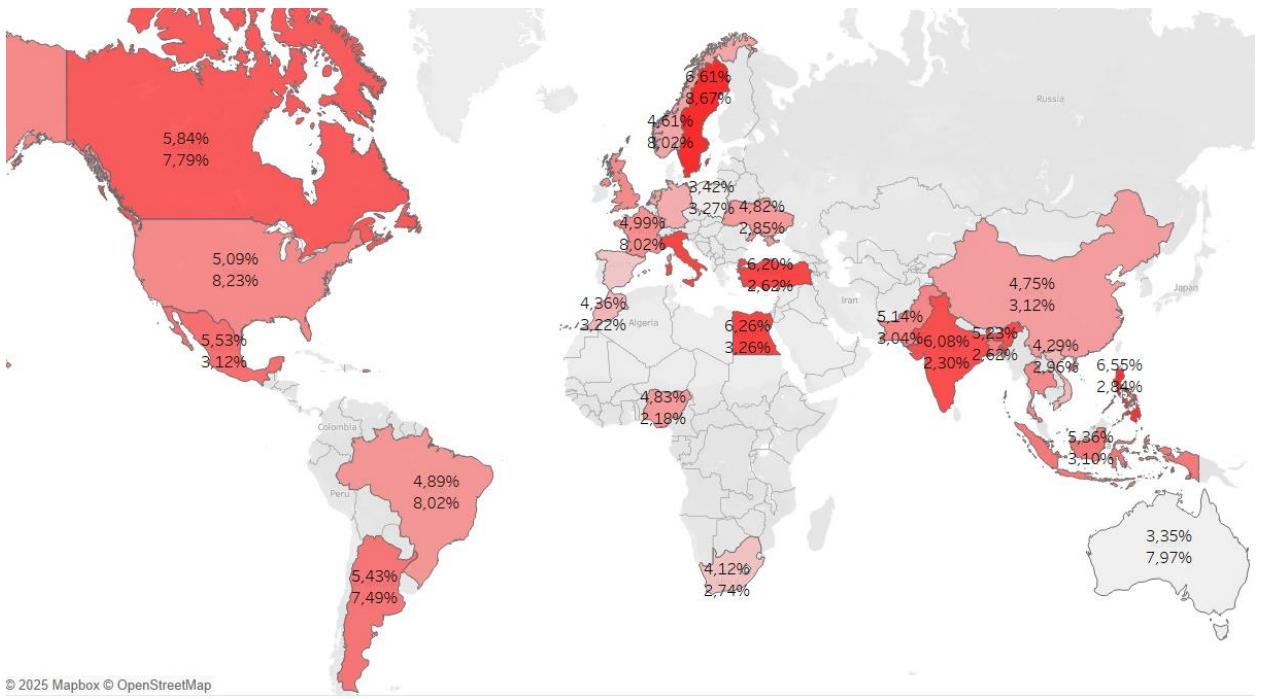
In fact, thanks to this map, we can conduct our first visual study. So, if our hypothesis is as follows: “Locations with a low proportion of active women have a higher level of risk,” this means that darker countries — where the proportion of active women is lower — should have a higher fraud rate, and vice versa, lighter countries — where the proportion of active women is higher — should have a lower fraud rate. Let's take a closer look at how this corresponds to reality.

It is important to note that since the proportion of women in our services is generally low compared to men (specifically, in the sample from our study, 541,783 women out of 3,856,650 users, or 14%), we will consider 10% of active women to be a very high number.

A (Web)



B (Web)



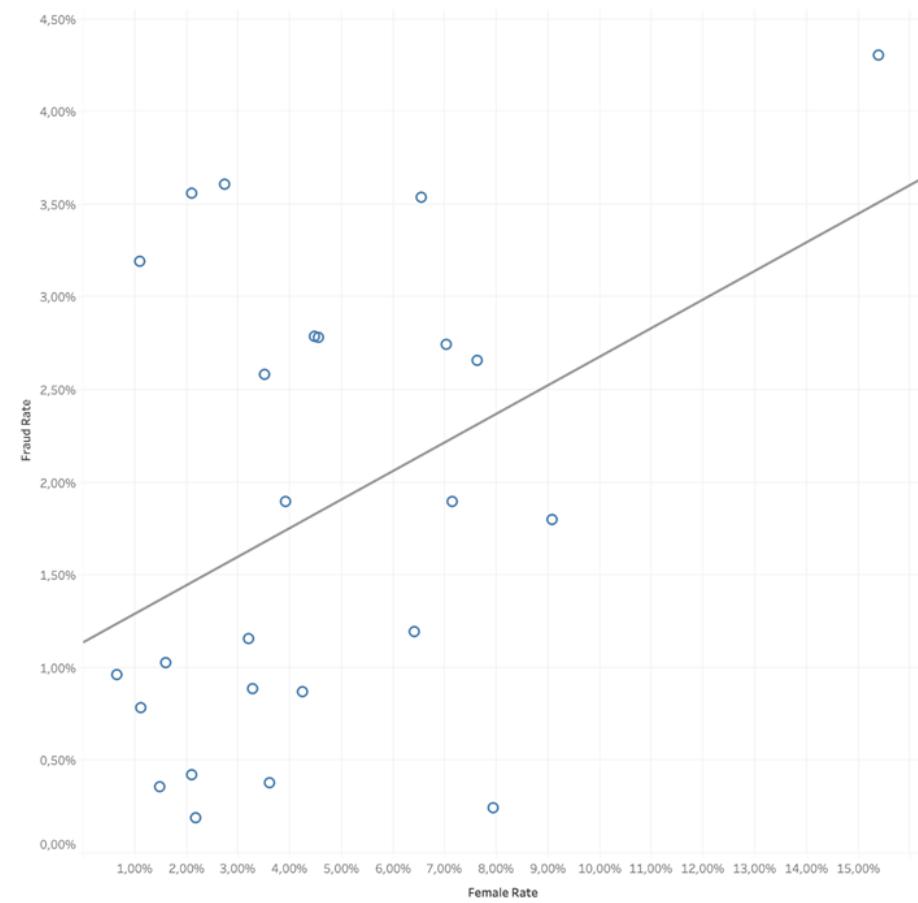
© 2025 Mapbox © OpenStreetMap

At first glance, it seems that there is a certain correlation between a high proportion of active women and a low level of fraud—for Country A, `active_women_rate = 7.08%`, and `fraud = 2.8%`, in Country B `active_women_rate = 6.93%`, `fraud_rate = 1.24%`, in Country C `active_women_rate = 7.41%`, `fraud_rate = 0.19%`, etc. The situation is similar in B group: in Country D, `activity_women_rate = 10.21%`, `fraud_rate = 1.31%`; in Country C, `activity_women_rate = 7.91%`, `fraud_rate = 3.07%`; in Country E, `activity_women_rate = 6.11%`, `fraud_rate = 4.91%`, etc. But in both cases, the opposite picture is also evident — there are countries where the percentage of women is high, and fraud is also high (such as Country F in B, where `activity_women_rate = 6.3%`, `fraud_rate = 4.5%`), and vice versa, countries where the percentage of women is low, and fraud is low (such as Country G in B, where `active_women_rate = 0.77%`, and fraud is 0% in general). And the problem is that these are not isolated cases; there are quite a few such countries. So, it is not yet clear that there is a correlation between the proportion of women and the level of fraud.

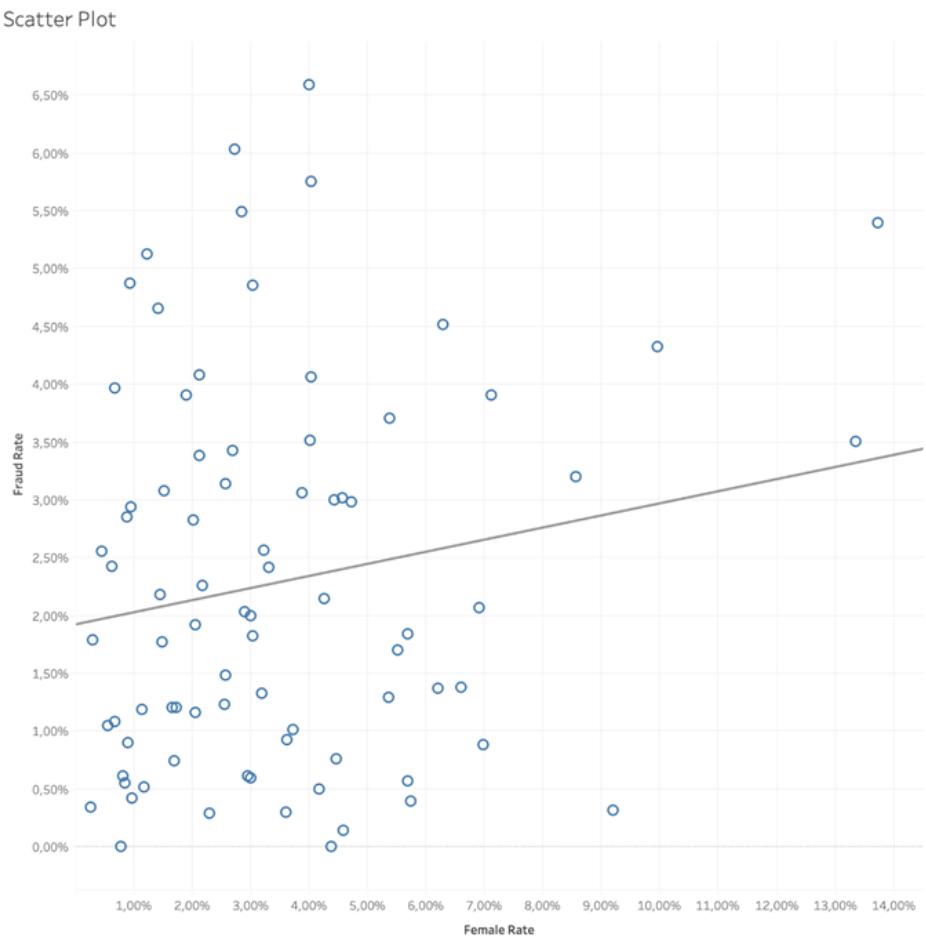
To avoid looking at each country separately, I suggest referring to another visualization.

A (Web)

Scatter Plot



B (Web)



In this case, we have a scatter plot graph of countries by activity\_women\_rate and fraud\_rate. As we can see, in the case of A and B, the countries are distributed quite chaotically across the coordinate plane. We see that we have countries with a small proportion of active women and low fraud, countries with a large proportion of women and high fraud, countries with a small proportion of active women and high fraud, and countries with a large proportion of active women and low fraud.

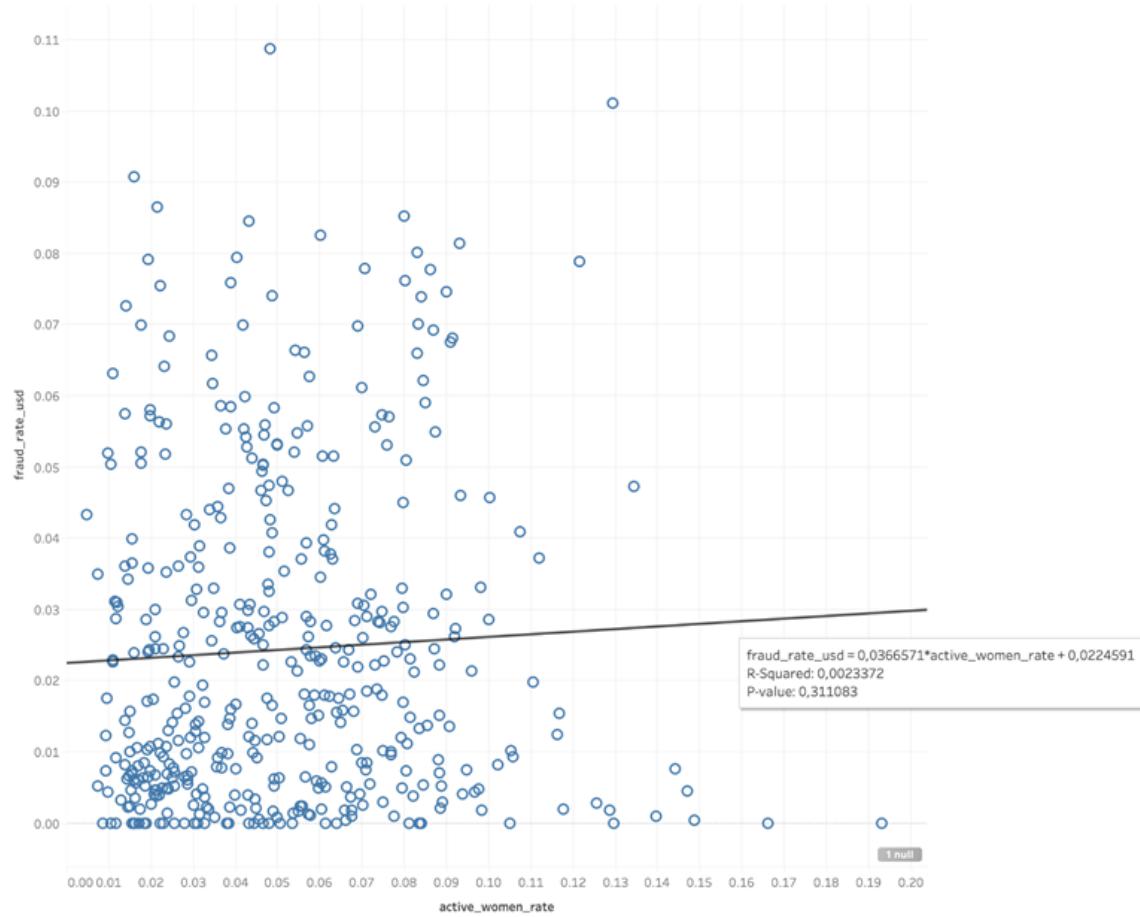
However, while in the case of B the trend line is quite flat, indicating that if there is any correlation, it is very insignificant, in A it is directed upwards at a much greater angle, indicating a greater direct dependence. So let's explore this in more detail.

The trend line indicates that between active\_women\_rate and fraud\_rate for B,  $R^2$  is approximately 0.0297, and p-value = 0.1235. P-value > 0.05, so there is no statistically significant evidence that active\_women\_rate affects fraud\_rate, i.e., there are no grounds for rejecting the null hypothesis. Pearson's coefficient square is 3%, meaning that the relationship between active\_women\_rate and fraud\_rate is quite small.

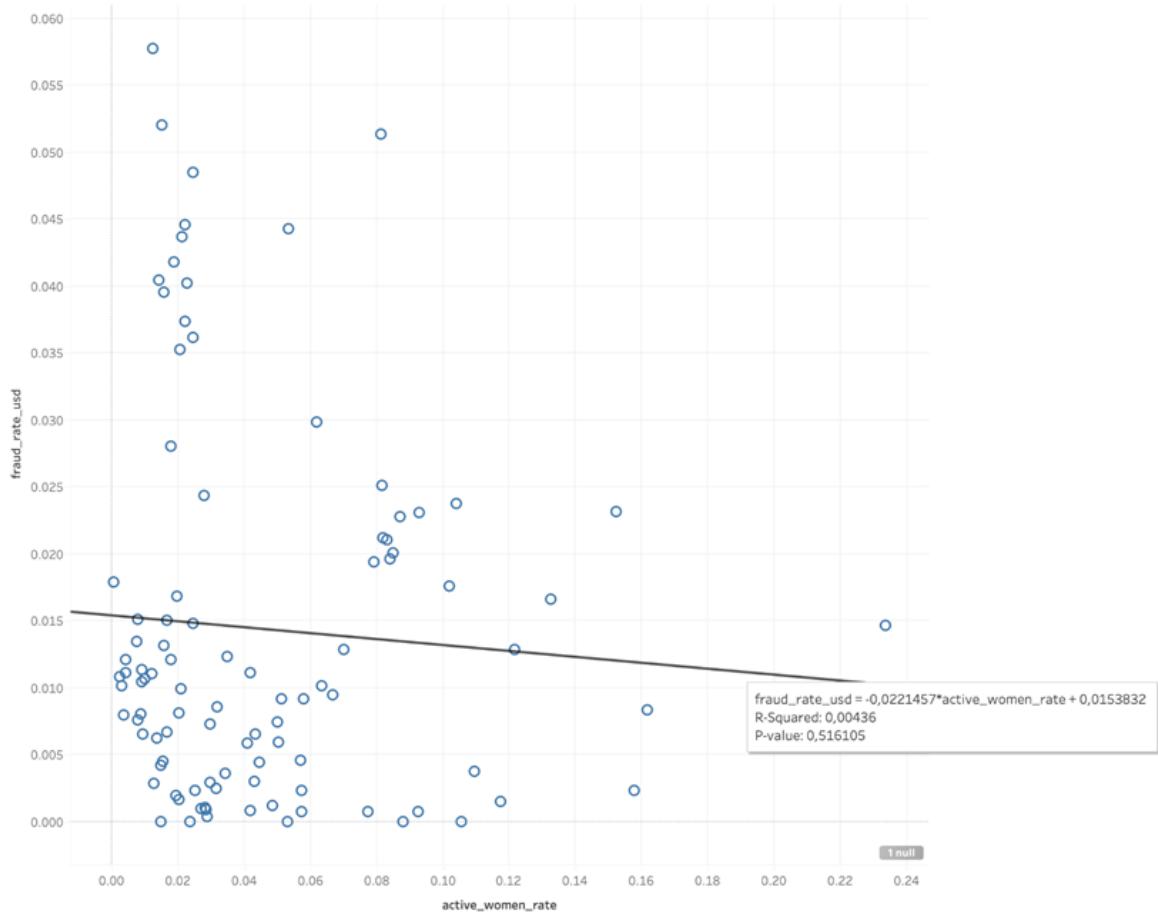
The situation is different at A:  $R^2 = 0.1663$  (i.e., 16%, which is still not a high correlation between the two metrics, but significantly higher than in the case of B), and p-value = 0.0429, i.e., less than 5%  $\Rightarrow$  there are signs of rejection of the null hypothesis. Does this mean that the proportion of active women in A affects fraud? Here, it is worth paying attention to the data we have. After filtering out the noise, only 25 countries remained in A, while in B the sample is much larger, which helps to see the trend better. The smaller number of countries distorts the data in A, so the result is incorrect.

In order to make the sample more representative, I suggest looking at the distribution not only of countries by active\_women\_rate and fraud\_rate, but also of countries by month. This will help us see the bigger picture in case the fraud dynamics of some countries have changed significantly. Let's create a Country + Month field and make a new scatter plot based on it. Also, since a single point on the graph is now not just a country, but a country for a specific month, we will filter out noise based on 10,000 users and 833 users (10,000 / 12) as the lower limit.

## B (Web)



## A (Web)

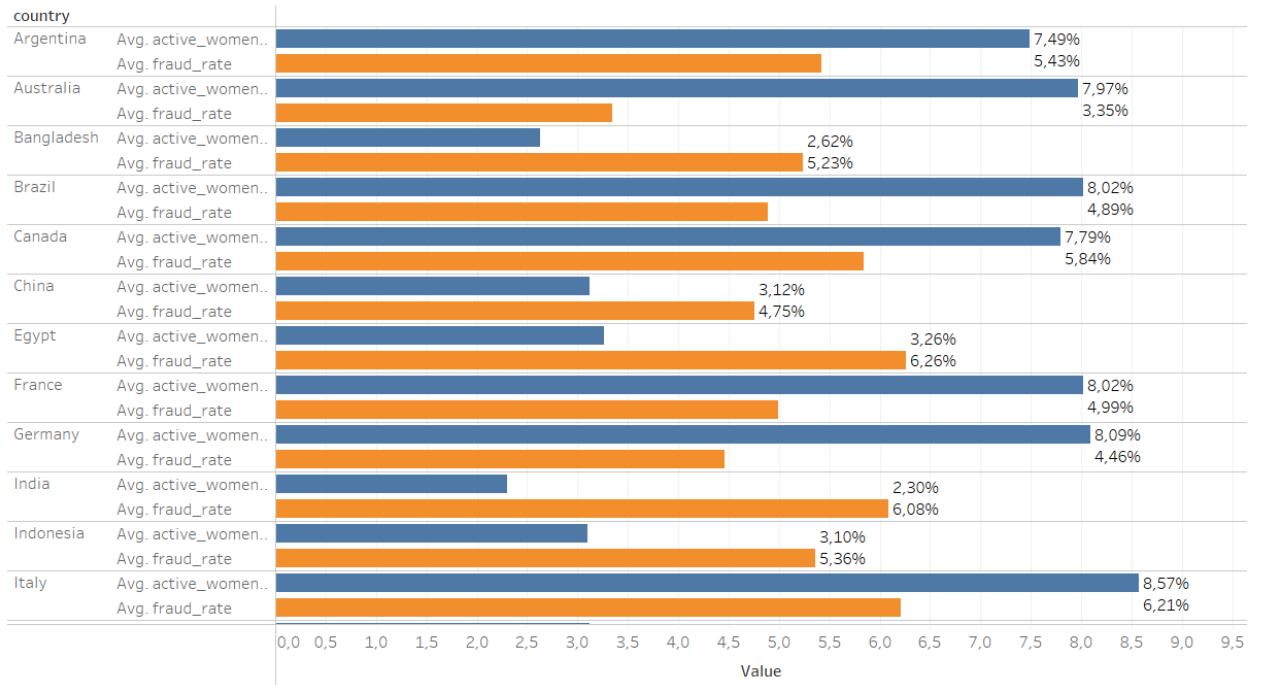


As we can see,  $R^2 = 0.0023$ ,  $p\text{-value} = 0.311$ , i.e., the  $p\text{-value}$  is still greater than 0.05, and  $R^2$  is still very small, everything converges, and in A  $R^2 = 0.0043$ ,  $p\text{-value} = 0.5161$   $\Rightarrow$  as a result, in A the relationship between `active_women_rate` and `fraud_rate` is very low, and there are no signs of rejecting the null hypothesis.

To make sure that our data is not distorted, I suggest calculating  $R^2$  and  $p\text{-value}$  for the top 15 countries by number of active women.

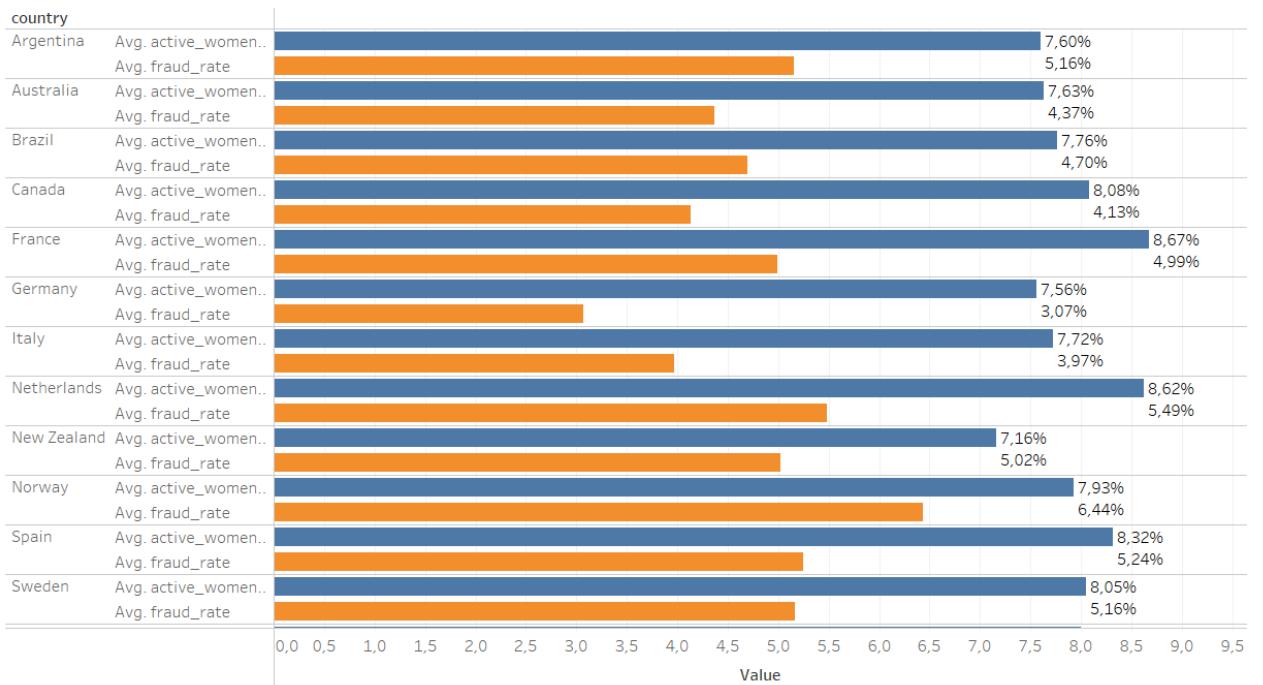
B (Web)

Female Rate Bar Chart



## A (Web)

Female Rate Bar Chart



As we can see, the list of top countries includes quite diverse states in terms of the number of fraud cases, the proportion of women, region, culture, population, etc. This means that even if we exclude a significant number of countries from this study, our sample will still be very diverse and will allow us to objectively look at trends specific to the countries that are most important for our products. This will be an additional study that will allow us to confirm that there is no direct connection between the two metrics we are interested in.

For A, we will take data from Country A, B, C, D, E, F, G, H, I, J, K, L, M, N, O.

```
'female_rate': [4.48, 9.08, 3.29, 1.61, 7.93, 2.12, 0.67, 2.18, 3.61, 6.41,
6.54, 7.63, 2.75, 7.03, 15.4],
'fraud_rate': [2.79, 1.8, 0.89, 1.03, 0.24, 3.56, 0.96, 0.19, 0.38, 1.19,
3.53, 2.66, 3.6, 2.74, 4.3]
```

For top 15 countries of B group we have these values:

```
'female_rate': [5.37, 5.68, 2.54, 1.68, 2.85, 4.03, 0.9, 3.59, 2.56, 7.11,
2.29, 0.81, 9.21, 4.25, 3.04],
'fraud_rate': [3.7, 1.84, 1.23, 0.74, 5.49, 4.06, 0.9, 0.3, 3.14, 3.91, 0.29,
0.61, 0.31, 2.15, 4.86]
```

Let's execute the following code:

```
import pandas as pd
from scipy.stats import pearsonr

data = {
    'country': ['Country A', 'Country B', 'Country C', 'Country D',
                'Country E', 'Country F', 'Country G', 'Country H',
                'Country I', 'Country J', 'Country K', 'Country L',
                'Country M', 'Country N', 'Country O'],
    'female_rate': [4.48, 9.08, 3.29, 1.61, 7.93, 2.12, 0.67, 2.18, 3.61,
6.41, 6.54, 7.63, 2.75, 7.03, 15.4],
    'fraud_rate': [2.79, 1.8, 0.89, 1.03, 0.24, 3.56, 0.96, 0.19, 0.38, 1.19,
3.53, 2.66, 3.6, 2.74, 4.3]
}

df = pd.DataFrame(data)

r, p_value = pearsonr(df['female_rate'], df['fraud_rate'])

print("Pearson r:", r)
print("p-value:", p_value)

data = {
    'country': ['Country 1', 'Country 2', 'Country 3', 'Country 4',
                'Country 5', 'Country 6', 'Country 7', 'Country 8',
                'Country 9', 'Country 10', 'Country 11', 'Country 12',
                'Country 13', 'Country 14', 'Country 15'],
```

```
'female_rate': [5.37, 5.68, 2.54, 1.68, 2.85, 4.03, 0.9, 3.59, 2.56, 7.11,
2.29, 0.81, 9.21, 4.25, 3.04],
'fraud_rate': [3.7, 1.84, 1.23, 0.74, 5.49, 4.06, 0.9, 0.3, 3.14, 3.91,
0.29, 0.61, 0.31, 2.15, 4.86]
}

df = pd.DataFrame(data)

r, p_value = pearsonr(df['female_rate'], df['fraud_rate'])

print("Pearson r:", r)
print("p-value:", p_value)
```

### Result:

A: p-value = 0.1220, r = 0.4169 |=> R2 = 0.1738

B: p-value = 0.655, r = 0.1257 |=> R2 = 0.0158

The result is the same — there are no signs of deviation from the null hypothesis, and the correlation is insignificant.