Research on the impact of user balance on multilateral platforms

Women and men on dating sites, drivers and passengers on taxi-hailing services, creators and consumers of content on social networks, etc., are united by the fact that all these user groups are actors in two-sided markets that supply and consume demand. The difference between multilateral markets and conventional vertical markets is that it is not just two actors who find each other and agree to provide certain services to each other using the laws of supply and demand, but there is also an intermediary between them — a platform that helps the two actors find each other more easily and implements the appropriate conditions for comfortable cooperation between the two parties.

In fact, the main rule to keep in mind when dealing with bilateral markets (an example of which is also dating services) is that both sides generate demand for each other: without drivers, passengers will not use the service to order a taxi, and vice versa, if there are few passengers on the service, drivers will also not use it because they have no one to order. We will see how to calculate this balance later.

One of the works that examines the topic we are interested in is the article by Jean-Charles Rochet and Jean Tirole, "**Two-Sided Markets: An Overview" (2004)**. This article examines in detail the features of two-sided markets, including basic concepts about them; categories of tariffs that are distributed among user groups; externalities; price structures, etc. What interests us at the moment is how the authors of this article calculate the balance between user groups.

The Roche-Tyrol model is as follows:

We have two sides of the market:

i is {B, S} - conditionally "buyers" and "sellers".

Each user on side i has a gain for each interaction bi, and a fixed cost/benefit Bi from stepping onto the platform. In addition, the platform charges a membership fee Ai, as well as a variable fee for using ai, and the platform itself has a fixed cost per user Ci and a variable cost per transaction c.

Thanks to this data, we can calculate the utility that a user receives if they join the platform:

$$U^i = (b^i - a^i)N^j + B^i - A^i,$$

where N^j is the number of users on the opposite side.

- The $(b^i - a^i)$ part shows that the more participants there are on the other side, the higher the benefit.
- $B^i - A^i$ is the net fixed benefit after the membership fee.

It is important to understand that a user from side *i* will join the platform provided that $U^i \geqslant 0$, i.e., if they receive less than zero profit.

The number of participants from side *i* is determined by the probability that among all potential users there will be those for whom $U^i \geqslant 0$:

$$N^i = Pr(U^i \geqslant 0)$$

That is, the number of users is a function of:

$$N^i = D^i(p^i, N^j),$$

where p^i is the effective "price" for party *i*:

$$p^i = a^i + \frac{Ai - Ci}{Nj}.$$

As a result, we have a system of equations:

$$N^B = n^B(p^B, p^S), N^S = n^S(p^B, p^S)$$

These equations are equilibrium equations that describe the balance of users: how many buyers and sellers will decide to join at the same time, taking into account the benefits and costs.

Profit from the platform:

$$\pi = (A^B - C^B)N^B + (A^S - C^S)N^S + (a^B + a^S - c)N^BN^S$$

This formula can be rewritten in terms of p^B and p^S:

$$\pi = (p^B + p^S - c)n^B(p^B, p^S)n^S(p^B, p^S)$$

The overall price level is determined by the standard Lerner formula:

$$\frac{p - c}{p} = \frac{1}{\eta},$$

where η is the elasticity of transaction volume relative to the total price.

The price structure (distribution between parties) is determined by the equality of the "semi-elasticities" of demand on both sides. That is, the platform establishes a balance of payments to optimize the total transaction volume.

Thus, the balance of users in the model is determined by a system of interdependent equations for the number of participants on both sides, taking into account both membership and variable payments, as well as network effects. The optimal strategy for the platform is to find a price structure that maximizes transactions and profits while balancing between the parties.

Now for the most interesting part: **how can this model help us describe the distribution of user groups on dating sites?**

Let's return to the canonical utility formula from the article by Rosche-Tirole.

$$U^i = (b^i - a^i)N^j + B^i - A^i$$

We also keep in mind that each potential user on side i will join if and only if $U^i \geqslant 0$. Then the number of users N^i is the probability (proportion) of those for whom $U^i \geqslant 0$.

Let's consider a hypothetical example:

We have two sides, B is women, and S is men. We have 100,000 users in each group (in reality, we are unlikely to have the same number of women and men, but this is a hypothetical example, so the numbers can be taken arbitrarily). There are no variable fees for each interaction (since users do not pay to interact with each other): $a^B = a^S = 0$.

The fixed "utility of joining" B^i for individuals is a random variable; for simplicity, let's assume it is uniformly distributed:

$$\mathbf{B^i \sim Uniform[-10, 10]}$$

We do this because different users have different motivations for using dating sites: some people enjoy meeting people online (in which case $B^i \geqslant 0$), while others find this format uncomfortable and use dating sites reluctantly (in which case $B^i \leq 0$). The usefulness can be calculated more accurately using various models, but that is not the subject of our task. For simplicity, let us assume that it is random.

The value of the benefit from each interaction is also conditional: $b^B = 0.02$ (a woman receives 0.02 of utility from each man), $b^S = 0.03$ (a man receives 0.03 of utility from each woman). The values may be different, but it is important for us that $b^i \geqslant 0$. We also need membership fees for using the platform. On dating sites, these are Premium subscriptions. For our example, let's assume that we have different rates for men and women. Then let $A^B = 2$ (women pay \$2), $A^S = 1$ (men pay \$1).

The platform's cost per user is a constant, so for simplicity, let's assume that in our example it is equal to $C^i = 0$.

Great, so users join if

$$U^B = b^B N^S + B^B - A^B \geqslant 0 \mapsto \quad B^B \geqslant A^B - b^B N^S$$

Since $B^B \sim$ Uniform[-10, 10], the proportion of women joining is equal to

$$frac^B = Pr(B^B \geqslant A^B - b^B N^S) = \frac{10 - (A^B - b^B N^S)}{20},$$

truncated in the interval [0, 1]. (Similarly for men).

Then the absolute numbers are:

$$N^B = 100{,}000 \times frac^B,\ N^S = 100{,}000 \times frac^S$$

This is a system of mutual equations, because $frac^B$ depends on N^S, and $frac^S$ depends on N^B.

Thus, we have that $b^B = 0.02$, $b^S = 0.03$, AB = 2, AS = 1, and $a^B = a^S = 0$. Substituting these values, we obtain the following system of equations:

$$N^B = 100{,}000 \times \frac{0.02N^s + 8}{20},$$

$$N^S = 100{,}000 \times \frac{0.03N^B + 9}{20}$$

As a result, we get:

$$N^B \approx 45{,}178 \text{ women}$$

$$N^S \approx 51{,}777 \text{ men}$$

Now let's see what happens if our platform subsidizes women, i.e., we make the $A^B = 0$ tariff free for women, while $A^S = 1$ remains unchanged. Then:

$$N^B = 100{,}000 \times \frac{10 - (A^B - b^B N^s)}{20} = 100{,}000 \times \frac{10 + 0.02N^s}{20},$$

$$N^S = 100{,}000 \times \frac{10 - (A^s - b^s N^B)}{20} = 100{,}000 \times \frac{9 + 0.03N^B}{20}$$

$$| \Rightarrow$$

$$N^B \approx 55{,}330 \text{ women}$$

$$N^S \approx 53{,}299 \text{ men}$$

So, what we see here is that this model suggests that by lowering the fees for women, we increased their number on the platform, and as a result, the number of men also increased due to the network effect.

Let's try the opposite experiment and raise the fees for men instead: $A^B = 2$, $A^S = 2$

$$N^B = 100{,}000 \times \frac{10 - (A^B - b^B N^s)}{20} = 100{,}000 \times \frac{8 + 0.02N^s}{20},$$

$$N^S = 100{,}000 \times \frac{10 - (A^s - b^s N^B)}{20} = 100{,}000 \times \frac{8 + 0.03N^B}{20}$$

$$| \Rightarrow$$

$$N^B \approx 44{,}670 \text{ women}$$

$$N^S \approx 46{,}701 \text{ men}$$

Increasing fees for men reduces their numbers on the platform, and due to the interdependence, it also reduces the number of women. From this example, we can see that if one side is in short supply (few women), even low membership fees for men will not lead to mass membership, because there is simply no one to interact with. That is why the rational approach would be to subsidize the scarce side.

Therefore, as we can see, the Roshe-Tyrol model is quite suitable for our case and can be used to calculate the impact of one group of users on another.

As for benchmarks, if we talk about specific numbers, we can expect that on all the most popular dating apps (at least for finding a heterosexual partner), the distribution of men and women will be heavily skewed in favor of men. For example, the mobile app data analysis service Priori Data states in its report on Tinder's results for 2024 that 75% of all Tinder users are men (of course, this is not official information from the resource itself, but for most popular dating apps, this is a realistic figure). Therefore, the figure of 20-25% women and 75-80% men can be considered a benchmark for gender distribution on dating sites.

There are many reasons for this. The main ones are that men generally compete for women's attention more than vice versa, and that women who receive excessive attention on dating apps are more prone to burnout (you can read more about this in the Financial Times article at the end of the report). The calculation of benchmarks directly follows from the assessment of the liquidity of the parties. The article **“WTF is Marketplace Liquidity”** by Julia Morrongiello describes in detail the importance of liquidity assessment for different user groups using the example of various services, from Uber to Amazon. She offers four key metrics:

- Search To Fill Rate (How often a buyer's search or request leads to a transaction)
- Utilization Rate (How effectively the supply is used)
- Time to Fill (How long it takes from request to fulfillment)
- Buyer to Supplier Ratio (How many buyers there are per seller in a given time period)

All these metrics are quite easily adaptable to dating services, as they are also a two-sided market, which is used as an example to illustrate liquidity assessment in this article, with the only exception being that the parties in our case do not pay each other money.

Search To Fill Rate is Match Rate, i.e., the number of matches received divided by the number of profiles viewed.

Utilization Rate can vary because it is usually used to calculate the proportion of sellers who sell effectively on the platform. So here it all depends on our definition of effectiveness. For example, in our case, it could be the ratio of the number of users who have at least one match to the number of all active users.

If Time to Fill is the time from request to fulfillment, then in dating we can consider it to be the average time from the first like to the first mutual match.

And Buyer to Supplier Ratio is, in our case, the ratio of women to men, which is what interests us most.

The article does not provide a ready-made solution on how to measure liquidity and benchmarks for all markets, as they are different and have different specifics. Instead, it emphasizes that these four key metrics should be evaluated among different age groups, in different locations, and at different times. When we evaluate them within our product, the benchmark can be considered the average of the most important metrics for us.

To assess women's sufficiency, we can refer to the analytical article **“Terms of Endearment: An Equilibrium Model Of Sex and Matching”** by Peter Archidiacono, Andrew Beachamp, and Marjorie McElroy, which presents a model of directed search in relationship formation that allows us to distinguish between men's and women's preferences for partner types and relationship conditions using only a cross-section of observed couples.

One of the key terms in this article is the so-called matching function:

$$X_{mwr} = A[(\varphi^{mwr}N^{m})^{p} + (\varphi^{wmr}N^{w})^{p}]^{1/p},$$

where X^{mwr} is the number of matches in the market, where men are of type m, women are of type w, and relationships are of type r;

N^m, N^w - the number of men and women of the corresponding type who are looking for a partner;

φ^{mwr}, φ^{wmr} - the proportion of those seeking men/women who are specifically looking in this market (this type of man-woman-relationship level ratio);

A - a parameter that measures search constraints;

p - a parameter that sets the elasticity of substitution between the parties (whether it is easy to replace one partner with another, etc.)

The authors of the article also express the probability that an m-type man will find a partner in this market as:

$$P^{m}{}_{wr} = \frac{Xmwr}{\varphi mwrNm}$$

That is, the number of matches divided by the number of men seeking partners in this market.

Then we have two probabilities:

$$P^{m}{}_{wr} = \frac{Xmwr}{\varphi mwrNm}, \; P^{w}{}_{mr} = \frac{Xmwr}{\varphi wmrNw}$$

And thanks to them, we can calculate the “sufficiency of women” index:

$$\frac{Pw}{Pm}$$

If this index is close to one, it means that there is a balance between the sexes on our service. If it is significantly less than one, there are not enough women (they receive fewer matches), and if it is significantly greater than one, there are too many women (men receive more matches).

Let's look at a specific example for the matching function:

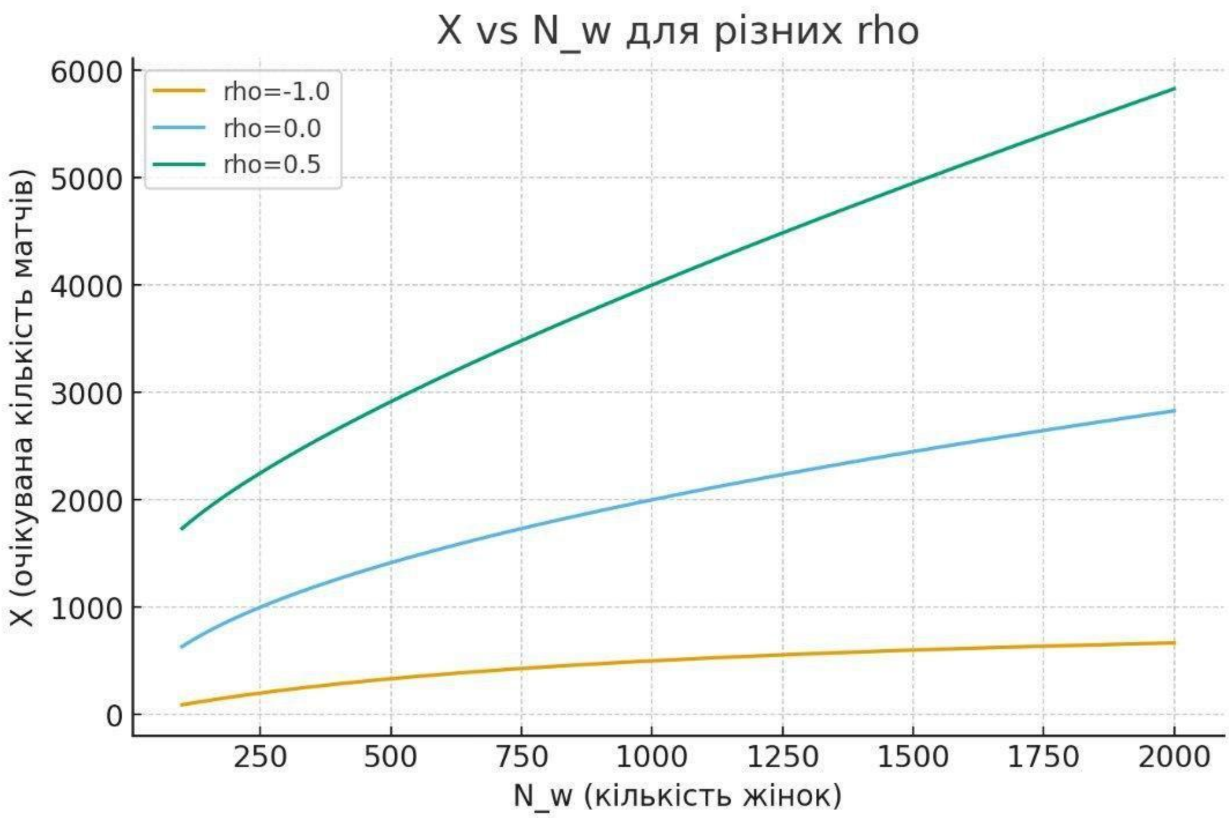
$N^m = 1000$, $N^w \in [100, 2000]$, and see how the number of matches will change in three scenarios:

1) p = -1;
2) p = 0;

3) p = 0.5.

We believe that since male users choose what they want to look for in women, and women choose what they want to choose in women, the proportion of users who are specifically looking for this market is 100%, i.e., $\varphi^{mwr} = \varphi^{wmr} = 1$.

For our example, let's assume that the search restriction parameter is equal to A = 1, because we only need to look at the change relative to each other.



If p = -1 (strong complementarity), then adding women greatly increases X (aggregated matches) in the initial ranges—each new woman “weighs heavily.” Elasticity here is high at low N^w and decreases as N^w increases.

For p = 0, elasticity is consistently 0.5: each side equally affects X (symmetric case).

For p = 0.5 (higher substitutability), the total number of matches increases more, but the elasticity of women at low N^w is lower — meaning that the shortage of women did not “break” the system as much, because the model allows the imbalance to be partially compensated for.

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Let us derive the elasticity formula from the matching function.

$$S := (a^m N^m)^p + (a^w N^w)^p, \quad X = AS^{1/p},$$

$$\frac{\partial X}{\partial Nm} = AS^{1/p-1}(a^w)^p N_w^{p-1}.$$

The elasticity of the number of matches X in relation to the number of women N^w is

$$\varepsilon_{X,Nw} := \frac{\partial X}{\partial Nw} \times \frac{Nw}{X} = \frac{(awNw)^p}{(amNm)^p + (awNw)^p} = \frac{(awNw)^p}{S}.$$

Similarly for men:

$$\varepsilon_{X,Ns} = \frac{(amNm)^p}{S}.$$

$\varepsilon_{X,Nw}$ lies between 0 and 1 and shows what percentage change in total matches will be caused by a 1% change in N_w. If $\varepsilon_{X,Nw}$ is close to 0, then adding women will hardly increase the total number of matches (the other side dominates here, or there is high substitutability). If $\varepsilon_{X,Nw}$ is close to 1, then matches are very sensitive to the number of women: the shortage is critical - adding women greatly increases X.

Sources:

- **Two-Sided Markets: An Overview" (2004), Jean-Charles Rochet, Jean Tirole**
- **Tinder Statistics | Revenue, Users & Demographics 2025, Priori Data**
- **"WTF is Marketplace Liquidity?", Julia Morrongiello**
- **Terms of Endearment: An Equilibrium Model Of Sex and Matching, Duke University**

Not entirely relevant, but potentially useful sources:

- **Young women fall out of love with dating apps, Stephanie Stacey**
- **Nonparametric Estimation of Matching Efficiency and Elasticity in a Marriage Agency Platform: 2014–2025, Suguru Otani**
- **Tinder Statistics 2025: Users, Gender Ratio, Success Rates & Most Popular App, DatingZest**