

Why Tinder Benefits the Beautiful

Search frictions and match fractions, and who is better off in a world of online dating.



UNREASONABLE DOUBT

NOV 12, 2024



Sh

By *Jeppe Johansen*

Online dating is still becoming a more and more popular tool for finding a partner — just look at the graph below [1](#). Intuitively, this makes sense. It's hard to see who is single and open for a relationship when roaming the real world. However, online dating allows for easy identification of other people looking for a relationship. Especially with the advent of Tinder, it is not uncommon for people to have hundreds if not thousands of matches. That is, singles have hundreds of potential relationships in the sense that both parties have, at least on a very superficial level, sent a signal of romantic interest. However, many of these people do not end up in relationships. If Tinder really worked, should we not expect a wave of relationships to be formed and a total extinction of singledom? Yet, this is not what statistics tells us. As the figure below shows, though people meet online they are [still more single than ever](#) — this blog post explores why. Specifically, this post distills why it is important to distinguish between *search friction* and *match friction*. Finally, it also investigates who are the winners and losers of Tinder (and more generally online dating) and why immense reductions in search frictions for partners do not necessarily benefit everyone.

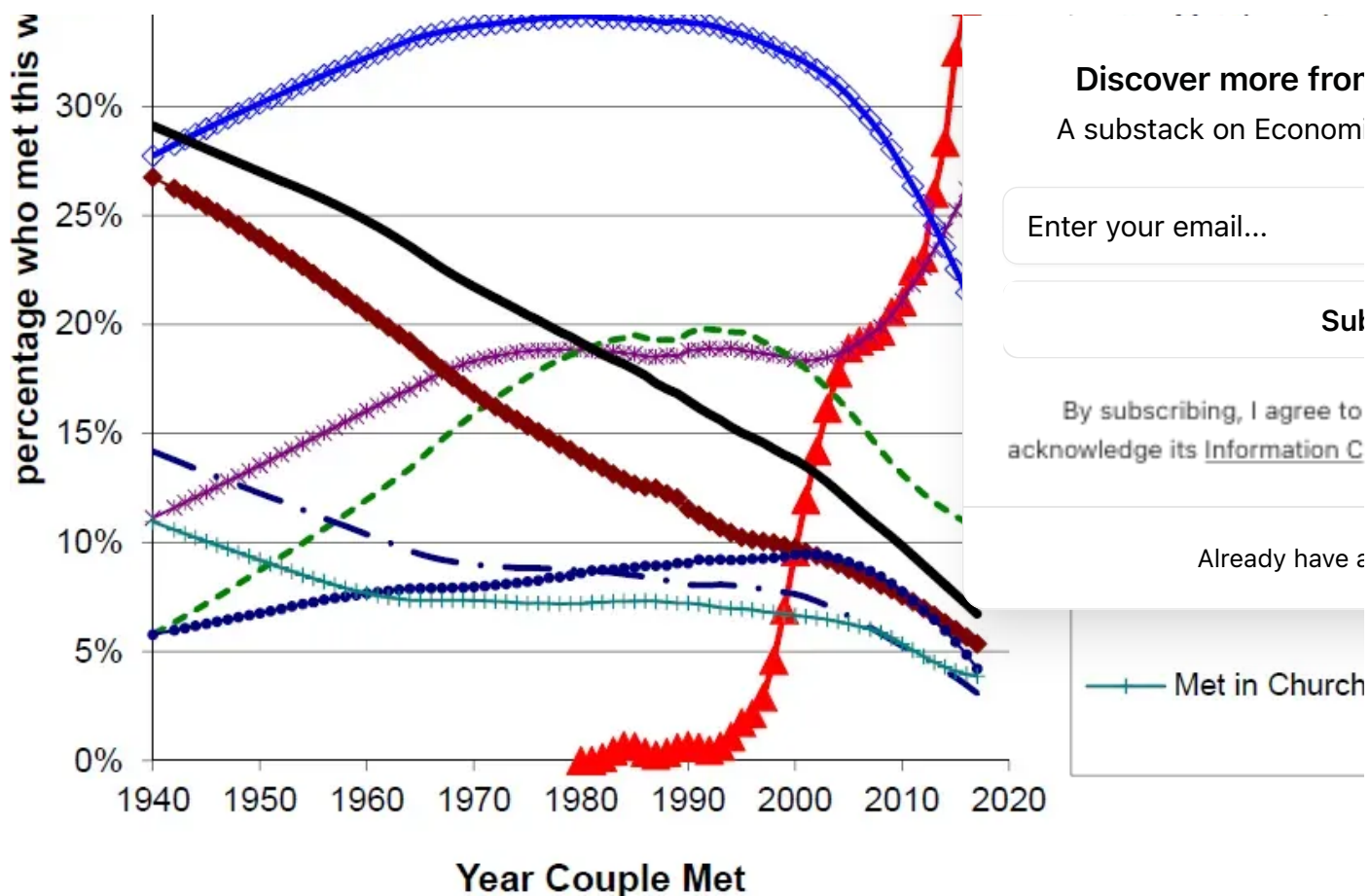
Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

Manage

Reject

Accept



The Model

Let's start by setting the stage. To explore the questions above we start by setting up a model. The model used in this post considers a world where men sequentially propose to women who tentatively accept the relationship until a better man swings by. When the men in the model have hit up all the women they were interested in the dating game ends.

Concretely, consider a single-period game, where all men in the "economy" are endowed with k possible women to ask out for a date (we only assume heterosexual

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

Manage Reject Accept

enough for the men to want to enter relationships with them (or vice versa), rather than consist of the pool of potential partners, i.e. singles.

Now, there is a specific cost to invest in getting a date. First, you use time and effort to get in contact, and secondly, humans allocate emotional real estate in getting a date. In this very simple world, only men ask women out. Again, a simplifying assumption for getting anywhere with the model.

Finally, we also assume that all men and women have a certain level of attractiveness. The attractiveness is defined below, where the attractiveness level is between 0 and 10. The attractiveness level is composed of two subcomponents:

1. A general attractiveness level (v)
2. A personal (unique/idiosyncratic) attractiveness level (v_i):

$$attractive_i = (1 - \alpha)v_i + \alpha v \quad v_i, v \sim Uniform(0, 10)$$

So intuitively the attractiveness of a person can be considered a weighted average between an attractiveness level shared by everyone, called v , and a unique (idiosyncratic) to the individual level denoted v with subscript i . So intuitively all women will rate the men on a scale from 1 to 10. If α (the funny looking α in the equation) is 1, all the women will rate the same man equally. Put differently under a regime of $\alpha=1$ a man rated by one woman as 7.2 will also be rated exactly as 7.2 by another woman. However, if $\alpha=0$ then there will be no correlation between ratings of the same man for different women, i.e. one woman will give a man 3.4, and other women will come to an entirely different level of attractiveness. Finally, men value 1

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#)
[Reject](#)
[Accept](#)

but it's costly to try to get a woman on a date. We model this the following way: The men rank all the women by attractiveness and then have a decision rule whether or they want to date them. The rule is given as attractiveness minus the cost needs to be above some threshold:

$$\text{Try to get date}_{ij} = \begin{cases} \text{Yes,} & \text{if } \alpha_{i,j} - j \times c \geq t \\ \text{No} & \text{else} \end{cases}$$

Here i denotes the man and j denotes the index of the woman. Again consider the k women sorted by attractiveness, then the third most attractive woman will be index with $j=3$. So the formula applied $a - j \times c$ is attractiveness minus the index j times the cost. The parameter t represents the threshold, that *attractiveness - cost* must be above for the man to try to get a date. Below is a simple example:

Mike has 5 single women in his life he potentially could get in a relationship with, ordered by his preferences, they are Anna, Beatrice, Caroline, Denice, and Ellen. On a 10-point scale a rank them 7,5,4,2,1, respectively (again, I hope this reader knows this does not reflect my actual view of how this goes, on but helps as a simplifying view) We can now calculate the values. For simplicity assume the cost parameter c is 1, and his threshold is 0:

- Anna: $7 - 1 \times 1 = 6 > 0$ (Mike invites Anna on a date)
- Beatrice: $5 - 2 \times 1 = 3 > 0$ (Mike invites Beatrice on a date)
- Caroline: $4 - 3 \times 1 = 1 > 0$ (Mike invites Caroline on a date)
- Denice: $2 - 4 \times 1 = -2 < 0$ (Mike *does not* invite Denice on a date)
- Ellen: $1 - 5 \times 1 = -4 < 0$ (Mike *does not* invite Denice on a date)

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)

Beatrice and Caroline will never get the chance, even if they would have liked to. Concretely, in this model, men interact with all the women that they find attractive enough, i.e. even though Mike can only get into a relationship with one, he contacts three candidates. This is explored in more depth in the next section. Finally, also note that had Mike only been presented to Denice (and not Anna, Beatrice, Caroline, and Ellen) he would have tried to go on a date with her, since she would be indexed with $j=1$, such that:

- Denice: $2 - 1 \cdot 1 = 1 > 0$ (Mike invites Denice on a date)

Again this is only the case because in this example, Mike has not been presented with other women than Denice, so he has not invested energy in trying to get on dates with other women. In other words, the women Mike decides to try to get into a relationship with is contingent on the total pool of potential partners he is presented with.

Clearing The (Dating) Market

After all the men have “suited” the women they deemed attractive enough, the women also sort the “suiters” by attractiveness. Following this the market is “cleared” that the matching process is performed by the [Gale-Shapley/Deferred acceptance algorithm](#). The process can heuristically be understood like this:

1. Initialization:

- Every man and woman is initially single.
- Each man has a list of women in order of his preference.
- Each woman has a list of men in order of her preference.

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)

- After the proposals, the women look at all their suitors of the day and if they're single, they'll "tentatively" accept the proposal from the man they like most. If they already have a tentative partner but prefer the new suitor more, they will "break up" with the current suitor and tentatively accept the new suitor's proposal. The rejected man will move on to the next woman on his list the following day.

3. Rejection and Further Proposals:

- The rejected men from the previous day will propose to the next woman on their list.
- Again, each woman will pick her most preferred suitor from her current tentative partner and the new suitors of the day.

4. Termination:

- This process continues with men proposing to the next woman on their list after facing rejections until every man and every woman is paired up. Or alternatively, the men's lists are exhausted.

The Gale-Shapley algorithm has multiple nice properties, but for this application, those are not necessary to hash out. More importantly is it, to a first-order approximation, a good description of the dating market.

Search Friction and Match Friction

Before moving to the next section, which more closely compares how Tinder impacts dating markets, let's first consider the difference between search friction and match friction. Search friction is commonly used to describe inefficiencies that arise when

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)

friction simply conveys how big the potential pool of relationship partners is, concretely k . So reducing search friction would correspond to increasing k in this model. Again we see this is an important parameter in dating markets. It has also been recognized earlier as a reason why sexual minorities move to big cities since if the pool of potential partners is very small, it is natural to think it is very hard to find a partner. In this model match friction is not captured by a parameter but *corresponds to the aggregate number of matches in the dating market*. A dating market with a lot of match friction will be characterized by a large number of singles, relative to the number of people in relationships. It is important to distinguish between these two types of frictions, since, one can easily see how one can make a mental leap from reducing search friction to implying a reduction in match friction. However, as the paragraph below investigates, this is not necessarily the case: When preferences are correlated i.e. people generally consider the same people attractive, reducing search cost might not lead to less match friction.

Simulating Tinder vs *The Good Old Days*

Let us finally consider the advent of Tinder. Tinder can be considered as a way to reduce search friction, or put differently, increase the number of women men can potentially try to get on a date, k . So, the question we can ask with this model is whether a world with reduced search frictions will be characterized by more match relationship, i.e. also reduce match friction. We use our model to simulate the different scenarios. We simulate 2500 men and 2500 women. We consider different scenarios along two dimensions:

1. The extent to which people share preferences.

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)

assume a range of values on the interval between 0 and 1 of *alpha*. Secondly the number of potential suiters k go from 3 to 60. We evaluate the output of the model on the following two metrics: 1) Total number of relationships (denoted matches in the plots) in the economy, and 2) The average attractiveness of men and women in a relationship. These metrics allow us to roughly reason about who is better off and worse off in a world with Tinder. Concretely, will a tool like Tinder create more or fewer relationships, and will the people in relationships appear more or less attractive ².

To summarize, when search friction is reduced, does the match friction then go up or down? Does it actually become easier to get in a relationship, in a world where Tinder exists?

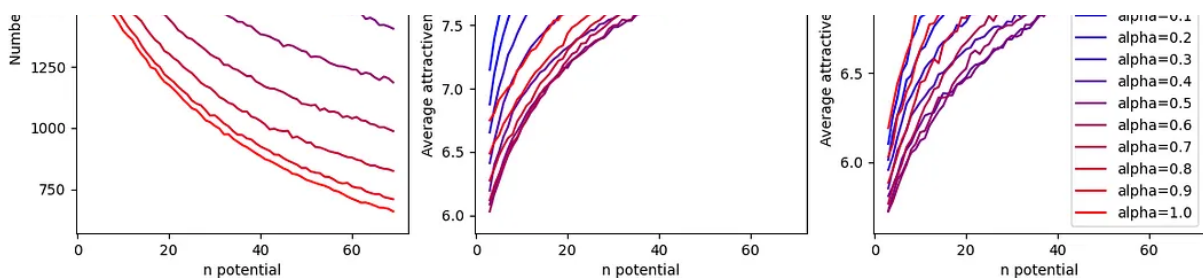
Simulation Results

The figures below show the results. The three plots show the number of potential partners on the x-axis (what is called k in the model). Again, consider a low number of potential partners as the pre-Tinder era, and conversely a high number of potential partners as the post-Tinder era. The colours of the lines denote the extent of how preferences correlate, going from blue to red, where blue captures where preferences are perfectly uncorrelated ($\alpha=0$), and red captures when they are perfectly correlated ($\alpha=1$). Note, that empirical preferences have been shown to display a high degree of correlation, i.e. the real world seems closer to the red than the blue line. ³

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)



The leftmost plot shows how the aggregate total number of relationships evolves under the different scenarios. This is captured by the y-axis that denotes the total number of relationships, which is denoted number of *matches* on the y-axis label. As the plot shows, the degree to which reducing search friction increases the number of relationships is very contingent on how correlated preferences are. Put differently, Tinder only increases the total number of relationships, if individuals' preferences differ. If everyone thinks the same people are attractive, Tinder actually *reduces* the total number of relationships.

Next, even though attractiveness is hard to reason about when it includes an idiosyncratic component, one finds a very consistent pattern, namely, that reducing search friction increases the (perceived) attractiveness of people in relationships, at least as experienced by their partner, because a larger dating pool allows people to match with more attractive partners. This can be seen from the middle and rightmost plot. The y-axis captures the average attractiveness of women and men in a relationship, respectively, which is seen increasing as k increases. Interestingly, the picture is more murky with respect α , where the α of approximately 0.5 (an intermediate value between the two extremes), is associated with the lowest perceived attractiveness. Intuitively this happens because now preferences are correlated, so congestion becomes a more prominent feature of the market, however, people are still able to find a high degree ending up in relationships, i.e. as α increases, still fewer will end

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)

Combining these two insights yields an important lesson. In a world with a high degree of shared preferences for partners, reducing search friction makes the world more of a winner-take-all market. Intuitively, this can be understood as when the dating pool expands, more people can approach the most attractive candidates, allowing for “mating congestion” where everyone flocks around the same few attractive candidates. Due to the cost component in the model, which we intuitively can think of as time or energy, women who would be deemed attractive to the male a model with fewer partners become unattractive as the pool increases.

Conclusion

Why has Tinder not caused a wave of new relationships, and reduced the number of singles in the modern dating environment? As outlined, Tinder reduces only one kind of friction, namely *search friction* and this is not the only important variable in a dating market. Concretely, as the simulations show, when people share preferences for partners, reducing the search friction **by increasing the pool of partners** can actually have the complete opposite effect of what is intended, namely more unwilling single. Additionally, the simulations show that the gains of the larger pool of potential romantic partners accrue to the people who in general are deemed attractive. Concretely, having access to a larger pool of potential partners does not help everyone; only the select few, everyone wants to end up with.

Jeppe Johansen is a regular writer at Unreasonable Doubt, where he writes about aliens, economics, the integrity of institutions, and everything in between – if anything really. Jepp is a Ph.D. fellow at the Center for Social data science at the University of Copenhagen.

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)



The Nature-Nurture-Nietzsche Newsletter

Graph of the Day: How Couples Meet, 1940-2020

Here's a graph that goes viral from time to time; perhaps you've seen it before. It shows the changing ways that couples met from 1940 to 2020. The main story, of course, is the red line. Note that the category "met online" doesn't just refer to online dating or dating apps, but also includes meeting through social media sites such as Facebook and Insta...

[Read more](#)

2 years ago · 19 likes · 3 comments · Steve Stewart-Williams

- 2 Attractiveness in this context is challenging to quantify due to its individual-specific component (v_i). A more accurate perspective is to view attractiveness not as an objective quality universally agreed upon, but rather as something defined from the partner's unique viewpoint.
- 3 [Cunningham, M.R., Roberts, A.R., Barbee, A.P., Druen, P.B., & Wu, C. \(1995\). "Their ideas of beauty are, on the whole, the same as ours": Consistency and variability in the cross-cultural perception of female physical attractiveness. Journal of Personality and Social Psychology 68, 261-279.](#)

Subscribe to Unreasonable Doubt

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)

By subscribing, I agree to Substack's [Terms of Use](#), and
acknowledge its [Information Collection Notice](#) and [Privacy Policy](#).

Discussion about this post

Comments Restacks



Write a comment...

Cookie Policy

We use cookies to improve your experience, for analytics, and for marketing. You can accept, reject, or manage your preferences. See our [privacy policy](#).

[Manage](#) [Reject](#) [Accept](#)
