

1 2 Replication / Game Theory 3 **[Re] Assortative matching and search**

4 Félix Geoffroy¹, 

5 ¹Department of Evolutionary Theory, Max Planck Institute for Evolutionary Biology, August-Thienemann-Straße 2, 24306 Plön,
6 Germany

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A reference implementation of

- Shimer, R., and Smith, L. (2000). Assortative matching and search. *Econometrica*, 68(2), 343–369. <http://doi.org/10.1111/1468-0262.00112>
- Smith, L. (2006). The Marriage Model with Search Frictions. *J. Political Econ.*, 114(6), 1124–1144. <https://doi.org/10.1086/510440>

8 Introduction

9 Understanding markets is one of the major issues in game theory. It has implications
10 in human economical markets [1, 2], as well as in biological markets [3, 4, 5, 6]. Search-
11 and-matching models have a very important place in the market literature. The general
12 principle is as follows: individuals meet two by two and may decide to interact for a
13 certain period of time and generate benefits. These models are widely used to try to
14 predict a fundamental property of markets: who interacts with whom. This question
15 is also called the *matching problem*. Historically, the search-and-matching literature is a
16 merger of Becker's matching theory [7] and search theory [8, 9].

17 Shimer and Smith have written two seminal articles [10, 11] in this field, in which they
18 (1) assume that individuals vary in their ability to generate benefits and (2) study who in-
19 teracts with whom when everyone plays the equilibrium strategy. More precisely, they
20 derive the conditions for which more productive individuals interact with other produc-
21 tive individuals. This situation is also called a Positive Assortative Matching (PAM).

22 Both articles address this question, but differ in the way individuals exchange services.
23 In Smith's article [11], each individual receives a payoff that depends on both types. This
24 case is called Non-Transferable Utility (NTU). In Shimer and Smith's article [10], two indi-
25 viduals generate a benefit whose size depends on the two types and, then, they split the
26 benefit. We decided to replicate results from both articles since the models are similar.
27 The authors use game theory to derive the equilibrium, namely the optimal strategy that
28 agents should adopt in a market situation. However, the equilibrium is defined by three
29 complex equations for which it is not possible to obtain a closed-form solution. The au-
30 thors use an algorithm to find numerical solutions which is derived from the proof of the
31 existence of an equilibrium (discussed in [12]). We contacted the authors and had access
32 to the code (Mathematica script) used for the first reference article [10]. Although the nu-
33 merical solutions are mostly illustrative in the two reference articles, similar algorithms
34 have been used in works which aim at fitting these models on economical markets data
35 [13, 14]. This is why we think it is important to replicate the results and have an openly

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Correspondence should be addressed to Félix Geoffroy (felix.geoffroy.fr@gmail.com)
The authors have declared that no competing interests exists.
Code is available at <https://github.com/rescience-c/template..>

36 available version of this algorithm for the scientific community. We are able to replicate
 37 all figures from both papers, except for one, which is discussed in *Results*.

38 Methods

39 Model description

40 We start by describing the search-and-matching model proposed in the first reference
 41 article [10]. In a population of arbitrary size, each individual is defined by a type $x \in$
 42 $[0, 1]$. The continuous distribution of types is given by the density function l . At any
 43 time, an individual is either matched with a partner, or unmatched. An unmatched
 44 individual encounters another one at rate ρ , and a pair of matched individuals splits at
 45 rate δ . The distribution of types for unmatched individuals is given by the **unmatched**
 46 **density function** u .

47 In the first reference article [10], the utility in transferable (TU): a pair of individuals
 48 generates a benefit of size $f(x, y)$ which is then split with a classic Nash bargaining pro-
 49 cedure [1, 10]. The benefit generated $f(x, y)$ is an increasing function of both types x
 50 and y . Individuals discount time at rate r .

51 Each individual must choose a strategy describing which types she is willing to accept
 52 as a partner. At the equilibrium, all individuals of the same type have the same strategy.
 53 We define the **matching set** function α such that $\alpha(x, y) = 1$ if individuals of type x
 54 accept individuals of type y as partners and if types y also accept types x . Otherwise,
 55 $\alpha(x, y) = 0$. Solving the matching problem –who interacts with whom– is equivalent to
 56 finding the equilibrium value of α .

57 Lastly, it is convenient to introduce a function v which represents, for each type, her
 58 **value**, i.e. her expected lifetime payoff when she is in the unmatched state. The optimal
 59 strategy is then clear: an individual should accept a partner if the payoff she will get
 60 from this interaction is higher than her unmatched payoff.

61 Shimer and Smith derive a system of three equations which defines a Nash equilibrium.
 62 For more details, see the proof in the article (sections 3 and 4 in [10]).

$$\begin{cases} u(x) = \frac{\delta l(x)}{\delta + \rho \int_0^1 \alpha(x, y) u(y) dy} & \forall x \in [0, 1] \\ v(x) = \theta \int_0^1 (f(x, y) - v(x) - v(y)) \alpha(x, y) u(y) dy & \forall x \in [0, 1] \\ \alpha(x, y) = \begin{cases} 1, & \text{if } f(x, y) \geq v(x) + v(y) \\ 0, & \text{otherwise} \end{cases} & \forall x, y \in [0, 1]^2 \end{cases}$$

63 with $\theta = \frac{\rho}{2(r+\delta)}$.

64 Unfortunately, it is not possible to derive a closed-form analytical solution. The trick
 65 used by Shimer and Smith [10] to get a numerical approximation is to discretize the type
 66 space in n types. The problem can then be written in terms of vectors and matrices.
 67 Integrals can be approximated by Riemman sums if n is large enough.

$$\begin{cases} u_i = \frac{\delta l_i}{\delta + \frac{\rho}{n} \sum_{j=1}^n \alpha_{i,j} u_j} & \forall 1 \leq i \leq n \\ v_i = \frac{\theta}{n} \sum_{j=1}^n (f_{i,j} - v_i - v_j) \alpha_{i,j} u_j & \forall 1 \leq i \leq n \\ \alpha_{i,j} = \begin{cases} 1, & \text{if } f_{i,j} \geq v_i + v_j \\ 0, & \text{otherwise} \end{cases} & \forall 1 \leq i, j \leq n \end{cases}$$

Because we implement the algorithm with the Numpy library, it is convenient to write the system in matrix notation. We use the following notation for column vectors $\mathbf{u} = (u_i)_{1 \leq i \leq n}$ and for square matrices $\mathbf{A} = (\alpha_{i,j})_{1 \leq i \leq n, 1 \leq j \leq n}$.

$$\begin{cases} \mathbf{u} = \frac{\delta \mathbf{1}}{\delta \mathbf{J}_{n,1} + \frac{\rho}{n} \mathbf{A} \mathbf{u}} & (1) \\ \left(\mathbf{A} \text{diag}(\mathbf{u}) + \mathbf{I}_n \circ \left(\frac{n}{\theta} \mathbf{J}_n + \mathbf{A} \mathbf{u} \right) \right) \mathbf{v} = (\mathbf{F} \circ \mathbf{A}) \mathbf{u} & (2a) \\ \mathbf{A} = \frac{1}{2} (\text{sgn}(\mathbf{F} - \mathbf{v} \mathbf{J}_{1,n} - \mathbf{J}_{n,1} \mathbf{v}^\top) + \mathbf{J}_n) & (3a) \end{cases}$$

Here, the symbol \circ denotes the Hadamard product (element-wise product) and the fraction symbol is used in the sense of Hadamard division (element-wise division). \mathbf{I}_i is the identity matrix of size i and $\mathbf{J}_{i,j}$ is the all-one matrix of dimensions $i \times j$ (\mathbf{J}_i denotes the square all-one matrix of dimensions $i \times i$).

In the second reference article [11], utility is non-transferable (NTU): an individual in a pair receives a payoff $f(x, y)$ which depends on her type x and her partner's type y . Accordingly, her partner receives a payoff $f(y, x)$. The Nash equilibrium, in this case, is determined by

$$\begin{cases} u(x) = \frac{\delta l(x)}{\delta + \rho \int_0^1 \alpha(x, y) u(y) dy} & \forall x \in [0, 1] \\ v(x) = \frac{\int_0^1 f(x, y) \alpha(x, y) u(y) dy}{\psi + \int_0^1 \alpha(x, y) u(y) dy} & \forall x \in [0, 1] \\ \alpha(x, y) = \begin{cases} 1, & \text{if } f(x, y) \geq v(x) \text{ and } f(x, y) \geq v(y) \\ 0, & \text{otherwise} \end{cases} & \forall x, y \in [0, 1]^2 \end{cases}$$

with $\psi = \frac{r+\delta}{\rho}$. We can also write these equations using matrix notation. The first equation is the same as (1) and the other two are:

$$\begin{cases} \mathbf{v} = \frac{(\mathbf{F} \circ \mathbf{A}) \mathbf{u}}{n\psi \mathbf{J}_{n,1} + \mathbf{A} \mathbf{u}} & (2b) \\ \mathbf{A} = \frac{1}{2} (\text{sgn}(\mathbf{F} - \mathbf{v} \mathbf{J}_{1,n}) + \mathbf{J}_n) \circ \frac{1}{2} (\text{sgn}(\mathbf{F} - \mathbf{J}_{n,1} \mathbf{v}^\top) + \mathbf{J}_n) & (3b) \end{cases}$$

Implementation of the algorithm

The authors use an algorithm to find the equilibrium numerical values of the unmatched densities \mathbf{u} , the values \mathbf{v} and, most importantly, the matching set \mathbf{A} . The algorithm is derived from the proof of the existence of an equilibrium (see [12] for details). The main idea is to start with an initial guess for the matching set \mathbf{A} , then, since one's probability of being unmatched depends on one's type and on the matching strategy of all players, we can update the unmatched densities \mathbf{u} accordingly. From this, we can update the values of each type \mathbf{v} and, finally, derive the new optimal matching strategy of each type \mathbf{A} according to their values. This value adjustment process can be described by the following algorithm:

0. Initialize $(\mathbf{u}, \mathbf{v}, \mathbf{A})$
1. Update \mathbf{u} by solving (1)
2. Update \mathbf{v} by solving (2a)
3. Update \mathbf{A} by solving (3a)
4. If \mathbf{A} has been modified by Step 3, return to Step 1, else stop the loop.

96 The algorithm is the same for the NTU case, one should simply replace equation (2a)
 97 with (2b), and equation (3a) with (3b).
 98 Although there is no formal proof that this algorithm converges to the desired equilib-
 99 rium it does in practice in the majority of cases (L. Smith, personal communication).
 100 Moreover, if the algorithm converges, by definition, its solution is the desired Nash
 101 equilibrium. However, it can happen that the algorithm gets into an infinite loop. This
 102 comes from the fact that discretization into n types can lead to the existence of mixed
 103 strategies (see [13]) which we want to avoid here. Therefore, in Step 4 of the algorithm,
 104 we also check if the current value of \mathbf{A} has already occurred, which would indicate an
 105 infinite loop.

106 Solving the equations

107 Equation (1) is actually a system of nonlinear equations. We use a simple fixed-point
 108 iteration to obtain a numerical solution with an accuracy of 10^{-12} (section 2.10 in [15]).
 109 In the algorithm used in the first reference article [10] communicated by the authors,
 110 the system is also solved with a fixed-point iteration with an additional damping factor
 111 and the same accuracy.
 112 Shimer and Smith [10] also use a fixed-point iteration for solving (2a). In our implemen-
 113 tation, we can take advantage of the fact that (2a) is a system of linear equations and
 114 can be written as $\mathbf{P}\mathbf{v} = \mathbf{q}$, with $\mathbf{P} = \mathbf{A} \text{diag}(\mathbf{u}) + \mathbf{I}_n \circ (\frac{n}{\theta} \mathbf{J}_n + \mathbf{A}\mathbf{u})$ and $\mathbf{q} = (\mathbf{F} \circ \mathbf{A})\mathbf{u}$.
 115 The vector of values \mathbf{v} is $\mathbf{v} = \mathbf{P}^{-1}\mathbf{q}$.
 116 Finally, equations (2b), (3a) and (3b) are straightforward to solve.
 117 The algorithm is implemented in Python.

118 Results

119 We were able to replicate almost all results from both reference articles [10, 11]. Figures
 120 1 and 2 replicate results from [10] (transferable utility) and Figure 3 replicates results
 121 from [11] (non-transferable utility).

122 Shimer & Smith 2000

123 Figure 1 replicates figure 1 from the first reference article [10]. It shows the matching set
 124 \mathbf{A} at the equilibrium for several values of the number n of discrete types. As n increases,
 125 the discrete case converges to the continuous case. All further results (with one excep-
 126 tion) are obtained with $n = 500$. Note that, in this case, the matching set is such that
 127 there is a Positive Assortative Matching (PAM, see *Introduction*): the higher one's type,
 128 the higher the minimum type that one is willing to accept as a partner.
 129 Figure 2A, 2B and 2C respectively replicate figures 3a, 3b and figure 4 from [10]. Here,
 130 there is no Positive Assortative Matching at the equilibrium. Figure 2B was obtained
 131 with $n = 501$ because an infinite loop occurs for $n = 500$. Note that, with the same
 132 parameters, the algorithm also fails to converge when we run the Mathematica script
 133 that the authors have provided. Lastly, Figure 2D replicates an extra figure not present
 134 in the first reference article [10], but in [12] (figure 4). We have decided to include it to
 135 increase the confidence in the robustness of our implementation.

136 Smith 2006

137 Figure 3A and 3B are two attempts at replicating figure 1 from the second reference
 138 article [11]. When we run our algorithm with the parameters provided in the figure
 139 caption in [11], replication fails (Fig. 3A). By comparing Figure 3A and figure 1 from
 140 [11], one can see that the resulting matching sets are qualitatively different. We do not

141 have access to the code which has been used in this article because it has been lost (L.
 142 Smith, personal communication). Thus, it is not possible to know where the discrepancy
 143 between the results comes from. Nevertheless, we would like propose an explanation
 144 for this discrepancy. Please note that **this is entirely speculative, since there is no way**
 145 **to run the exact algorithm** used in [11]. The caption of figure 1 in [11] specifies that
 146 the author used “ $\delta = .1$ ”, which usually means “0.1”. Still, this notation is not used for
 147 the parameter “ $r = 0.3$ ”. We think that there might be a typo in “ $\delta = .1$ ”^a. We run the
 148 algorithm for $\delta = 1.1$ and the resulting figure (Fig. 3B) seems to replicate figure 1 from
 149 [11].
 150 In Figure 3C, were able to replicate figure 2 of [11]. However, in [11], the caption below
 151 figure 2 states that “the parameters in fig. 1 are assumed, except $\rho = 3$ ”. We therefore
 152 use $\delta = 0.1$, which leads to a good replicate of figure 2 from [11]. Changing δ to 1.1, as
 153 we did for the previous figure, would lead to a replication failure (results not shown).

154 Gaussian distribution

155 In both reference articles, the distribution of types is always assumed to be uniform,
 156 i.e. $\forall x \in [0, 1] : l(x) = 1$. This is not necessarily the case in real-life applications of
 157 search-and-matching models (see [13]). In Figure 4, we show an example of matching
 158 sets at the equilibrium for the transferable utility case with a Gaussian distribution of
 159 types. There is no replication purpose for this result, but we think it might be useful to
 160 include it given the importance of this assumption.

161 Conclusion

162 All the figures in the first reference article [10] have been successfully replicated (Fig. 1
 163 and 2). Only one of the two figures in the second article [11] has been replicated (Fig. 3A
 164 and 3B). We have explored the possibility that our replication failure comes from an er-
 165 ror in a parameter value given in a figure caption, yet, this is really uncertain, given that
 166 the same parameter value leads to a replication success for the second figure (Fig. 3C).
 167 We are unable to provide a clear explanation for this, since the code has been lost. This
 168 shows how important the archiving and replicating processes are, even for computa-
 169 tional works. Finally, we have extended the algorithm to include additional assump-
 170 tions about the distribution of types (Fig. 4) to match the current use of this algorithm
 171 in the search-and-matching literature. We hope this replication can help clarify the
 172 method used in two papers of great importance, and that it can promote future research
 173 in the domain.

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 176 of the articles, and for useful information.
 177 We also thank Dirk Eddelbuettel who reviewed this article and provided an [R script](#) for
 178 performing a visual comparison between the output of the Python script and the figures
 179 in this article.

^aNote that a slightly different version of the second reference article [11] was previously published in the *Social Science Research Network* in 1997 [16]. However, the parameter values given in the figure caption are identical.

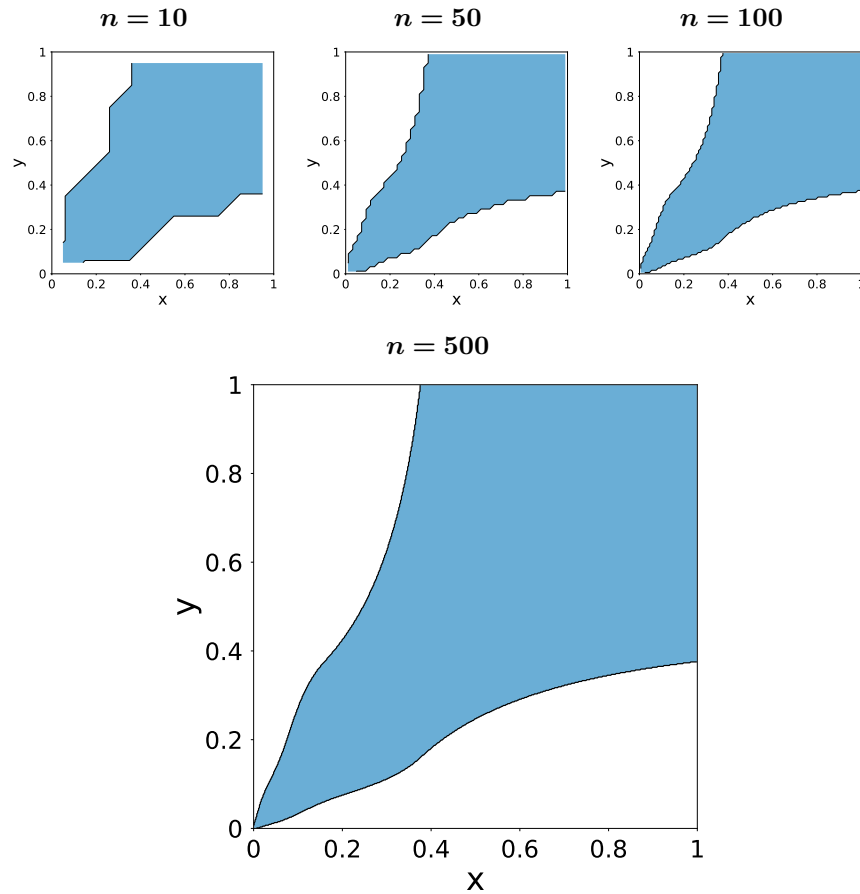


Figure 1. Matching set at the equilibrium for several values of n . The points (x, y) for which $\alpha(x, y) = 1$ are colored in blue and the points for which $\alpha(x, y) = 0$ are in white. This figure replicates figure 1 from the first reference article [10] in which utility is transferable. Parameters are $\delta = 1$; $\rho = 100$; $r = 1$; $f(x, y) = xy$; $n = 500$.

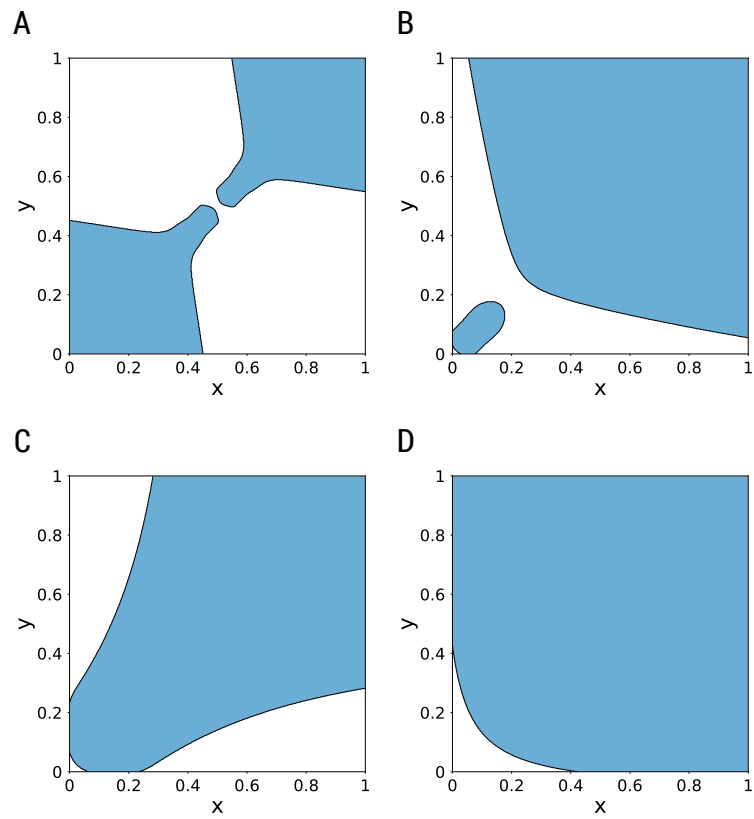


Figure 2. Matching set at the equilibrium for transferable utility. (A), (B) and (C) respectively replicate figures 3a, 3b and figure 4 from the first reference article [10], and (D) replicates figure 4 from [12]. Parameters are (A) $\delta = 1$; $\rho = 100$; $r = 1$; $f(x, y) = (x + y - 1)^2$. (B) $\delta = 1$; $\rho = 35$; $r = 1$; $f(x, y) = (x + y)^2$; $n = 501$. (C) $\delta = 1$; $\rho = 750$; $r = 1$; $f(x, y) = x + y + xy$. (D) $\delta = 0.5$; $\rho = 50$; $r = 1$; $f(x, y) = x + y + xy$

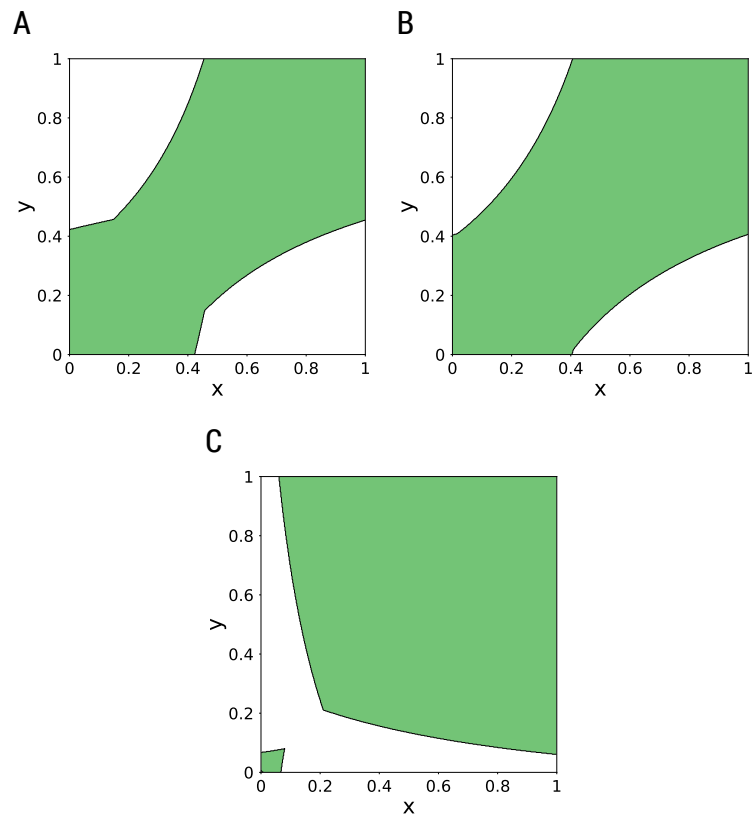


Figure 3. Matching set at the equilibrium for non-transferable utility. (A) and (B) are attempts at replicating figure 1 from the second reference article [11]. (C) replicates figure 2 from [11]. Parameters are (A) $\delta = 0.1$; $\rho = 30$; $r = 0.3$; $f(x, y) = e^{xy}$. (B) $\delta = 0.1$; $\rho = 30$; $r = 0.3$; $f(x, y) = e^{xy}$. (C) $\delta = 0.1$; $\rho = 3$; $r = 0.3$; $f(x, y) = x + y + xy$.

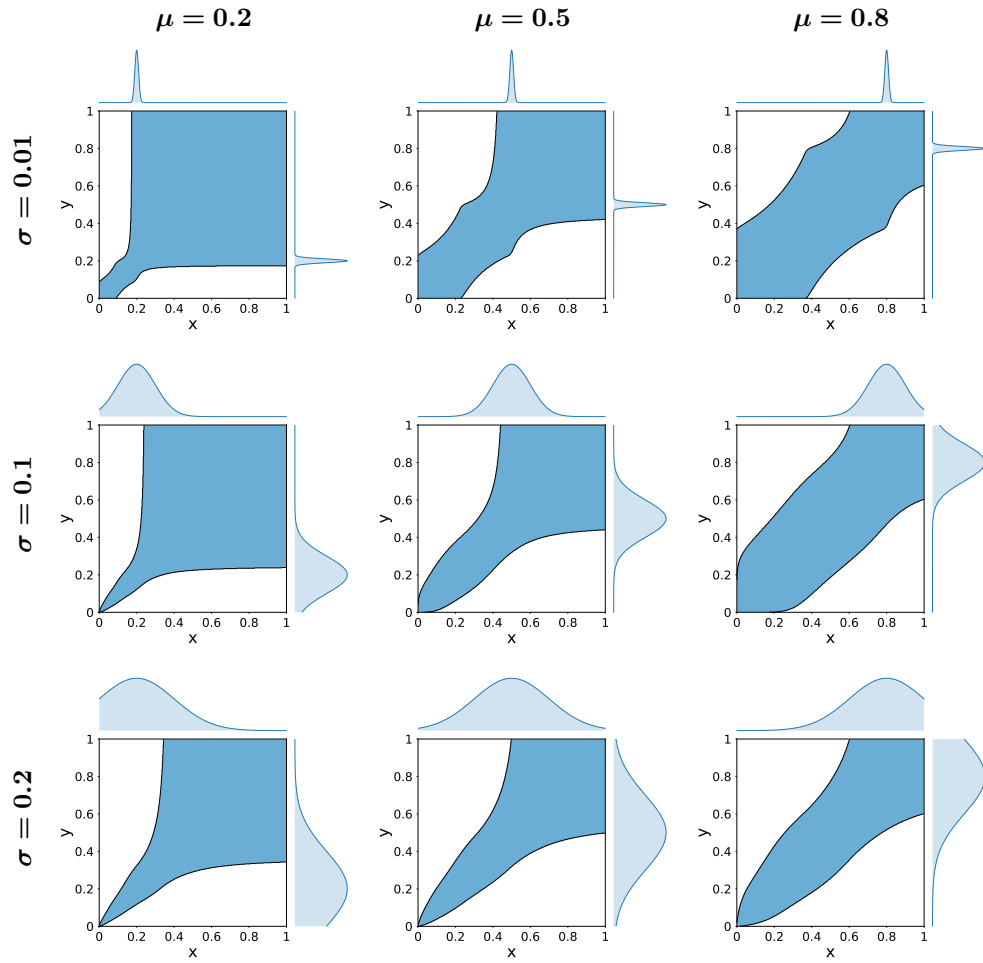


Figure 4. Matching set at the equilibrium for a Gaussian distribution of types. Results are shown for three values of the mean of the distribution $\mu \in \{0.2, 0.5, 0.8\}$ and for three values of the standard deviation $\sigma \in \{0.01, 0.1, 0.2\}$. The Gaussian distribution is truncated between 0 and 1. Parameters are $\delta = 1$; $\rho = 1000$; $r = 1$; $f(x, y) = xy$.

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