Online Appendices to "A Field Study on Matching with Network Externalities"

By Mariagiovanna Baccara, Ayse Imrohoroglu, Alistair J. Wilson and Leeat Yariv *

In Appendix B, we inspect the trade-off between efficiency and fairness of outcomes across different classes of faculty . Also, under some simplifying assumptions, we estimate the welfare generated by commonly used variations of the serial-dictator mechanism in the presence of network externalities. In Appendix C, we detail the ant-colony algorithm used to search for optimal assignments with externalities. Finally, in Appendix D we report the individual survey questions, the aggregate responses, and, in square brackets, the number of respondents to each question.

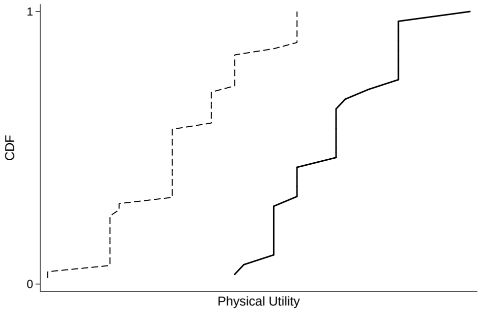
Appendix B: Fairness and Welfare Properties of Serial Dictatorship

Having identified individuals' preferences and an efficiency benchmark in the paper, we here study some properties of assignment mechanisms. First, we compare the assignment implemented by the school with the best-found assignment in terms of fairness across seniority levels and departmental affiliations. We find that the best-found assignment implies more egalitarian outcomes across seniority, but somewhat less egalitarian outcomes across departments. Second, we consider several commonly used versions of the serial-dictatorship mechanism (varying the order in which the individuals choose and banning ex-post swaps), and evaluate their efficiency performance. In the presence of externalities, outcomes appear consistently lower than the socially optimal benchmark.

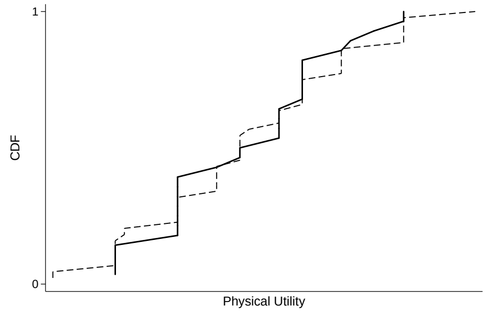
B1. Fairness Properties in the Observed and Best-Found Assignments

One aspect traditionally addressed by the matching literature has to do with fairness (see, for instance, Chapter 7 in Moulin 2003 for an overview). Namely, one might desire a rather homogeneous division of welfare across different classes of individuals. Therefore, a natural question that arises is whether efficiency in our context comes at the expense of fairness.

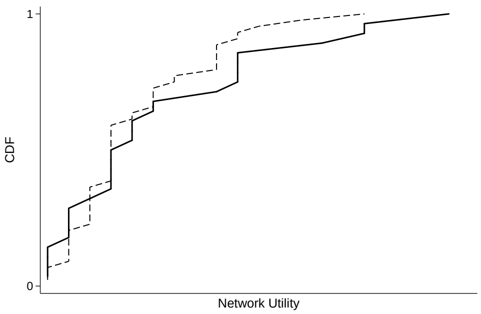
* Baccara: Olin School of Business, Washington University in St.Louis, Campus Box 1133, One Brookings Drive, St.Louis, MO 63130, mbaccara@wustl.edu. Imrohoroglu: Department of Finance and Business Economics, Marshall School of Business, 3670 Trousdale Parkway, University of Southern California, Los Angeles, CA 90089, aimrohor@marshall.usc.edu. Wilson: Department of Economics, University of Pittsburgh, 230 S. Bouquet St, Pittsburgh, PA 15260, alistair@pitt.edu. Yariv: Division of Humanities and Social Sciences, California Institute of Technology, 1200 E. California Blvd., Pasadena, CA 91125, lyariv@hss.caltech.edu.



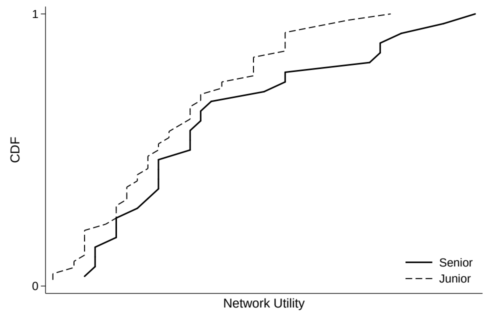
(a) Physical, Observed



(b) Physical, Best-Found



(c) Network, Observed



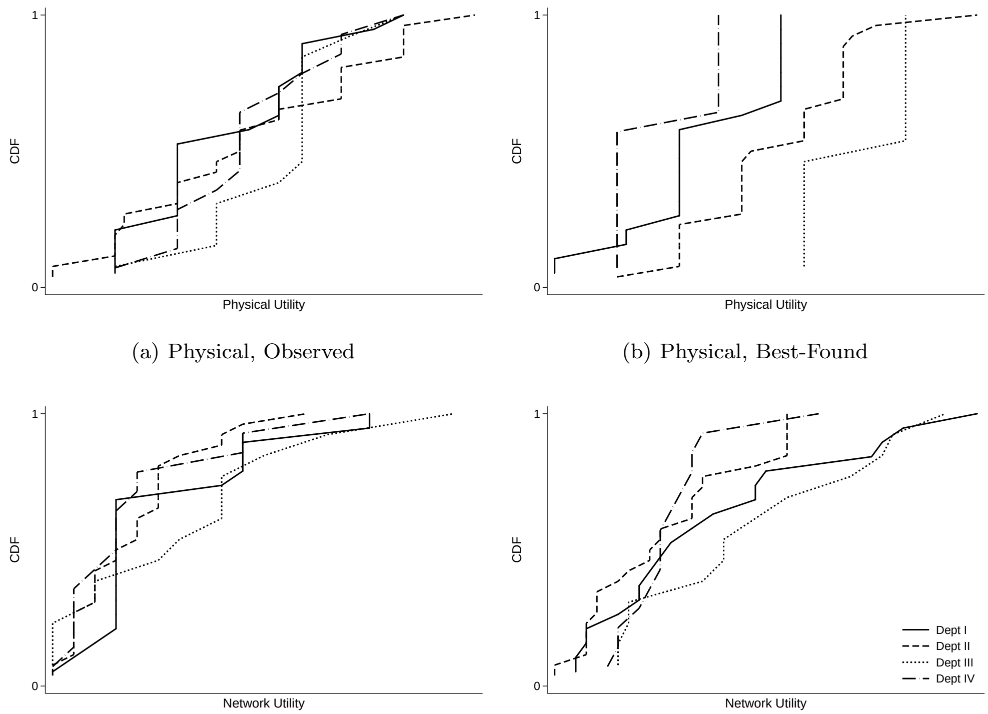
(d) Network, Best-Found

Figure B1. : Utility Cumulative Distribution, by Seniority

In our application, there are two obvious dimensions according to which faculty can be classified: seniority and department affiliation. It is interesting to compare faculty outcomes at different seniority levels and across different departments under the observed assignment and the best-found one. Distributions over the assessed outcomes under each assignment are presented in Figures B1 and B2.

Panels (a) and (b) in Figure B1 illustrate the comparison between seniors' and juniors' physical outcomes, evaluated according to the weights estimated in $CL(i)$ for the physical office attributes.[1] As can be seen, the wedge between outcomes experienced by different seniority levels is substantially greater under the observed assignment relative to the best-found one. Panel (a) shows that in the observed assignment the physical utility distribution of senior faculty first-order stochastically dominates that for the junior faculty. This is intuitive: senior faculty chose first, and got better selections. Note that in Figure 2 of the paper,

[1]Note that efficiency levels remain the same if individuals on floors 5 and 7 or floors 6 and 8 are exchanged. Such a switch could, however, affect fairness levels (if juniors and seniors are not uniformly distributed across floors). Hence, exchanges of floors could, in principle, raise the similarity of outcomes in Panel (b).



(a) Physical, Observed

(b) Physical, Best-Found

(c) Network, Observed

(d) Network, Best-Found

Figure B2. : Utility Cumulative Distribution, by Department

white nodes, corresponding to senior faculty, are located predominantly on one side of the building, the more desirable western side. In contrast, in the best-found assignment, represented in Panel (b), the distributions for juniors and seniors are much closer.

In terms of network utility, junior and senior faculty experience similar outcomes under both assignments, as can be seen in panels (c) and (d). Ultimately, in terms of seniority, there does not seem to be a trade-off between fairness and efficiency. In fact, the best-found assignment appears to generate more egalitarian outcomes in terms of physical office attributes.

Figure B2 illustrates outcomes for faculty within different departments under the observed and best-found assignments. Panels (a) and (b) suggest that, with respect to department, there could be a tension between efficiency and fairness. Indeed, under the best-found assignment, the physical utility distribution of the departments are first-order stochastically ranked. The underlying reason for this is that, while efficiency pushes same-department faculty to be placed in proximity, this is likely to result in individual departments dominating different floors.

Consequently, departments occupying higher floors will experience greater physical utility levels.[2] Panels (c) and (d) suggest that, even in terms of network utility, the best-found assignment entails greater variance in outcomes across departments.

B2. Welfare Properties of the Serial-Dictatorship Mechanism

The analysis presented in the paper allows the evaluation of different mechanisms. Indeed, our estimates from Section 5 provide individual utilities, while the analysis of Section 6 provides a benchmark against which to compare any mechanism in welfare terms. In this section, we consider a class of variations of the mechanism implemented by the school. Namely, we consider several natural re-orderings of the faculty, and as is often the case in standard implementations of serial dictatorship, we do not allow for ex-post swaps.

As described in the paper, assessing the welfare properties of these mechanisms by calculating the corresponding Nash equilibria is computationally unfeasible. We therefore make simplifying assumptions on agents' strategic sophistication in predicting subsequent choices. In particular, we assume that each agent believes that all successors will select the office preferred according to its physical attributes.[3]

We simulate the following three versions of serial-dictatorship: *Random Ordering*, under which faculty are allocated a draft order at random; *Seniority-Random Ordering*, in which higher seniority levels are given priority, and draft order within each seniority level is determined at random (as in the implemented mechanism); and *Department-Random Ordering*, in which departments choose in sequence, and within departments, members are ordered randomly.[4]

To compute the overall utilities obtained by these mechanisms, we exploit the observed choices in our data as follows. We use the simplified beliefs described above to generate, for each individual's feasible office at the time of choice, a projected final assignment. Using the estimates of $PS(iii)$ in the paper to weight the relative importance of the network attributes, we can therefore simulate the likelihood function for each choice, and estimate the scale of the network components vis-à-vis the physical ones by maximizing this likelihood. The estimated marginal effects of the network component on utility are reported as *Network Utility Scale* in Table B1.

As in Section 6 of the paper, Table B1 includes three specifications for the relative network weights (derived from the results of $PS(iii)$ in the paper), using the lower bounds of the estimated intervals, the lower bounds of the confidence

[2]The fact that efficient outcomes imply more fairness across seniority levels but less fairness across departments is robust to aggregating physical and network utilities into an overall utility using the methodology presented in section B2.

[3]This notion is reminiscent of the level-1 behavior described in the cognitive hierarchy literature (see, for example: Stahl and Wilson, 1994, 1995; Costa-Gomes et al., 2001, and references therein)

[4]Among all possible department orderings, we report results for the one generating the highest welfare levels.

Table B1—: Welfare Analysis of Serial Dictatorship

	$S(i)$	$S(ii)$	$S(iii)$
Network Weights			
Department	1.00	1.00	1.00
Coauthor	3.00	0.35	3.75
Coauthor and Friend	6.00	2.95	8.00
Estimates			
Network Utility Scale (†)	7.3%	11.9%	5.9%
	(1.5)	(2.2)	(1.2)
Lower Bound	67.8%	66.2%	69.2%
Simulations			
Seniority-Random Ordering	36.2% [79.5%]	40.3% [79.5%]	35.9% [80.3%]
	(5.8)	(5.6)	(5.5)
Random Ordering	33.2% [78.5%]	37.8% [79.0%]	32.2% [79.2%]
	(5.2)	(5.6)	(5.5)
Department-Random Ordering	46.2% [82.7%]	54.5% [84.6%]	44.7% [83.0%]
	(6.4)	(6.8)	(6.5)

Note: Standard errors in parentheses under estimates of network effect; standard deviations in the simulations. (†) *Network Utility Scale* is measured as an increase in the offices' selection probability given an additional department link, as in Table 3 from the paper.

intervals, and the mid-points of the estimated intervals. We name these specifications $S(i)$, $S(ii)$, and $S(iii)$, respectively. In each column, we first report the network weights used. The *Lower Bound* is the portion of the utility derived from physical office attributes only. Since we assume that faculty value offices' physical characteristics identically, this value does not depend on the assignment chosen and represents a lower bound on the overall utility obtained by any assignment. The remaining percentages are all expressed relative to the relevant best-found assignment detailed in Section 6 of the paper. Each mechanism's performance is measured in two ways: in terms of the network utility, and in terms of the overall utility (the latter reported in square brackets and calculated using the *Network Utility Scale*).

The best ordering we identify corresponds to individuals belonging to the same department choosing in sequence. In particular, the *Department-Random Ordering* obtains up to 54.5% of the maximal network utility and 84.6% of the maximal overall utility level (see $S(ii)$). However, the wedge between the maximal welfare generated by serial dictatorship and the best-found assignment remains important. In fact, even in $S(ii)$, the best performance of the serial dictatorship mechanism generates utility levels that approximately mid-way between the lower bound on utility levels (given by 66.2%) and the best found assignment (100% by construction).

As a robustness check, we have also conducted similar analyses with more sophisticated beliefs. Specifically, we suppose that faculty members believe that subsequent individuals select offices under the assumption that *their followers* will base their decision only using offices' physical characteristics (thereby adding another 'level' to the cognitive process). The results are similar to the ones obtained with the described, more naive, belief specification.

Appendix C: The Ant Colony Algorithm

Ant Colony Algorithms are probabilistic search methods for optimization in combinatorial problems, first introduced by Dorigo (1992). They are named after the natural process they emulate: in the task of finding and retrieving food, ants deposit a pheromone trail along the path between a new food source and their colony. Other ants are attracted by these trails and follow them to the food source, leaving their own trail as they go. Given some randomness in the ants' behavior, and the fact that old pheromone deposits decay over time, the shortest path ends up being chosen more frequently. The pheromones act as a method of communication between the individuals, helping the colony as a whole optimize. The algorithm utilizes a number of probabilistic agents, the 'ants,' that make successive random assignments within a graph. Assignments that are ranked highly by the objective are reinforced through a larger likelihood of occurring in the future, a process that Dorigo et al. (1996, DMC henceforth), term *autocatalytic*—a self-sustaining positive-feedback process.

In our application, each faculty in $\mathcal{F} = \{1, \ldots, N\}$ and each office in $\mathcal{O} = \{1, \ldots, N\}$ constitute nodes on a completely connected bipartite graph. That is, each 'faculty' node f is connected to each 'office' node o, and vice-versa. Therefore, each edge is indexed by a faculty-office pair (f, o), which represents the assignment of faculty f to office o. The algorithm describes a process in which a probability distribution over the edges of the graph is used to generate M sample assignments. The sample assignments are then assessed by the objective function, and the probability distribution is updated to increase the likelihood of better assignments.

The probability distribution is constructed from two matrices: a *pheromone matrix* $\boldsymbol{\Xi}(t)$, which changes over the algorithm's run, and a fixed matrix $\boldsymbol{\Omega}$, termed *the heuristic*. Each has a specific function within the algorithm. The heuristic, $\boldsymbol{\Omega}$, provides an *ex ante* measure for the desirability of each edge (f, o), and guides the assignments in the early phase of the algorithm. The pheromone $\boldsymbol{\Xi}(t)$ encodes the information learned during the algorithm's run. At the outset, we start with an initial distribution of the pheromone $\boldsymbol{\Xi}(0) = \{\xi_{f,o}(0)\}$ that assigns a small equal level to all the edges in $\mathcal{F} \times \mathcal{O}$ (i.e., for each faculty-office pair (f, o), $\xi_{f,o}(0) = \varepsilon$). We follow DMC in constructing the heuristic as follows: Given the network connection matrix $\mathbf{B}$, and the office proximity matrix $\mathbf{H}$, we define $\boldsymbol{\Omega} = \mathbf{B}\boldsymbol{\iota}(\mathbf{H}\boldsymbol{\iota})'$.[5] That is, the heuristic for each pair (f, o) is given by $\omega_{f,o} = (\sum_{f' \in \mathcal{F}} b_{ff'}) \cdot (\sum_{o' \in \mathcal{O}} h_{oo'})$, the product of the faculty member f's total connection value and the office o's neighbors.[6] As such, higher values in $\boldsymbol{\Omega}$ are given to faculty-office pairs in which the office allows for many neighbors and the faculty member has many connected colleagues.

[5]From Section 6.1, recall that B describes the overall intensity of network externalities between any two agents f and f' and H describes the proximity of any two offices o and o'.

[6]In our program, we actually used the normalized heuristic matrix $\widetilde{\boldsymbol{\Omega}} = \frac{\boldsymbol{\Omega}}{\overline{\omega}}$, where $\overline{\omega}$ was the average entry of $\boldsymbol{\Omega}$.

We now outline the assignment algorithm in detail, given the heuristic $\mathbf{\Omega}$ and a particular starting level of the pheromone matrix $\mathbf{\Xi}(0)$. At each iteration $t \geq 0$, the algorithm carries out the following procedure.

(a) Ordering Randomization. Determine a random ordering of faculty, $\{f_1, \ldots f_N\}$.

(b) Faculty Assignment. For $n = 1, .., N$, assign each faculty f_n to a particular location o_n among the offices still unassigned, i.e., $o_n \in \mathcal{O}_n$, where $\mathcal{O}_1 \equiv \mathcal{O}$, and $\mathcal{O}_n \equiv \mathcal{O}_{n-1} \setminus \{o_{n-1}\}$. The probability of a particular location $o \in \mathcal{O}_n$ being chosen for faculty f is given by

$$g^t_{f_n,o} = \frac{\xi^{\rho}_{f,o}(t)\ \omega^{\sigma}_{f,o}}{\sum_{k \in \mathcal{O}_n} \xi^{\rho}_{f,k} \omega^{\sigma}_{f,k}},$$

where $\xi_{f,o}(t)$ is the generic element of the pheromone level matrix in period t, $\mathbf{\Xi}(t)$, and ρ and σ are parameters that control the weight given to the heuristic and the pheromone levels, respectively, in determining the location probabilities.

(c) Ant iteration. At each iteration $t \geq 0$, steps (a) and (b) are repeated M times (where each run represents a particular ‘ant’). Each repetition generates a candidate assignment $\widetilde{\mu}^t_m$.

(d) Pairwise stability. For all $n = 1, \ldots, N$, $m = 1, .., M$, we then use our notion of pairwise stability to improve the candidate assignment $\widetilde{\mu}^t_m$ through a local search.[7] Formally, the local search starts at $\widetilde{\mu}^t_m$, draws a random faculty pair (f, f') and checks if an office swap (with transfers) would be mutually profitable. If it is, the pair swap is implemented and the pairwise-stability process starts over with the new assignment $\left(\widetilde{\mu}^t_m\right)^{f'}_f$. If no office swap is profitable, the process selects another faculty pair (f, f') from those remaining. The local-search algorithm ends when the assignment is pairwise stable.[8] The benefit of adding this step is that the local search algorithm is fairly quick, and can move quite far from the initial candidate assignment $\widetilde{\mu}^t_m$, taking the local network structure into account more explicitly. The initial placements are structured by the ant-colony probabilities, so assignments ‘closer’ to previous local maxima are more likely to occur, but the algorithm’s “deviations” are now used in a more efficient way.[9] The denote the resulting assignment by μ^t_m.

(e) Welfare Computation. The value for the assignment resulting from step (d), μ^t_m, is calculated according to the aggregate welfare function, given by

$$W(\mu^t_m) = \sum_{f \in \mathcal{F}} u_f(\mu^t_m) = \sum_{f=1}^{N} \sum_{l=1}^{L} \beta_l k(f, \mu, l))$$

[7]Note that Proposition 1 guarantees, given our assumptions, that any bilateral improvement is also a global improvement.

[8]Because any profitable swap strictly increases total welfare, and the globally best assignment is pairwise stable, this process ends in a finite number of iterations at a pairwise-stable assignment.

[9]In particular, simulation evidence suggests that in lower-dimensional problems, the ant-colony algorithm with local search is better at finding global maxima than the ant-colony alone.

where, according to the notation used in Section 5, $k(f, \mu, l)$ is the number of faculty from network layer l, $l = 1, ..., L$ that are in f's neighborhood under the assignment μ, and β_l is the estimated coefficient associated with network layer l. Let μ^* be the current best-found assignment. If $W(\mu_m^t) > W(\mu^*)$, we set $\mu^* = \mu_m^t$.

(f) Updating the pheromone matrix $\Xi(t)$ between t and $t+1$. The algorithm changes the distribution from which assignments are drawn by making the assignments that generate high welfare levels more likely to occur. In the simplest formulation, this is achieved by adding the term $\gamma W(\mu_m^t)$ (where γ is a chosen scale parameter) to the pheromone level of all edges used in each assignment. More specifically, for every edge (f, o), we calculate the new pheromone level according to

$$\xi_{f,o}(t+1) = \lambda \xi_{f,o}(t) + \gamma \sum_{i=1}^{M} W(\mu_m^t) 1\{\mu_m^t(f) = o\},$$

where λ is the decay parameter of pheromones. If we write the assignment function μ as an assignment matrix $\mathbf{X}(\mu)$ (so that $x(\mu)_{f,o} = 1$ whenever $\mu(f) = o$, and 0 otherwise), this has the matrix form:

$$\Xi(t+1) = \lambda \Xi(t) + \gamma \sum_{i=1}^{M} W(\mu_m^t) \mathbf{X}(\mu_m^t).$$

The process places higher weight on highly efficient assignments (i.e., assignments that generate more network connections).

Alternatively, it is possible to reward each edge via its contribution to total welfare—that is, we could instead deposit $\sum_{l=1}^{L} \beta_l k(f, \mu, l))$ pheromones on each utilized edge $(f, \mu(f))$. This process is called an *Ant-Quantity* algorithm, as opposed to the previous specification, which is known as an *Ant-Cycle* algorithm. DMC provide simulation results suggesting better performance from the Ant-Cycle specification in the Traveling-Salesman Problem, attributing the effect to the higher saliency for global placements in the latter stages of an algorithm's run. One final variation on the procedure is called an *Elitist Ant Colony*, in which we follow the above algorithm with an additional pheromone component derived from the best assignment μ^* found over the M repetitions. That is, the pheromone update process is given by

$$\Xi(t+1) = \lambda \Xi(t) + \gamma \left[m^* W(\mu_m^t) \mathbf{X}(\mu^*) + \sum_{i=1}^{M-m^*} W(\mu_m^t) \mathbf{X}(\mu_m^t) \right],$$

where m^* is a parameter representing the number of elitist ants who follow the best-found assignment.

(g) End Condition. Since for any two consecutive periods the objective $W(\mu^*)$ is likely to remain the same, a convergence condition cannot easily be used as an end condition. Consequently, the end-condition for the algorithm is either a certain number of iterations T, or a limit on the run-time. However, during the algorithm's run it is sometimes necessary to reset the process. This is because the pheromone matrix can converge in a way that does not leave enough variation to the stochastic assignment process. One way to avoid this is to reduce the parameter ρ, keeping in mind that, as we do that, the positive-feedback process becomes less important.[10]

In our specific application, a problem arising with the procedure is that location probabilities for faculty members are independent. Ideally, we would like to probabilistically re-sample the location for a defined group. However, the algorithm internalizes the social network structure only through the objective W and the heuristic matrix $\mathbf{\Omega}$, and samples deviations of individual members independently. While we added Step (d) to the DMC procedure to mitigate this limitation, more complicated structures might allow for correlated locations of small groups within the innermost loop.

The main advantages of the ant-colony algorithm are its fairly robust global-search properties and relatively simple implementation. In addition, the algorithm seems flexible and easy to customize to particular applications, for example by treating pheromone levels in alternative ways as illustrated above. The main drawbacks are the large number of parameters that need to be specified by the user.

[10]DMC recommends setting $\rho = 1$, and $\sigma = 5$ and $\lambda = 0.5$. However, in general, one may have to experiment with different parameters to uncover potential trade-offs. Decreasing λ leads to a greater ability to forget previous assignments, but decreasing it too much results in a large variance in the path of the algorithm. Increasing ρ leads to a greater focus on the pheromone process and less on the heuristic one, which has negative implications in the early iterations, where we want to use the heuristic to guide search. Similarly, increasing σ places greater weight on the heuristic, which is beneficial in early iterations, but reduces the global search properties in later iterations. In many ways, the algorithm provides an interesting starting point from which one can set up search procedures tailored for a specific problem.

Appendix D: The Faculty Survey

Hello and thank you for responding!

Your survey responses will be strictly confidential and data from this research will be reported only in the aggregate. Your information will be coded and will remain confidential. Please start with the survey now by clicking on the Continue button below.

1) Your name:

   Department:

2) How many days a week do usually come into your office? [38 and 37]

Teaching period	1(2.63%)	2(2.63%)	3(13.16%)	4(39.47%)	5(23.68%)	>5(18.42%)
Non-teaching period	1(2.70%)	2(18.92%)	3(10.81%)	4(32.43%)	5(27.03%)	>5(8.11%)

3) How many hours (on average) do you spend at the office? [38]

Teaching period	<2(0%)	$2-5$(5.26%)	$5-8$(39.47%)	>8(55.26%)
Non-teaching period	<2(0%)	$2-5$(2.63%)	$5-8$(60.53%)	>8(36.84%)

4) In a typical week, which days of the week to do you come into your office? [38]

Monday:	(18.24%)
Tuesday:	(19.50%)
Wednesday:	(17.61%)
Thursday:	(18.87%)
Friday:	(22.01%)
Weekend:	(3.77%)

5) Do you try to come to the office when your office neighbors are around? [38]

Yes, I try to coordinate:	(31.58%)
I do not think about it:	(68.42%)
No, I try to arrive when they are not there:	(0%)

6) Please name up to 5 people you have lunch with on a regular basis and specify the number of times in a typical week that you have lunch with each of these. [27]

7) Please name up to 5 of your most recent coauthors within the business school and the year in which you have last worked together. [21]

8) Please name up to 5 personal friends (people with whom you interact socially with outside school at least once a month) from within the business school. [13]

9) Please name up to 5 colleagues that would be valuable for you to have on your floor. [28]

10) On a scale of 1-10, how important to you are the floor (4-8), exposure (east, west, or south), and size (corner office or standard office) for the quality of an office (where 1 is least important and 10 is most important)? [37]

Floor:	1(10.81%)	2(5.41%)	3(8.11%)	4(5.41%)	5(10.81%)
	6(5.41%)	7(13.51%)	8(8.11%)	9(10.81%)	10(21.62%)
Exposure:	1(8.11%)	2(8.11%)	3(5.41%)	4(8.11%)	5(18.92%)
	6(8.11%)	7(8.11%)	8(16.22%)	9(8.11%)	10(10.81%)
Size:	1(10.81%)	2(5.41%)	3(2.70%)	4(8.11%)	5(18.92%)
	6(10.81%)	7(5.41%)	8(13.51%)	9(10.81%)	10(13.51%)

11) For a particular exposure and size of office, please rank the floors from 1-5 (where 1 would be your most preferred floor and 5 would be your least preferred floor). [43]

Floor 4:	1(14.29%)	2(0.00%)	3(5.71%)	4(0.00%)	5(80.56%)
Floor 5:	1(0.00%)	2(14.29%)	3(11.43%)	4(71.43%)	5(2.78%)
Floor 6:	1(8.57%)	2(11.43%)	3(74.29%)	4(5.71%)	5(0.00%)
Floor 7:	1(8.57%)	2(68.57%)	3(2.86%)	4(17.14%)	5(2.78%)
Floor 8:	1(68.57%)	2(5.71%)	3(5.71%)	4(5.71%)	5(13.89%)

12) On a scale of 1-10, what was the importance of your office neighbors to you prior to moving (where 1 is least important and 10 is most important)? [37]

1(10.81%) 2(0.00%) 3(5.41%) 4(8.11%) 5(2.70%) 6(10.81%)
7(5.41%) 8(8.11%) 9(24.32%) 10(24.32%)

13) If you are part of a particular research cluster within your department, please identify it. [26]

14) On a scale of 1-10, how important is it for you to be on the same floor with members of your own department and research cluster (where 1 is least important and 10 is most important)? [37 and 35]

Department:	1(5.41%)	2(2.70%)	3(2.70%)	4(2.70%)	5(5.41%)
	6(10.81%)	7(13.51%)	8(16.22%)	9(16.22%)	10(24.32%)
Research Cluster:	1(8.57%)	2(0.00%)	3(5.71%)	4(0.00%)	5(2.86%)
	6(5.71%)	7(8.57%)	8(8.57%)	9(14.29%)	10(45.71%)

15) On a scale of 1-10, how important is it for you to be a direct neighbor, that is, sit in an adjacent office to, or across the hallway from members of your own department and research cluster (where 1 is least important and 10 is most important)? [37 and 35]

Department:	1(16.22%)	2(2.70%)	3(10.81%)	4(5.41%)	5(13.51%)
	6(5.41%)	7(10.81%)	8(10.81%)	9(16.22%)	10(8.11%)
Research Cluster:	1(8.57%)	2(2.86%)	3(14.29%)	4(2.86%)	5(8.57%)
	6(2.86%)	7(8.57%)	8(17.14%)	9(17.14%)	10(17.14%)

16) At the time of your selection, how likely did you think you were to switch offices (where 1 corresponds to no switch and 10 corresponds to sure switch)? [36]

1(22.22%)	2(11.11%)	3(22.22%)	4(8.33%)	5(5.56%)
6(8.33%)	7(2.78%)	8(8.33%)	9(2.78%)	10(8.33%)

17) To what extent was your initial selection of a new office influenced by the possibility of ex-post trade, that is, by how desirable the office would be for others (where 1 corresponds to unimportant and 10 corresponds to very important)? [36]

1(36.11%)	2(5.56%)	3(13.89%)	4(11.11%)	5(5.56%)
6(11.11%)	7(2.78%)	8(5.56%)	9(5.56%)	10(2.78%)

18) Did you exhaust your research account this past year? [34]

Yes	(61.76%)
No	(38.24%)

19) Did you exchange offices with anyone using your research account? [35]

Yes	(11.43%)
No	(77.14%)
Tried but failed	(11.43%)

20) Did you exchange offices with anyone without using your research account? [33]

Yes	(6.06%)
No	(81.82%)
Tried but failed	(12.12%)

21) We would appreciate it greatly if you could describe to us how you would made your decision of office in the space below. [29]

22) Suppose that an additional office were made available and auctioned off in the business school. Please specify your 3 top choices for the location of that office (in terms of floor - 4 through 8 and exposure - east, west, or south) and the maximal bid you would be willing to pay out of your research account in order to move from your current allocated office to the new available one. Thus, if you specify an amount X for any particular office, and all other bids fall below that, you would move to that office and pay X out of your research account. If any other bid surpasses X, you would stay in your current office. If several other colleagues would specify precisely the same X, we would randomly select one of you and exchange their office for X out of their research account.

*

REFERENCES

Costa-Gomes, Miguel, Vincent P. Crawford, and Bruno Broseta, "Cognition and Behavior in Normal-Form Games: An Experimental Study," *Econometrica*, 2001, *69* (5), 1193–1235.

Dorigo, Marco, "Optimization, learning and natural algorithms." PhD dissertation, Politecnico di Milano, Italy 1992.

_, Vittorio Maniezzo, and Alberto Colorni, "Ant system: optimization by a colony of cooperating agents," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 1996, *26* (1), 29–41.

Moulin, Hervé, *Fair division and collective welfare*, MIT Press, 2003.

Stahl, Dale O. and Paul W. Wilson, "Experimental evidence on players' models of other players," *Journal of Economic Behavior & Organization*, 1994, *25* (3), 309–327.

_ and _, "On Players' Models of Other Players: Theory and Experimental Evidence," *Games and Economic Behavior*, 1995, *10* (1), 218–254.