Near-Feasible Stable Matchings with Couples

Thành Nguyen* and Rakesh Vohra†

August 2015, this version March 2018

Abstract

The National Resident Matching program seeks a stable matching of medical students to teaching hospitals. With couples, stable matchings need not exist. Nevertheless, for any student preferences, we show that each instance of a matching problem has a 'nearby' instance with a stable matching. The nearby instance is obtained by perturbing the capacities of the hospitals. Given a reported capacity k_h for each hospital h, we find a redistribution of the slot capacities, k_h^*, satisfying $|k_h - k_h^*| \leq 2$ for all hospitals h and $\sum_h k_h \leq \sum_h k_h^* \leq \sum_h k_h + 4$, such that a stable matching exists with respect to k^*.

Keywords: stable matching, complementarities, Scarf's lemma

JEL classification: C78, D47

1 Introduction

Each year, about 20,000 medical school graduates are matched to teaching hospitals via the National Resident Match Program (NRMP).[1] This service has been in operation since 1952 and its high rates of participation and longevity is ascribed to the fact that the matching produced is stable (Roth [1984]). Stability means no doctor-hospital pair can improve their outcomes by matching with each other outside the NRMP. Absent stability, a pair who find a mutually beneficial match compared to the one delivered by the centralized market will abandon the market, triggering a chain of exits that may cause the market to collapse.

*Krannert School of Management, Purdue University, nguye161@purdue.edu

†University of Pennsylvania, rvohra@seas.upenn.edu

[1] http://www.nrmp.org/wp-content/uploads/2014/04/Main-Match-Results-and-Data-2014.pdf

When each doctor submits a separate preference list, stable matchings exist and can be found using the Deferred Acceptance (DA) algorithm (Gale and Shapley [1962]). However, in the presence of couples who submit joint preference lists over pairs of hospitals, a stable matching need not exist, which could lead to the unraveling of the centralized market (see Roth [1984]). Roth and Peranson [1999] proposed a heuristic modification of the DA algorithm to accommodate couples' preferences. It has, without fail, returned matches that are stable with respect to reported preferences.

Kojima et al. [2013] and Ashlagi et al. [2014] explain this success within a large market with random preferences and a vanishingly small proportion of couples. In the same model Ashlagi et al. [2014] show that as the proportion of couples increases, a stable matching does not exist with high probability. In the NRMP, the proportion of couples is between 5% and 10%, but elsewhere, the proportion of couples is as high as 40% (see Biró and Klijn [2013]). Moreover, resident matching is not the only setting with a 'couples' problem. Biró et al. [2013] points to the task of assigning high school teachers in Hungary to pairs of majors.

In this paper we propose an entirely different approach that does not rely on appeals to scale, randomness or a small proportion of couples.[2] To bypass the problem of nonexistence of a stable matching, we assume that hospital capacity constraints are 'soft'. In particular, we show that for any instance of the stable matching problem with couples, our algorithm finds a stable matching with respect to a 'nearby' instance, which is obtained by altering the initial capacities of the hospitals.

Adjusting the capacities of hospitals is not uncommon. The NRMP allows hospitals to choose if they wish to be matched with an even or odd number of students. Thus, a hospital can choose to reduce its capacity by 1. In fact, slots are sometimes reallocated between hospitals.[3] Further, in some specialties where supply outstrips demand, slots go unfilled. In these cases, hospitals have 'work arounds', one of which is to use the money that would have

[2] Our approach applies to more general complementarities.

[3] https://www.acponline.org/advocacy/where_we_stand/assets/iii4-redistribution-graduate-medica-education-slots.pdf

gone to the unfilled slot to incentivize existing doctors to 'pick up the slack'.

To formalize the notion of nearby, call a matching α-feasible if the number of slots allocated by each hospital to doctors differs (up or down) from its actual capacity by at most α. Our iterative rounding (IR) algorithm returns a 2-feasible stable matching that neither decreases the total number of slots nor increases it by more than 4 (Theorem 2.1). This guarantee does not depend on any restriction in the preferences of doctors (single or otherwise) and is independent of the size of the instance.

Regarding a possible increase of at most 4 slots in total, every additional resident, according to the American Medical Association, costs about $100,000 on average. The bulk of the funding for such positions comes from the US Government via Medicaid. Currently, the total expenditure on resident training is upward of $10 billions.[4]

A reduction of up to 2 slots in a small hospital's capacity could be dramatic. In internal medicine, for example, the number of slots can be as small as 4 and as large as 30.[5] However, programs with a small number of slots tend to be concentrated in rural areas. Couples participating in the NRMP are advised to apply to urban areas with many hospitals so as to increase their chances of obtaining positions close to each other. Our algorithm has the property that if no couple applies to a rural hospital, then that rural hospital's capacities are unchanged (Theorem 2.2).

Preliminary simulations of the IR algorithm suggest that only a very small fraction of hospitals see a change in their capacities.[6] The first set of experiments is based on 200 randomly generated instances involving 270 doctors, 18 hospitals and the proportion of couples ranging from 10% to 90%.

The total capacity of hospitals is equal to the number of applicants. Hospitals were

[4] These numbers are from an AMA pamphlet in support of the current approach to funding residency programs. `http://savegme.org/wp-content/uploads/2013/01/graduate-medical-education-action-kit.2-3.pdf`

[5] See `http://www.nrmp.org/wp-content/uploads/2015/05/Main-Match-Results-and-Data-2015_final.pdf`.

[6] A comprehensive test of the IR is beyond the scope of this paper. The results we report are based on work in progress jointly with Dengwang Tang and Vijay Subramaniam.

randomly assigned to one of 5 regions in such a way that each region had at least one hospital. The total number of slots for a hospital in region i ($i = 1, 2, \ldots, 5$) is proportional to $1/i$ (i.e. follows a Zipf distribution). Slots within the region are assigned with equal probability among the hospitals. This is designed to mimic the fact that hospitals in metropolitan areas have significantly more slots than those in rural areas.

Hospitals have the same randomly generated priority ordering over individual doctors. Doctors and couples' preferences are generated to mimic features of reported preferences. Single doctors' preferences are based on the 'popularity' of the hospitals, and couples are assumed to prefer hospitals in the same region rather than different regions. Appendix A describes in more details how these preferences were generated.

The table below provides summary statistics of the proportion of hospitals that see a change in capacity for varying proportions of couples. The margin of error for the 95% confidence interval is displayed in brackets.

	% hospitals with capacity adjustment (95% confidence interval MoE)				
% couples	no change	+1 position	-1 position	+2 position	-2 position
10%	97.78% (2.04)	1.03% (1.40)	1.14% (1.47)	0.03% (0.24)	0.03% (0.24)
30%	92.61% (3.63)	3.42% (2.52)	3.75%(2.63)	0.19% (0.61)	0.03% (0.24)
50%	85.53% (4.88)	6.53% (3.42)	7.22%(3.59)	0.53% (1.00)	0.19 % (0.61)
70%	80.64% (5.48)	7.89%(3.74)	9.53%(4.07)	1.36% (1.61)	0.58% (1.06)
90%	75.72% (5.94)	9.89%(4.14)	11.86% (4.48)	1.75% (1.82)	0.78 % (1.22)

The proportion of hospitals with a capacity of 3 or less that saw a change in their capacity is very small. One has to increase the fraction of couples to see this. For example, at 30% couples, on average at most 2% of hospitals with a capacity of 2 or smaller saw a change in their capacity.

The second set of experiments are on 1000 instances involving 500 doctors, kindly provided by Peter Biró. These instances are known to have stable matchings because couples are endowed with weakly responsive preferences (see Klaus and Klijn [2005]). This is done to determine how well the IR algorithm performs on instances where a stable match is known to exist.[7] The IR algorithm always returns an exact stable matching on these instances. Biró et al. [2013] report that their implementation of the Roth and Peranson algorithm frequently fails to terminate in a stable matching on these instances when a high proportion of couples are present. In their experiments, with at least 175 couples, the Roth and Peranson algorithm fails to find a stable matching in at least 90% of the 1000 instances.[8]

Unlike all prior algorithms employed in matching problems (with the exception of Biró et al. [2013]), our algorithm does *not* use the DA algorithm introduced in Gale and Shapley [1962]. It employs, instead, a combination of Scarf's lemma (Scarf [1967]) and the iterative rounding method, developed in Lau et al. [2011] and Nguyen et al. [2016]. In the first stage, Scarf's lemma is used to extend the notion of stability to fractional matchings as well as to identify a fractional matching that is stable.[9] In the second stage, this fractional matching is carefully rounded into an actual matching such that stability is preserved.[10]

Below, we discuss the related literature. In Section 2, we give a formal definition of the stable matching problem with couples. Section 3 states Scarf's lemma and formulates the matching problem in a way to invoke the lemma. Section 4 outlines the IR in this context. Section 5 concludes. Proofs are given in the Appendix.

Related work. Roth [1984] establishes the non-existence of a stable matching when some agents are couples. Subsequently, the more general problem of matching in the presence of complementarities has become an important topic. See Biró and Klijn [2013] for a brief survey. The literature has taken four approaches to circumventing the problem of non-existence.

[7] The Roth and Peranson algorithm is not guaranteed to find a stable matching if one exists.

[8] The need to deal with a large proportion of couples arises in settings like assigning teachers to pairs of courses in Hungary (see Biró et al. [2013]).

[9] Biró et al. [2013] also use Scarf's lemma and in their simulations report how often the matching returned is integral.

[10] Our approach, while constructive, relies on Scarf's lemma, which is PPAD complete, Kintali [2008]. Thus, it has a worst-case complexity equivalent to that of computing a fixed point. This is not a barrier to implementation. For example, building on Budish [2011], a course allocation scheme that relies on a fixed-point computation has been proposed and implemented at the Wharton School.

- Restrict couple's preferences to ensure the existence of a stable matching (Cantala [2004], Klaus and Klijn [2005], Pycia [2012], and Sethuraman et al. [2006].)

  These restrictions rule out very many plausible preferences.

- Argue that instances of non-existence are rare in large markets.

  Kojima et al. [2013] and Ashlagi et al. [2014] show that in a setting where applicant preferences are drawn independently from a distribution, as the size of the market increases and the proportion of couples approaches 0, the Roth and Peranson algorithm terminates in a stable matching. But, Ashlagi et al. [2014] shows that when the proportion of couples is positive, the probability that no stable matching exists is bounded away from 0 even when the market's size increases. The results of Azevedo and Hatfield [2015] as well as Che et al. [2015] imply that stable matchings with complementaries exist with a continuum of agents on one side.

- Ignore the indivisibility of agents and provide interpretations of 'fractional' stable matchings (Dean et al. [2006], Aharoni and Holzman [1998], Aharoni and Fleiner [2003], Király and Pap [2008], and Biro and Fleiner [2016]).

  Dean et al. [2006] is closest to this paper. It solves a restricted instance of the stable matching problem with couples. In that instance, couples prefer to be together, rather than apart, and a hospital must accept either both members of the couple or none. This restriction considerably simplifies the problem because each blocking constraint only involves the preferences of a single hospital. In fact, in practice, many sources advise couples *not* to apply to the same specialty at a hospital to avoid being scheduled in such a way that they do not see each other. Dean et al. [2006] adapt the DA algorithm to identify a stable matching that is 2-feasible. They are unable to bound the aggregate increase in capacity.

- Modify the notion of stability (Klijn and Masso [2003], Jiang and Tan [2014], and Manlove et al. [2016].)

The modifications need not capture the original spirit of the notion of stability.

2 Matching with Couples and Main Result

In this section we describe the standard matching model with couples, that is studied, for example, in Roth [1984] and Kojima et al. [2013]. Let H be the set of hospitals, D^1 be the set of single doctors, and D^2 the set of couples. Let D be the set of all doctors listed as individuals. Denote the outside option of each doctor, couple and hospital by $\emptyset$.

Each single doctor in D has a strict preference ordering over H and her outside option. Each couple in D has a strict preference ordering over ordered pairs of hospitals as well as their outside option. The need for ordered pairs arises because couples will have preferences over which member is assigned to which hospital. We say a hospital or an ordered pair of hospitals is acceptable to a single doctor or a couple, if they are ranked above the outside option in the doctor and couple's preference, respectively.

Each hospital $h \in H$ has a fixed capacity $k_h > 0$. The preference of a hospital h over subsets of doctors is assumed to be responsive. This means that h has a strict priority ordering $\succ_h$ over elements of D and its outside option. A doctor ranked above the outside option by the priority ordering is said to be acceptable for hospital h.[11]

A matching μ is an assignment of each single doctor to a hospital or his/her outside option, an assignment of couples to at most two positions (in the same or different hospitals) or their outside option, such that the total number of doctors assigned to any hospital h does not exceed its capacity k_h.

A matching satisfies individual rationality if all hospitals receive only acceptable doctors, and all doctors and couples are assigned to acceptable choices.

A matching μ can be 'blocked' in three different ways. First, by a pair (d, h) such that $d \in D^1$ prefers h to $\mu(d)$ and h would select d possibly over a doctor currently assigned to it. Second, by a couple, $c \in D^2$ and a hospital h such that the couple prefers to be assigned

[11] To avoid trivialities we assume that there is at least one acceptable doctor for each hospital.

to h over their current assignments and h would accept them, possibly over some of its current assignments. Third, by a couple and two distinct hospitals. In this case, the couple would prefer to be assigned to the two hospitals (one to each) over their current assignment and each of the hospitals would accept a member of the couple over at least one of their current assignment. A matching μ is **stable with respect to a capacity vector** k if μ is individually rational and cannot be blocked in any of the three ways just described. A formal definition and further discussion of stability appear in Appendix B and D, where we show that our approach actually finds a matching satisfying a stronger stability condition than the standard one described above.

Our main result is the following:

THEOREM 2.1 *Suppose each doctor in D^1 has a strict preference ordering over the elements of $H \cup \{\emptyset\}$, each couple in D^2 has a strict preference ordering over $H \cup \{\emptyset\} \times H \cup \{\emptyset\}$, and each hospital has responsive preferences. Then, for any reported capacity vector k, the IR algorithm returns a k^* and a stable matching with respect to k^*, such that $\max_{h \in H} |k_h - k^*_h| \leq 2$. Furthermore, $\sum_{h \in H} k_h \leq \sum_{h \in H} k^*_h \leq \sum_{h \in H} k_h + 4$.*

We don't know if the bound on individual hospitals can be improved to $\max_{h \in H} |k_h - k^*_h| \leq 1$. In appendix G.1 we outline why our method cannot yield such a result.

Recall from Section 1 that our preliminary simulations show that only a small fraction of hospitals see changes in capacity. Furthermore, if one restricts the preferences of the couples, some hospitals will see no change in capacity. To illustrate, note that couples participating in the NRMP are usually advised to avoid isolated hospitals so as to increase their chances of obtaining positions close to each other. These isolated hospitals usually have fewer slots and the theorem below says that their capacities will not be altered.

THEOREM 2.2 *Let H^R be the set of hospitals that receive no applications from couples, then, the IR algorithm can be modified so that in addition to the guarantees in Theorem 2.1, $k^*_h = k_h$ for all $h \in H^R$.*

In the remainder of the paper, we provide the proof of Theorem 2.1. The proof of Theorem 2.2 is based on similar ideas and may be found in Appendix H.

3 Scarf's Lemma and Fractional Stable Matching

To state Scarf's lemma, we need the following definition which is closely related to the notion of stability.

DEFINITION 3.1 *Let $\mathcal{Q}$ be an $n \times m$ nonnegative matrix with at least one non-zero entry in each row and $q \in \mathbb{R}^n_+$. Associated with each row $i \in \{1, .., n\}$ of $\mathcal{Q}$ is a strict order $\succ_i$ over the set of columns j for which $\mathcal{Q}_{i,j} > 0$. A vector $x \geq 0$ satisfying $\mathcal{Q}x \leq q$* **dominates** *column j of $\mathcal{Q}$ if there exists a row i such that $\sum_{j=1}^{m} \mathcal{Q}_{ij}x_j = q_i$ and $k \succeq_i j$ for all $k \in \{1, .., m\}$ such that $\mathcal{Q}_{i,k} > 0$ and $x_k > 0$. In this case, we also say x* **dominates column j at row i.**

To interpret this definition it is helpful to consider the case when $\mathcal{Q}$ is a 0-1 matrix. Associate each row of $\mathcal{Q}$ with an agent and interpret each column to be the characteristic vector of a coalition of agents. Hence, $\mathcal{Q}_{ij} = 1$ means that agent i is in the j^{th} coalition. Then, $\succ_i$ can be interpreted as agent i's preference ordering over all the columns/coalitions of $\mathcal{Q}$ that contain agent i. Each non-zero component of a vector x such that $\mathcal{Q}x \leq q$ corresponds to a coalition. To interpret domination, consider a coalition, S, not selected by x. If x dominates this coalition it means that there is at least one agent, $i \in S$, who strictly prefers all of the coalitions in the support of x that includes it, over S.

We use the following version of Scarf's lemma, which can be found in Király and Pap [2008] as well as an unpublished paper of Scarf [1965]:

LEMMA 3.1 (SCARF [1967]) *Let $\mathcal{Q}$ be an $n \times m$ nonnegative matrix and $q \in \mathbb{R}^n_+$. Then, there exists an extreme point of $\{x \in \mathbb{R}^m_+ : \mathcal{Q}x \leq q\}$ that dominates every column of $\mathcal{Q}$.*

Scarf [1967] gives an algorithm for finding a dominating extreme point.

To understand the connection of domination to stability, it is helpful to consider an example.

Example 1 *Consider an instance with two hospitals* (h_1, h_2)*, each with capacity 1, two single doctors* (d_1, d_2)*, and no couples. This is the setting of Gale and Shapley [1962]. The preferences are as follows:* $d_1 \succ_{h_1} d_2; d_1 \succ_{h_2} d_2$*;* $h_2 \succ_{d_1} h_1; h_2 \succ_{d_2} h_1$.

We will describe the set of feasible matchings as the solution to a system of inequalities. The constraint matrix of this system will be the matrix $\mathcal{Q}$ *that will be used when invoking Scarf's lemma.*

Introduce variables $x_{(d_i,h_j)} \in \{0,1\}$ *for* $i \in \{1,2\}; j \in \{1,2\}$ *where* $x_{(d_i,h_j)} = 1$ *if and only if* d_i *is assigned to* h_j *and zero otherwise. In the* 4×4 *matrix,* $\mathcal{Q}$*, below, each row corresponds to an agent (a hospital or a doctor), and each column corresponds to a doctor-hospital pair. An entry* $\mathcal{Q}_{ij}$ *of the matrix* $\mathcal{Q}$ *is* 1 *if and only if the agent corresponding to row* i *is a member of the coalition corresponding to column* j*. Otherwise,* $\mathcal{Q}_{ij} = 0$*.* $\mathcal{Q}x \leq q$ *models the capacity constraints of the hospital and the constraints that each doctor can be assigned to at most one hospital. In this example* $q = \mathbf{1}$*. For each row* i *of* $\mathcal{Q}$*, the strict order on the set of columns* j *for which* $\mathcal{Q}_{ij} \neq 0$ *is the same as the preference ordering of agent* i*. Specifically, we have the following system:*

$$
\begin{array}{c}
\\ h_1 \\ h_2 \\ d_1 \\ d_2
\end{array}
\begin{array}{c}
\begin{array}{cccc} (d_1,h_1) & (d_1,h_2) & (d_2,h_1) & (d_2,h_2) \end{array} \\
\left[\begin{array}{cccc}
1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 \\
1 & 1 & 0 & 0 \\
0 & 0 & 1 & 1
\end{array}\right]
\end{array}
\cdot x \leq
\left[\begin{array}{c} 1 \\ 1 \\ 1 \\ 1 \end{array}\right]; \quad order:
\begin{array}{c}
column_1 \succ column_3 \\
column_2 \succ column_4 \\
column_2 \succ column_1 \\
column_4 \succ column_3.
\end{array}
$$

Every integer solution to $\mathcal{Q}x \leq \mathbf{1}$ *corresponds to a matching and vice versa. Notice,* $x = (1,0,0,1)^T$ *corresponds to the matching* $(d_1, h_1); (d_2, h_2)$*. It is not stable because it is blocked by* (d_1, h_2)*. In the language of Scarf's lemma,* $x = (1,0,0,1)^T$ *is not a dominating solution because* x *does not dominate the column corresponding to* (d_1, h_2)*. The solution* $x = (0,1,1,0)^T$ *is a dominating solution and corresponds to a stable matching.*

By the Birkhoff-von Neumann theorem, every non-negative extreme point of the system

$Qx \leq \mathbf{1}$ is integral. Therefore, it follows by Scarf's lemma that a stable matching exists. It is easy to see that the conclusion generalizes to more than two single doctors and unit-capacity hospitals.

We now show how to apply Scarf's lemma to the problem of matching with couples. For each single doctor d and hospital h, that are mutually acceptable, let $x_{(d,h)} = 1$ if d is assigned to h and 0 otherwise. Similarly, for each couple $c \in D^2$ and distinct $h, h' \in H$, such that (h, h') is acceptable to c and the first and second member of c are acceptable to h and h', respectively, let $x_{(c,h,h')} = 1$ if the first member of c is assigned to h and the second is assigned to h'. Let $x_{(c,h,h')} = 0$ otherwise.[12] Finally, for a couple c and a hospital h that are mutually acceptable, let $x_{(c,h,h)} = 1$ if both members of the couple are assigned to hospital $h \in H$ and 0 otherwise. Every 0-1 solution to the following system is a feasible matching and vice versa.

$$\sum_{d \in D^1} x_{(d,h)} + \sum_{c \in D^2} \sum_{h' \neq h} x_{(c,h,h')} + \sum_{c \in D^2} \sum_{h' \neq h} x_{(c,h',h)} + \sum_{c \in D^2} 2x_{(c,h,h)} \leq k_h \ \forall h \in H \tag{1}$$

$$\sum_{h \in H} x_{(d,h)} \leq 1 \ \forall d \in D^1 \tag{2}$$

$$\sum_{h,h' \in H} x_{(c,h,h')} \leq 1 \ \forall c \in D^2 \tag{3}$$

Let $\mathcal{Q}$ be the matrix whose entries are the coefficients of the system (1-2-3). In (1-2-3), each agent (single doctor, couple and hospital) is represented by a single row. Each column/variable corresponds to a coalition of agents (an assignment of a single doctor to a hospital or a couple to a pair of hospital slots, that are mutually acceptable).

We need each of the rows in (1-2-3) to have an ordering over the columns that are in the support of that row. This is clearly true for the rows associated with a single doctor and a couple as we can just use their preference ordering over the hospitals (and pairs of hospitals in the case of couples).

[12]Note that $x_{(c,h,h')}$ does not represent the same thing as $x_{(c,h',h)}$.

It is not true for the rows associated with hospitals. To apply Scarf's lemma, each hospital h must have an ordering over columns associated with coalitions involving either a single doctor or a couple and the hospital h. We use hospital h's priority ordering, $\succ_h$, to generate an ordering $\succ_h^*$ with the property that domination with respect $\succ_h^*$ corresponds to stability in the sense defined.

Hospital h will order these columns based on its ranking of the corresponding doctors assigned to h. If the column corresponds to an assignment of both members of a couple to h, then, h's ranking of this column depends on the ranking the 'worst' member of the couple, as determined by $\succ_h$. Under this ordering there can be ties between columns that correspond to different ways a couple is assigned. For example, one member is assigned to h, while the other is assigned elsewhere. To break the ties between these columns, h uses the preference ordering of the couple. We denote by $\succ_h^*$ this new ordering. We illustrate the construction of $\succ_h^*$ in the following example. A formal definition of $\succ_h^*$ is given in Appendix C.

EXAMPLE 2 *Suppose two hospitals h, h', one couple $c = (d_1, d_2)$, and a single doctor, d_3. The priority ordering of h is $d_1 \succ_h d_3 \succ_h d_2$. Consider the order of hospital h for the columns corresponding to $x_{(c,h,h')}, x_{(c,h',h)}, x_{(c,h,h)}$, and $x_{(d_3,h)}$. In the coalition (c, h, h'), d_1 is assigned to h; in (c, h', h), d_2 is assigned to h; in (d_3, h), d_3 is assigned to h, and in (c, h, h) both d_1 and d_2 are assigned to h. The ordering $\succ_h^*$ ranks (c, h, h) based on h's priority ordering of the worst member, which is d_2. Thus,*

$$(c, h, h') \succ_h^* (d_3, h) \succ_h^* (c, h', h) \sim (c, h, h).$$

The tie between (c, h', h) and (c, h, h) is broken based on the preference ordering of c. Namely,

$$(c, h', h) \succ_h^* (c, h, h) \text{ if and only if } (h, h') \succ_c (h, h).$$

Under the ordering $\succ_h^*$, we obtain the following result. Its proof is given in Appendix E.

Lemma 3.2 *Let $\bar{x}$ be a dominating solution of (1-2-3). If $\bar{x}$ is integral, then $\bar{x}$ is a stable matching for the matching with couples problem.*

If the extreme points of (1-2-3) are integral, then, by Scarf's lemma, one of these is dominating. By Lemma 3.2, this matching will be stable. Unfortunately, (1-2-3) is not an integral polytope. The example below, from Klaus and Klijn [2005], shows that there need be no integral dominating extreme point when couples are present. This explains the need for the rounding step in our algorithm discussed in Section 4.

Example 3 *We have two hospitals (h_1, h_2) each with capacity 1, one couple (d_1, d_2) and one single doctor (d_3). The preferences of each are listed below:*

$$h_1\text{: } d_1 \succ_{h_1}\succ d_3 \succ_{h_1} \emptyset \succ_{h_1} d_2 \qquad h_2\text{: } d_3 \succ_{h_2}\succ d_2 \succ_{h_2} \emptyset \succ_{h_2} d_1$$

$$c = \{d_1, d_2\}\text{: } (h_1, h_2) \succ_{(d_1,d_2)} (\emptyset, \emptyset) \qquad d_3\text{: } h_1 \succ_{d_3} h_2.$$

System (1-2-3) for this example appears below. Not all possible variables are included because some assignments can be ruled out from the preferences alone. It is straightforward to verify that every integer solution to the system below corresponds to a matching of doctors and couples to hospitals.

$$\begin{array}{c} \\ h_1 \\ h_2 \\ c{=}d_1d_2 \\ d_3 \end{array}
\begin{array}{c} (c,h_1h_2) \quad (d_3,h_1) \quad (d_3,h_2) \\ \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix} \end{array} \cdot x \leq \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \; ; \; order: \begin{array}{l} column_1 \succ column_2 \\ column_3 \succ column_1 \\ column_1 \\ column_2 \succ column_3 \end{array}$$

The preference list of hospitals, single doctors, and couples gives us an order for each row of the matrix over the columns whose corresponding entries are positive. There is no ordering for the third row as this row contains a single non-zero entry.

It is straightforward to check that this system does not have an integral dominating solution. Its only dominating extreme point solution is $(1/2, 1/2, 1/2)^T$.

4 Iterative Rounding Algorithm

This section introduces the IR algorithm used to obtain a near-feasible stable matching from a fractional dominating solution. The IR algorithm starts from a dominating extreme point (which may be fractional) and iteratively *rounds* it into a dominating integral solution. This will produce a stable matching of doctors to hospitals that may violate the capacity constraints of some of the hospitals. Our main result shows that the violation is not too large.

Let $\bar{x}$ be a dominating extreme point of (1-2-3). Under allocation $\bar{x}$, some hospitals can be under-demanded. However, we can, with the introduction of dummy doctors, assume without loss that positions at every hospital are fully allocated. See Appendix F.2 for a formal proof. For economy of exposition, let $\mathcal{H}$ be the constraint matrix associated with hospital constraints (1). Then, (1) can be expressed as $\mathcal{H}\bar{x} = k$.

The IR algorithm will round $\bar{x}$ into an integral x^* such that $\mathcal{H}x^* = k^*$, where k^* is close to k. For the matching corresponding to x^* to be stable with respect to k^*, we need x^* to satisfy the properties in the following lemma whose proof is given in Appendix F.1.

LEMMA 4.1 *Let $\bar{x}$ be a fractional dominating extreme point of (1-2-3) and $x^* \geq 0$ be an integral solution satisfying:*

(i). For a single doctor d and a hospital h, if $\bar{x}_{(d,h)} = 0$ then $x^*_{(d,h)} = 0$. Similarly, for a couple c and hospitals h, h', if $\bar{x}_{(c,h,h')} = 0$ then $x^*_{(c,h,h')} = 0$.

(ii). For a single doctor d, if $\sum_h \bar{x}_{(d,h)} = 1$, then $\sum_h x^*_{(d,h)} = 1$. Similarly, for any couple c, if $\sum_{h,h'} \bar{x}_{(c,h,h')} = 1$, then $\sum_{h,h'} x^*_{(c,h,h')} = 1$.

Let $k^* = \mathcal{H}x^*$; then, x^* is a stable matching with respect to k^*.

Property (i) ensures that the support of x^* is contained within the support of $\bar{x}$ and therefore, x^* will also be dominating. Property (ii) ensures that if a single doctor or couple is fully assigned under $\bar{x}$, then they are fully assigned under x^*. Both are needed to ensure that the rounded solution x^* continues to be a dominating solution with respect to the new hospital capacities. Recall that in the definition of domination, all components of $\bar{x}$ are dominated via a binding constraint. Property (ii) ensures that if a constraint corresponding to a doctor or a couple binds under $\bar{x}$, then it continues to bind under x^*.

Before describing the IR algorithm that rounds a dominating solution $\bar{x}$ to an x^* satisfying Lemma 4.1, we provide some intuition. All integral (0-1) components of $\bar{x}$ will remain fixed. The fractional components of $\bar{x}$ are rounded up to 1 or down to 0. This may lead to the violation of the capacity constraints. The extent of the violation for a given hospital h depends on the number of fractional components of $\bar{x}$ associated with h. The essence of the argument is that there must be a hospital with only a small number, two in fact, of fractional components of $\bar{x}$ associated with it. How can that be? If it were not so, *every* hospital capacity constraint must contain within its support at least three fractional components of $\bar{x}$. However, each component of $\bar{x}$ appears in at most two hospital constraints. The nub of the argument is that there are simply not enough fractional components to go around.

This shows that we can ensure that the capacity of at least one hospital is not violated by more than 2. How can we guarantee this for all hospitals? We treat the already rounded variables as constants, ignore the capacity constraint of the one hospital whose capacity is violated and resolve the linear program. By the argument above, there will be another hospital with a small number of fractional components. The algorithm continues until all components are integral.

The Algorithm: To describe the IR algorithm for our matching problem, let $\bar{x}$ be a dominating extreme point of (1-2-3), and let $\mathcal{D}_0$, $\mathcal{D}_1$ be the matrices that correspond to the constraints of (2)-(3) that are binding, slack under $\bar{x}$, respectively. To maintain property (ii) of Lemma 4.1, $\bar{x}$ is iteratively rounded into x^* so that all intermediate solutions satisfy

$$\mathcal{D}_0 \cdot x = 1; \mathcal{D}_1 \cdot x \leq 1; x \geq 0. \tag{4}$$

We maintain $\mathcal{D}_0 \cdot x = 1$ so that condition (ii) of Lemma 4.1 holds. Condition (i) of Lemma 4.1 is maintained because all zero components of $\bar{x}$ remain zero. It is an important feature of the algorithm that whenever any component of $\bar{x}$ becomes integral, it remains fixed at that value.

To limit the aggregate capacity of hospitals we impose an additional constraint on aggregate capacity: $\sum_{d,h} x_{(d,h)} + \sum_{c,h,h'} 2x_{(c,h,h')} \leq \sum_h k_h$. We write this constraint in matrix form as $a \cdot x \leq \sum_h k_h$, where $a_{(d,h)} = 1; a_{(c,h,h')} = a_{(c,h,h)} = 2$.

Denote by $\mathcal{H}_h$ the row vector of $\mathcal{H}$ corresponding to $h \in H$. The IR starts with $\bar{x}$ that satisfies (2)-(3) as well as the following:

$$\mathcal{H}_h \cdot \bar{x} = k_h \text{ for all hospital } h \quad \text{and} \quad a \cdot \bar{x} \leq \sum_h k_h. \tag{5}$$

The constraints of (5) will gradually be discarded during the execution of the algorithm. Call a constraint in (5) **active** if it has not yet been eliminated.

The IR algorithm is described in Figure 1 in which we use the following notation. For a vector x, denote by $\lceil x \rceil$ the vector whose i^{th} component is $\lceil x_i \rceil$. Similarly, $\lfloor x \rfloor$ is the vector whose i^{th} component is $\lfloor x_i \rfloor$. Thus, the i^{th} component of $\lceil x \rceil - \lfloor x \rfloor$ is 1 if the corresponding component of x is fractional and 0 otherwise.

We use the instance from example 3 to illustrate the IR algorithm.

Example 4 *From example 3, we know that* $\bar{x} = (1/2, 1/2, 1/2)^T$ *is the only dominating extreme point. The couple is assigned to* (h_1, h_2) *with weight 1/2 and the single doctor 3 is assigned to* h_1, h_2 *with weight 1/2, each.*

Beginning with $\bar{x}$*, we see that the constraint corresponding to doctor* d_3 *binds. The constraints corresponding to* h_1, h_2 *and the aggregate constraint all bind. Each hospital capacity constraint satisfies the elimination criteria. Eliminate the capacity constraint associated with* h_1*. The active constraints now consist of the aggregate constraint and the capacity constraint of* h_2*. None of the variables is integral. Thus, in Step 2, we solve the following linear program to get a new extreme point.*

Step 0 Start from $x := \bar{x}$ a dominating solution satisfying (4) and (5).
Initialize the active constraints to be all the constraints in (5).

Step 1 If x is integral, stop; otherwise, among the active constraints that bind at the solution x, we eliminate one of them. The rule for selecting which constraint to eliminate is described:

- Choose any binding hospital constraint, $\mathcal{H}_h \cdot x = k_h$, such that $\mathcal{H}_h \cdot (\lceil x \rceil - \lfloor x \rfloor) \leq 3$ and eliminate it.
- If no binding hospital constraint can be eliminated, check if there are at most 2 non-binding constraints among (4) such that each contains at least one fractional variable. If so, eliminate the aggregate capacity constraint.

If no constraint can be found to eliminate, stop, x must be integral. If a constraint is eliminated, denote by $\mathcal{A}x \leq b$ the system of remaining (active) constraints in (5).

Step 2 Find an extreme point $\bar{z}$ to maximize the number of slots allocated:

$$\begin{aligned} \max a \cdot z : \quad & z_i = x_i \text{ if } x_i \text{ is either 0 or 1} \textit{(fix the integral components)} \\ & \mathcal{D}_0 \cdot z = 1; \mathcal{D}_1 \cdot z \leq 1; z \geq 0 \textit{ (doctor/couple constraints as in (4))} \\ & \mathcal{A}z \leq b \textit{ (active hospital constraints).} \end{aligned}$$

Step 3 Update x to be the extreme point solution $\bar{z}$ found in step 2. Update $\mathcal{D}_0$ to include the new constraints from (4) that become binding at $\bar{z}$ from step 2. Update $\mathcal{D}_1$ to remove the new constraints from (4) that become binding at $\bar{z}$ from step 2. Return to step 1.

Figure 1: IR algorithm

$$
\begin{aligned}
\max\ & 2x_{(c,h_1h_2)} + x_{(d_3,h_1)} + x_{(d_3,h_2)} \\
st:\ & x_{(d_3,h_1)} + x_{(d_3,h_2)} && = 1 \text{ (doctor } d_3\text{'s constraint to maintain (ii) in Lemma 4.1)} \\
& x_{(c,h_1h_2)} && \leq 1 \text{ (constraint for couple } c\text{)} \\
& x_{(c,h_1h_2)} + x_{(d_3,h_2)} && = 1 \text{ (constraint for hospital } h_2\text{)} \\
& 2x_{(c,h_1h_2)} + x_{(d_3,h_1)} + x_{(d_3,h_2)} && \leq 2 \text{ (aggregate constraint)}
\end{aligned}
$$

The solution is again $x_{(c,h_1h_2)} = \frac{1}{2}$; $x_{(d_3,h_1)} = \frac{1}{2}$; $x_{(d_3,h_2)} = \frac{1}{2}$.

With this solution, the IR algorithm goes to the next iteration. Hospital h_2*'s capacity constraint binds and satisfies the elimination criteria. Eliminate it. In the next iteration we solve the following linear program.*

$$
\begin{aligned}
\max\ & 2x_{(c,h_1h_2)} + x_{(d_3,h_1)} + x_{(d_3,h_2)} \\
st:\ & x_{(d_3,h_1)} + x_{(d_3,h_2)} && = 1 \text{ (doctor } d_3\text{'s constraint to maintain (ii) in Lemma 4.1)} \\
& x_{(c,h_1h_2)} && \leq 1 \text{ (constraint for couple } c\text{)} \\
& 2x_{(c,h_1h_2)} + x_{(d_3,h_1)} + x_{(d_3,h_2)} && \leq 2 \text{ (aggregate constraint)}
\end{aligned}
$$

The solution is $x_{(c,h_1h_2)} = \frac{1}{2}$; $x_{(d_3,h_1)} = 1$; $x_{(d_3,h_2)} = 0$. *Now, variables* $x_{(d_3,h_1)}$ *and* $x_{(d_3,h_2)}$ *are integral and fixed.* $x_{(c,h_1h_2)}$ *is the only variable, and* $x_{(c,h_1h_2)} \leq 1$ *is the only constraint. Solving this, we obtain the final solution* $x_{(c,h_1h_2)} = x_{(d_3,h_1)} = 1$; $x_{(d_3,h_2)} = 0$. *While integral, it only violates the discarded constraint associated with hospital* h_1 *by exactly 1.*

Remark. The decision to eliminate the capacity constraint associated with h_1 was arbitrary. We could have eliminated the constraint corresponding to h_2 instead. The resulting solution would have violated hospital 2's capacity constraint instead. This flexibility allows one to prioritize one hospital over another based on the relative 'softness' of their capacity constraints. The IR algorithm can also prioritize hospitals through the choice of objective function in Step 2 of the algorithm. See Appendix H.2 for a more detailed discussion.

Example 4 also shows that in order to obtain a stable matching without reducing any hospital's capacity, we need to add a new position to hospital h_1. Thus, the total number of slots increases by 1. Imagine an economy consisting of n identical copies of this example. If we would like to obtain a stable matching by adjusting the capacity of hospitals so that no hospital suffers a reduction, then, we need to add at least n slots. The bound of 4 on aggregate capacity we deliver in Theorem 2.1 is obtained by shuffling positions between hospitals. Some hospitals will get more and some will get fewer positions, but in aggregate we don't add more than 4 positions, independent of the size of the market.

Proof of Theorem 2.1. Let x^* be the outcome of the IR algorithm. We show that x^* satisfies Lemma 4.1 and that the new hospital capacity vector, $k^* := \mathcal{H}x^*$, is not too far from k.

First, in Step 2, a variable of $\bar{x}$ at zero remains at zero throughout the algorithm. Hence, the first property in Lemma 4.1 is maintained. Second, in Step 2, we always maintain the doctor/couple constraints (4), so the second property in Lemma 4.1 is also satisfied.

At Step 2 of the IR algorithm, both z and x are feasible for the same linear program, but z was selected to maximize az, therefore, $a \cdot z \geq a \cdot x$. This guarantees that we never reduce the number of slots available. If the aggregate constraint is never eliminated during the course of the algorithm, then, trivially, the aggregate capacity never increases. If the aggregate constraint is eliminated, it means at most two constraints from (4) do not bind and contain fractional variables. Each of these constraints corresponds to either a single doctor or a couple. These are the only single doctors or couples not yet fully allocated. Collectively they would occupy at most 4 slots. Hence, in the worst case we will need to add 4 additional slots to accommodate them.

We argue that the error bound for each hospital is at most 2. Consider, first, any hospital whose corresponding hospital constraint $\mathcal{H}_h \cdot x = k_h$ was eliminated at some stage during the execution of the algorithm. Therefore, $\mathcal{H}_h \cdot (\lceil x \rceil - \lfloor x \rfloor) \leq 3$. This implies

$$\mathcal{H}_h \cdot (\lceil x \rceil - x) + \mathcal{H}_h \cdot (x - \lfloor x \rfloor) \leq 3. \tag{6}$$

We have two cases. First, if either $\mathcal{H}_h \cdot (\lceil x \rceil - x)$ or $\mathcal{H}_h \cdot (x - \lfloor x \rfloor)$ is 0, then all the variables that appear in this constraint are integral. According to the algorithm, these variables will be fixed at their current values. Thus, the corresponding hospital constraint will never be violated.

In the second case, both $\mathcal{H}_h \cdot (\lceil x \rceil - x)$ and $\mathcal{H}_h \cdot (x - \lfloor x \rfloor)$ are strictly greater than 0. Because $\mathcal{H}_h \cdot x = k_h$, it follows that $\mathcal{H}_h \cdot x$ is integral. As $\mathcal{H}_h \cdot \lceil x \rceil$, and $\mathcal{H}_h \cdot \lfloor x \rfloor$ are integral as well, $\mathcal{H}_h \cdot (\lceil x \rceil - x) \geq 1$ and $\mathcal{H}_h \cdot (x - \lfloor x \rfloor) \geq 1$. But because of (6), this would imply that $\mathcal{H}_h \cdot (\lceil x \rceil - x) = \mathcal{H}_h \cdot \lceil x \rceil - k_h \leq 2$ and $\mathcal{H}_h \cdot (x - \lfloor x \rfloor) = k_h - \mathcal{H}_h \cdot \lfloor x \rfloor \leq 2$. Thus, after eliminating this hospital constraint, at worst, we might violate its right hand side by at most 2.

To verify that the algorithm terminates, we must show that at Step 1, if no integral solution is found, there is a binding constraint to be eliminated. Suppose the current solution is x, and the algorithm has not yet terminated. If no binding hospital constraints remain, x is an extreme point of (4) (equivalently (2), (3)). The corresponding constraint matrix is totally unimodular (see Vohra [2005] for a definition) because every variable appears in at most one constraint. Therefore, x is integral. This contradicts the fact that the algorithm has not yet terminated. Hence, there must be at least one active binding constraint in (5) that satisfies the condition for elimination. If none, we use a counting argument to show that this would contradict the extreme point property of x. This argument is given in Appendix G.

5 Conclusion

A key goal in the design of centralized matching markets is to eliminate the incentive for participants to contract outside of the market. This is formalized as stability and is considered crucial for the long-term sustainability of a market. In the presence of complementarities, stable matchings need not exist. Others have responded to this challenge by restricting preferences or weakening the notion of stability. We, instead, weaken ‘feasibility’ and establish the existence of near-feasible stable matchings in the presence of complementarities.

Acknowledgements

We thank Nicholas Arnosti, Eric Budish, Fuhito Kojima, Ben Roth and the associate editor and anonymous referees for their useful comments. Peter Biró and Bertan Turhan were particularly helpful with extensive suggestions.

References

R. Aharoni and T. Fleiner. On a lemma of Scarf. *Journal of Combinatorial Theory, Series B*, 87:72—80, 2003.

R. Aharoni and R. Holzman. Fractional kernels in digraphs. *Journal of Combinatorial Theory, Series B*, 73(1):1–6, 1998.

I. Ashlagi, M. Braverman, and A. Hassidim. Stability in large matching markets with complementarities. *Operations Research*, 62(4):713–732, 2014.

E. Azevedo and J. W. Hatfield. Existence of equilibrium in large matching markets with complementarities. 2015.

P. Biro and T. Fleiner. Fractional solutions for capacitated ntu-games, with applications to stable matchings. *Discrete Optimization*, 22:241–254, Dec. 2016.

P. Biró and F. Klijn. Matching With Couples: A Multidisciplinary Survey. *International Game Theory Review*, 15(02), 2013.

P. Biró, T. Fleiner, and R. Irving. Matching couples with Scarf's algorithm. *Proc. 8th Hungarian-Japanese Symposium on Discrete Mathematics and its Applications*, 2013.

E. Budish. The combinatorial assignment problem: Approximate competitive equilibrium from equal incomes. *Journal of Political Economy*, 119(6):1061 – 1103, 2011.

D. Cantala. Matching markets: the particular case of couples. *Economics Bulletin*, 3(45): 1–11, 2004.

Y.-K. Che, J. Kim, and F. Kojima. Stable matching in large economies. 2015.

B. C. Dean, M. X. Goemans, and N. Immorlica. The unsplittable stable marriage problem. In *Fourth IFIP International Conference on Theoretical Computer Science-TCS 2006*, pages 65–75. Springer US, 2006.

D. Gale and L. S. Shapley. College Admissions and the Stability of Marriage. *The American Mathematical Monthly*, 69(1):9–15, 1962.

Z. Jiang and G. Tan. Matching with couples: Semi-stability and algorithm. 2014.

Y. Kelner. Medical students fight over internships at central israeli hospitals, 2015.

S. Kintali. Scarf is PPAD-complete. *CoRR*, abs/0812.1601, 2008.

T. Király and J. Pap. Kernels, stable matchings, and Scarf's lemma. *Working paper, Egerváry Research Group, TR-2008-13*, 2008.

B. Klaus and F. Klijn. Stable matchings and preferences of couples. *Journal of Economic Theory*, 121(1):75–106, 2005.

F. Klijn and J. Masso. Weak stability and a bargaining set for the marriage model. *Games and Economic Behavior*, 42:91–100, 2003.

F. Kojima, P. A. Pathak, and A. E. Roth. Matching with couples: Stability and incentives in large markets. *The Quarterly Journal of Economics*, 128(4):1585–1632, 2013.

L.-C. Lau, R. Ravi, and M. Singh. *Iterative Methods in Combinatorial Optimization*. Cambridge University Press, New York, NY, USA, 2011.

D. Manlove, I. McBride, and J. Trimble. "almost-stable" matchings in the hopsitals/residents problem with couples. 2016.

T. Nguyen, A. Peivandi, and R. Vohra. Assignment problems with complementarities. *Journal of Economic Theory*, 165:209–241, 2016.

M. Pycia. Stability and preference alignment in matching and coalition formation. *Econometrica*, 80(1):323–362, 2012. ISSN 1468-0262.

A. Roth and M. Sotomayor. *Two-Sided Matching: A Study in Game-Theoretic Modeling and Analysis*. Econometric Society Monographs. Cambridge University Press, 1992. ISBN 9780521437882.

A. E. Roth. The evolution of the labor market for medical interns and residents: A case study in game theory. *Journal of Political Economy*, 92(6):pp. 991–1016, 1984.

A. E. Roth and E. Peranson. The redesign of the matching market for american physicians: Some engineering aspects of economic design. *American Economic Review*, 89(4):748–780, 1999.

H. E. Scarf. An elementary proof of a theorem on the core of an n person game. 1965.

H. E. Scarf. The core of an $n-$ person game. *Econometrica*, 35(1):pp. 50–69, 1967.

J. Sethuraman, C.-P. Teo, and L. Qian. Many-to-one stable matching: Geometry and fairness. *Mathematics of Operations Research*, 31(3):581–596, 2006.

R. Vohra. *Advanced Mathematical Economics*. Routledge, New York, NY, USA, 2005.

Appendix

A Preferences

Doctor's preferences over hospitals are based on a model fitted from Israeli hospital preference data (see Kelner [2015]). We first generate a number p_h representing the 'popularity' of a hospital h, where $p_h = 0.99K(0.8)^{X_h} + 0.01 \times 18$, X_h is an integer chosen i.i.d. uniformly from 1 to 18, and K is the total number of slots, which is equal to the number of doctors.

Preferences of each single doctor are generated by selecting hospitals iteratively at random without replacement. At each iteration, the probability of selecting hospital h from among those that remain is proportional to p_h.

To generate the preferences of the couples, we assume that couples would like to be allocated to hospitals in the same region rather than different regions. So, we choose lotteries over ordered pairs of hospitals with the property that pairs in the same region are favored over pairs in different regions.

Choose $\lambda \in (0, 1)$ and set

$$\nu_{h,h'} = \begin{cases} \lambda p_h p_{h'} & \text{if hospital } h, h' \text{ are in the same region,} \\ (1-\lambda) p_h p_{h'} & \text{otherwise.} \end{cases} \tag{7}$$

Preferences of each couple are generated by selecting ordered pairs of hospitals iteratively at random without replacement. At each iteration, the probability of selecting the ordered pair (h, h') from among the ordered pairs that remain is proportional to $\nu_{h,h'}$.

When λ is close to 1, hospitals in the same region are more likely to be at the top of a couple's preference ordering. If $\lambda < 0.5$, then couples prefer not to be in the same region. For the results reported we set $\lambda = 0.7$.

To generate the preferences of a couple over all hospital pairs including the outside option, we order all pairs of form $(h_1, \emptyset)$ or $(\emptyset, h_2)$ uniformly at random. Finally we construct the full preference ordering so that it is 'unemployment-averse', i.e.

$$\begin{aligned} (h_1, h_2) \succ (h_3, \emptyset) \succ (\emptyset, \emptyset) \\ (h_1, h_2) \succ (\emptyset, h_3) \succ (\emptyset, \emptyset) \end{aligned} \tag{8}$$

for any $h_1, h_2, h_3 \in H$.

B Stability

Let H be the set of hospitals, D^1 the set of single doctors, and D^2 the set of couples. Each couple $c \in D^2$ is denoted $c = (f, m)$ where f_c and m_c are the first and second member of c, respectively. The set of all doctors, D, is given by $D^1 \cup \{m_c | c \in D^2\} \cup \{f_c | c \in D^2\}$.

Each single doctor $d \in D^1$ has a strict preference ordering $\succ_d$ over $H \cup \{\emptyset\}$ where $\emptyset$ denotes the outside option for each doctor. If $h \succ_d \emptyset$, we say that hospital h is acceptable for d. Each couple $c \in D^2$ has a strict preference ordering $\succ_c$ over $H \cup \{\emptyset\} \times H \cup \{\emptyset\}$–i.e., over pairs of hospitals, including the outside option.

Each hospital $h \in H$ has a fixed capacity $k_h > 0$. The preference of a hospital h over subsets of D is summarized by h's choice function $ch_h(.) : 2^D \to 2^D$. While a choice function can be associated with every strict preference ordering over subsets of D, the converse is not true. The information contained in a choice function is only sufficient to recover a partial order over the subsets of D. Therefore, it isn't always possible to say whether a hospital prefers a couple over some pair of single doctors.

We assume, as is standard in the literature, that $ch_h(.)$ is responsive. This means that

h has a strict priority ordering $\succ_h$ over elements of $D \cup \{\emptyset\}$. If $\emptyset \succ_h d$, we say d is not acceptable to h. For any set $D^* \subset D$, hospital h's choice from that subset, $ch_h(D^*)$, consists of the (up to) k_h highest priority doctors among the acceptable doctors in D^*. Formally, $d \in ch_h(D^*)$ if and only if $d \in D^*; d \succ_h \emptyset$ and there exists no set $D' \subset D^* \setminus \{d\}$, such that $|D'| = k_h$ and $d' \succ_h d$ for all $d' \in D'$.

A matching μ is an assignment of each single doctor to a hospital or his/her outside option, an assignment of couples to at most two positions (in the same or different hospitals) or their outside option, such that the total number of doctors assigned to any hospital h does not exceed its capacity k_h. Given matching μ, let μ_h denote the subset of doctors matched to h; μ_d and μ_{f_c}, μ_{m_c} denote the position(s) that the single doctor d, and the female and male members of the couple c obtain in the matching, respectively.

We say μ is *individually rational* if $ch_h(\mu_h) = \mu_h$ for any hospital h; $\mu_d \succeq_d \emptyset$ for any single doctor d and $(\mu_{f_c}, \mu_{m_c}) \succeq_c (\emptyset, \mu_{m_c})$; $(\mu_{f_c}, \mu_{m_c}) \succeq_c (\mu_{f_c}, \emptyset)$; $(\mu_{f_c}, \mu_{m_c}) \succeq_c (\emptyset, \emptyset)$ for any couple c.

Roth and Sotomayor [1992], we list the ways in which different small coalitions can block a matching μ.

Definition B.1 *The following are called blocking coalitions for a matching μ.*

1. *A pair $d \in D^1$ and $h \in H$ can block μ if $h \succ_d \mu(d)$ and $d \in ch_h(\mu(h) \cup d)$.*

2. *A triple $(c, h, h') \in D^2 \times (H \cup \{\emptyset\}) \times (H \cup \{\emptyset\})$ with $h \neq h'$ can block μ if $(h, h') \succ_c \mu(c)$, $f_c \in ch_h(\mu(h) \cup f_c)$ when $h \neq \emptyset$ and $m_c \in ch_{h'}(\mu(h') \cup m_c)$ when $h' \neq \emptyset$.*

3. *A pair $(c, h) \in D^2 \times H$ can block μ if $(h, h) \succ_c \mu(c)$ and $(f_c, m_c) \subseteq ch_h(\mu(h) \cup c)$.*

C Construction of $\succ_h^*$

Definition C.1 *Hospital h's priority ordering over the individual doctors, $\succ_h$, and the preferences of the couples $\{\succ_c : c \in D^2\}$ is used to construct a strict ordering, $\succ_h^*$, over the the coalitions representing the assignment of a doctor or a couple to at least one position at h–namely, coalitions of the form $(d, h), (c, hh')$, $(c, h'h)$, and (c, hh).*

Denote a generic instance of one of these coalitions by $(\cdot, h)$ *. For each coalition* $(\cdot, h)$*, let* $d(\cdot, h)$ *be the doctor assigned to* h*. If* $(\cdot, h)$ *represents the assignment of both members of a couple to* h*, let* $d(\cdot, h)$ *denote the least preferred member of the couple according to* $\succ_h$*. Then,* $\succ_h^*$ *is defined as follows. For two different coalitions* $(a, h) \neq (b, h)$*, if* $d(a, h) \succ_h d(b, h)$*, then* $(a, h) \succ_h^* (b, h)$*. If* $d(a, h) = d(b, h)$*, then* (a, h) *and* (b, h) *represent two different assignments of a couple* c*, in which case,* $(a, h) \succ_h^* (b, h)$ *if and only if* $(a, h) \succ_c (b, h)$*.*

D Discussion of Stability

Under responsive choice functions, Definition B.1 can have an undesirable implication. The following example suggested by a referee illustrates this.

Suppose two single doctors d, d', a couple $c = (f, m)$ and a hospital h with capacity 2. Recall, that for the couple c and hospital h to block a matching we require $\{f, m\} \subset ch_h(\mu(h) \cup \{f, m\})$, thus it is a stable matching for h to hire (d, d'), who are in 2^{nd} and 4^{th} positions, while the hospital may actually prefer the couple, whose members are ranked 1^{st} and 3^{rd}.

Because $\succ^*$ is defined based on the least preferred member of a couple, the stable matching we construct actually satisfies a stronger notion of stability. In particular, replace item 3 in Definition B.1, with the following:

$$3'. \text{ A pair } (c, h) \in D^2 \times H \text{ can block } \mu \text{ if } (h, h) \succ_c \mu(c)$$
$$\text{and both } f_c \subseteq ch_h(\mu(h) \cup f_c) \text{ and } m_c \subseteq ch_h(\mu(h) \cup m_c).$$

Under this definition, the matching in which $\mu(h) = \{d, d'\}$ is not stable because it is blocked by (c, h).

The ordering $\succ^*$ in Definition C.1 is *not* a primitive of the model but a technical device introduced to invoke Scarf's lemma. We prove domination with respect to $\succ^*$ and show in Lemma 3.2 that this corresponds to stability with respect to Definition B.1.

The same referee points out that domination with respect to $\succ^*$ can be restrictive. Specifically, change the hospital's priority ordering in the previous example to $f \succ_h d \succ_h d' \succ_h m$. The hospital's modified ranking is $d \succ_h^* d' \succ_h^* c$. The only dominating extreme point will assign $\{d, d'\}$ to h. This might be considered restrictive because it is possible that the hospital will prefer the couple c to the pair (d, d'). However, to evaluate such choices, one needs to extend the standard model because hospitals are not endowed with orderings over pairs of doctors. This is beyond the scope of this paper.

E Proof of Lemma 3.2

The proof is by contradiction. Let $\bar{x}$ be an integral dominating solution of (1-2-3), and assume that the corresponding assignment μ in the residency matching with couples is not stable. This means that at least one of the three items below is true.

1. A pair $d \in D^1$ and $h \in H$ blocks μ because $h \succ_d \mu(s)$ and $d \in ch_h(\mu(h) \cup d)$.

2. A triple $(c, h, h') \in D^2 \times H \times H$ with $h \neq h'$ blocks μ because $(h, h') \succ_c \mu(c)$, $f_c \in ch_h(\mu(h) \cup f_c)$ and $m_c \in ch_{h'}(\mu(h') \cup m_c)$.

3. A pair $(c, h) \in D^2 \times H$ blocks μ because $(h, h) \succ_c \mu(c)$ and $(f_c, m_c) \subseteq ch_h(\mu(h) \cup \{f_c, m_c\})$.

The first type of blocking coalition corresponds to the column associated with variable (d, h). Now, because $ch_h(.)$ is a responsive choice function over *individual* doctors, $d \in ch_h(\mu(h) \cup d)$ implies that d is among the best k_h candidates among $\mu(h) \cup d$. Therefore, $\bar{x}$ does not dominate column (d, h): this is a contradiction because $\bar{x}$ is a dominating solution.

The second type of blocking coalition corresponds to column (c, h, h'). Following the same argument, the blocking coalition implies that f_c is among the best k_h candidates among $\mu(h) \cup f_c$ (similar for m_c and h'.) Together with the tie-breaking rule of $\succ_h^*$, this implies that $\bar{x}$ does not dominate the column (c, h, h').

In the third type of blocking coalition, the pair (f_c, m_c) and a hospital h correspond to a column (c, h, h). Because $(f_c, m_c) \subseteq ch_h(\mu(h) \cup c)$, *both* f_c and m_c are among the k_h best candidates, even when we consider the order $\succ^*$ for the columns, because both members are still ranked highly among $\mu_h \cup \{f_c, m_c\}$. In the matching μ, the couple c is not assigned to h, thus, either h's capacity is not fully allocated, or a doctor worse than both f_c and m_c is assigned to h. Both cases imply that $\bar{x}$ does not dominate column (c, h, h). ■

F Maintaining Stability in Rounding

F.1 Proof of Lemma 4.1

First of all, x^* is a feasible matching with respect to capacities k^*. Because $\bar{x}$ only contains assignments of mutually acceptable hospital-doctors, so does x^*. Thus, x^* is individually rational. Given that $\bar{x}$ dominates all columns of $\mathcal{Q}$, and x^* is obtained from $\bar{x}$, we show that under the new capacity vector k^*, x^* dominates all columns of $\mathcal{Q}$.

Consider the column associated with the assignment of couple c_0 to hospital h_1 and h_2, (c_0, h_1, h_2). (A similar argument will apply to the other columns). $\bar{x}$ dominates (c_0, h_1, h_2) either at the constraint corresponding to c_0 or at $h_1 \in H$ or at $h_2 \in H$.

Suppose first $\bar{x}$ dominates (c_0, h_1, h_2) at c_0. Then $\sum_{h,h'} \bar{x}_{(c_0,h,h')} = 1$, and couple c_0 does not like the allocation h_1, h_2 strictly more than any of the assignments that they obtained under $\bar{x}$. Now because x^* is a $0-1$ vector rounded from $\bar{x}$ that satisfies Lemma 4.1:

(i.) ${x^*}_{(c_0,h,h')} > 0 \;\Rightarrow \bar{x}_{(c_0,h,h')} > 0$

(ii.) $\sum_{h,h'} \bar{x}_{(c_0,h,h')} = 1 \;\Rightarrow\; \sum_{h,h'} x^*_{(c_0,h,h')} = 1.$

These imply that c_0 (weakly) prefers the assignments that they gets in x^* more than (h_1, h_2) (we use 'weakly prefers' because it is possible that $x^*_{(c_0,h_1,h_2)} = 1$).

Next, suppose $\bar{x}$ dominates (c_0, h_1, h_2) at h_1 (a similar argument will apply to h_2). This implies that the capacity of hospital h_1 binds: $\mathcal{H}_{h_1}\bar{x} = k_{h_1}$. Furthermore, h_1 weakly prefers all columns in which the corresponding component of $\bar{x}$ is positive to (c_0, h_1, h_2). Now because of property (i) in Lemma 4.1, a component of x^* can be positive only when the corresponding component of $\bar{x}$ is positive. Thus, $\bar{x}$ dominates (c_0, h_1, h_2) when we change the capacity at h_1 to be $k^*_{h_1} := \mathcal{H}_{h_1}x^*$.

F.2 When a hospital's capacity constraints do not bind

Given a fractional dominating solution $\bar{x}$, let H^0 be the set of hospitals for which (1) does not bind. Denote the total slack in these non-binding constraints by K (not necessarily integral).

Introduce $\lceil K \rceil$ dummy single doctors $d_1, \ldots, d_{\lceil K \rceil}$. Choose a strict ordering over the hospitals in H^0, and assign it to each of the dummy doctors. The remaining hospitals will be ranked below $\emptyset$ by all the dummy doctors. Augment the priority ordering of hospitals in H^0 by appending $d_1 \succ \ldots \succ d_{\lceil K \rceil}$ to the bottom of these hospitals' orderings but above $\emptyset$. The priority ordering of hospitals not in H^0 is augmented by appending $d_1 \succ \ldots \succ d_{\lceil K \rceil}$ to the bottom of these hospitals' preference above $\emptyset$.

Extend $\bar{x}$ to include the dummy doctors so that all slots in H^0 are filled. We can do this by going through the list of dummy doctors from d_1 to $d_{\lceil K \rceil}$ and assigning each doctor to the best position available. Because we are working with a fractional assignment, a doctor can be split between different positions. Let $\bar{\bar{x}}$ be the resulting assignment. It is straightforward to see that $\bar{\bar{x}}$ is a dominating solution of the instance with dummy doctors, and this solution fully allocates all positions. Let x^{**} be an integral solution obtained by rounding $\bar{\bar{x}}$ according to the IR algorithm. Let k^{**} be the new capacity of the hospitals–that is, $k^{**} := \mathcal{H} \cdot x^{**}$. According to Lemma 4.1, x^{**} is a stable solution with respect to k^{**}, and our algorithm bounds the difference between k^{**} and k.

We show that after eliminating the variables corresponding to dummy doctors from x^{**}, the resulting assignment, x^*, is stable with respect to k^{**}. This is true because under $\bar{x}$, the constraints (1) corresponding to hospitals in H^0 do not bind. Hence, $\bar{x}$ dominates all columns of the constraint matrix $\mathcal{Q}$ either at a couple/doctor constraint or at a hospital h constraint where $h \notin H^0$. As dummy doctors are never assigned to hospitals outside of H^0, it follows that for all $h \notin H^0$, $\mathcal{H}_h \cdot x^{**} = \mathcal{H}_h \cdot x^*$. Hence,

$$k_h^{**} = \mathcal{H}_h \cdot x^{**} = \mathcal{H}_h \cdot x^* = k^* \text{ for } h \notin H^0.$$

With these observations, and following the same argument as in Section F.1, we obtain that x^* is stable with respect to k^{**}.

G Termination of the IR algorithm

To show that the IR algorithm terminates with an integral solution, we prove that if it has not yet terminated, we can always eliminate a constraint. It relies on the following lemma (Lemma 2.1.4, page 14, Lau et al. [2011]).

LEMMA G.1 (RANK LEMMA) *Let* $P = \{x : Ax \geq b, x \geq 0\}$ *and let* x *be an extreme point of* P *such that* $x_j > 0$ *for every* i. *Then, the maximal number of linearly independent binding constraints of the form* $A_i x = b_i$ *for some row* i *of* A *equals the number of variables.*

We reformulate Lemma G.1 below, to apply in our setting.

LEMMA G.2 *Let* x *be an extreme point of* $Q = \{x : \mathcal{Q}x = q, 0 \leq x \leq 1\}$. *Let* J *be the index set of non-integral components of* x. *Let* $\mathcal{Q}|_J$ *be the submatrix of* $\mathcal{Q}$ *consisting of the columns indexed by* J. *Then, the number of non-integral components of* x, $|J|$, *is equal to the maximum number of linearly independent rows of* $\mathcal{Q}|_J$.

To prove Lemma G.2, let I be the index set of integral components of x, that is x_j is either 0 or 1 for all $j \in I$. We can rewrite $\mathcal{Q}x = \mathcal{Q}|_J \cdot x|_J + \mathcal{Q}|_I \cdot x|_I = q$. Let $q' := \mathcal{Q}|_J \cdot x|_J = q - \mathcal{Q}|_I \cdot x|_I$, and consider $Q|_J = \{y \in \mathbb{R}^{|J|} : \mathcal{Q}|_J \cdot y = q', y \geq 0\}$. The solution $x|_J$ is an extreme point of $Q|_J$ and all of its components are strictly positive. Applying Lemma G.1 to $Q|_J$ and $x|_J$ we obtain Lemma G.2.

To see how to use this lemma in our proof, let $\mathcal{D}^*, \mathcal{A}^*$ be the submatrices of $\mathcal{D}$ and $\mathcal{A}$, respectively, corresponding to the binding constraints of the linear program in Step 1. Thus, x is an extreme solution of $\left\{ \begin{bmatrix} \mathcal{D}^* \\ \mathcal{A}^* \end{bmatrix} x = \begin{bmatrix} 1 \\ b^* \end{bmatrix}; 0 \leq x \leq 1 \right\}$. Let J be the index of a non-integral component of x. Assume, for a contradiction, that we cannot eliminate any binding constraints. Credit every component of $x|_J$ with one token. Subsequently, we redistribute these tokens to the constraints (rows) of $\begin{bmatrix} \mathcal{D}^*|_J \\ \mathcal{A}^*|_J \end{bmatrix}$ in such a way that each constraint will get at least 1 token. We show this to be possible because each column of the matrix has a relatively small number of non-zero entries. This redistribution shows that the number of binding constraints is at most the number of non-integral components. Furthermore, we show that equality arises only when the binding constraints are linearly dependent. This implies that the maximum number of linearly independent constraints is less than the number of non-integral components, which contradicts Lemma G.2.

Token distribution

To complete the proof we show that if the algorithm has not yet terminated, we can always find a constraint to eliminate. Suppose, for a contradiction, we are at an iteration where no constraint can be eliminated and each component of $x|_J$ is fractional. Endow each fractional component of $x|_J$ with 1 token and redistribute that token among the constraints in (4) and (5) as follows:

- The 1 token associated with the variable $x_{(c,h,h')}$ is apportioned as follows: a $\frac{1}{4}$ tokens to each of the constraints $\mathcal{H}_h \cdot x = k_h$ and $\mathcal{H}_{h'} \cdot x = k_{h'}$ (if $h = h'$, then $\mathcal{H}_h \cdot x = k_h$ gets $\frac{1}{2}$ tokens) and the remaining $\frac{1}{2}$ token assigned to the couple c constraint–that is, $\sum_{h,h'} x_{(c,h,h')} \leq 1$.
- The one token associated with the variable $x_{(d,h)}$ is apportioned as follows: a $\frac{1}{4}$ tokens to the constraints $\mathcal{H}_h \cdot x = k_h$; the remaining $\frac{3}{4}$ tokens are allotted to the doctor d constraint–that is, $\sum_h x_{(d,h)} \leq 1$.

We now argue that each binding constraint in (4) and (5) receives at least one token. Consider a binding constraint $\mathcal{H}_h \cdot x = k_h$ associated with hospital h. By the assumption that no constraint can be eliminated, we know that $\mathcal{H}_h \cdot (\lceil x \rceil - \lfloor x \rfloor) \geq 4$. Keep in mind that $\lceil x_i \rceil - \lfloor x_i \rfloor = 1$ if x_i is non-integral, and 0 otherwise. According to the token distribution scheme, a non-integral component of x gives the hospital h constraint $\frac{1}{4}$ or $\frac{1}{2}$ tokens if the corresponding assignment requires 1 or 2 slots from h, respectively. Thus, the number of tokens constraint $\mathcal{H}_h \cdot x = k_h$ gets is at least

$$\frac{1}{4}\mathcal{H}_h \cdot (\lceil x \rceil - \lfloor x \rfloor) \geq 1.$$

Next, consider a binding constraint corresponding to couple c. As this constraint binds–that is, $\sum_{h,h'} x_{(c,h,h')} = 1$–and it contains at least 1 non-integral variable, it must contain at least 2. Each of the fractional variables contributes $\frac{1}{2}$ a token, thus this constraint also obtains at least 1 token.

Similarly, for the constraint corresponding to a single doctor d. If this constraint binds and contains at least one non-integral variable, it must contains at least 2. Therefore, it also gets at least $2 \times \frac{3}{4} \geq 1$ token.

The total number of tokens distributed cannot exceed the number of fractional components of $x|_J$ which is $|J|$. By Lemma G.2, total number of tokens received by binding constraints in (4) and (5) is at least the number of such binding constraints, $|J| - 1$. This is because the aggregate capacity constraint may bind. We have two cases.

Case 1: The aggregate capacity constraint has not yet been eliminated.
We know that the total number of tokens allocated to binding constraints in (4) and (5) is at least $|J| - 1$. Because the aggregate constraint has not yet been eliminated, there are at least three *non binding* doctor/ couple constraints that contain fractional variables. According to the token distribution scheme, we gave to these constraints at least $3 \times \frac{1}{2}$ tokens. Hence, the total number of tokens assigned to constraints in (4) and (5), binding or not, is at least $|J| + \frac{1}{2}$. This exceeds the the total number of tokens to be distributed, a contradiction.

Case 2: The aggregate constraint was eliminated at some earlier iteration.
By the extreme point property of $x|_J$, the $|J|$ binding constraints belong to (4) and (5). Each one of the binding constraint receives at least one token. Hence, none can receive strictly more than one token. This means no constraint in (2) can bind. Similarly, no non-binding constraint can receive any tokens. Hence, in $x|_J$, all variables associated with single doctors take the value zero. Furthermore, if $x(c, h, h') > 0$, the capacity constraints associated with h and h' must bind. If we apply these observations to the system (1, 2, 3), the relevant binding constraints have the form:

$$\sum_{c \in D^2} \sum_{h' \neq h} x_{(c,h,h')} + \sum_{c \in D^2} \sum_{h' \neq h} x_{(c,h',h)} + \sum_{c \in D^2 \cup \{\emptyset\}} 2x_{(c,h,h)} = k_h \tag{9}$$

$$\sum_{h,h' \in H \cup \{\emptyset\}} x_{(c,h,h')} = 1 \tag{10}$$

If we add up the binding constraints of the form (10) we get the sum of the binding constraints of the form (9). This violates the assumption that the binding constraints must be linearly independent. Hence, if we add up the binding constraints in (3) we get the sum of the binding constraints in (1). This violates the assumption of linear independence.

G.1 Tightness

We outline why the token argument we used cannot be modified to give an improved bound. We will allow the quantity of tokens allocated to hospital h to depend on h.[13] For each hospital h let $r_h = \mathcal{H}_h \cdot (\lceil x \rceil - \lfloor x \rfloor)$. As before, suppose we are at an iteration where no constraint can be eliminated and each component of $x|_J$ is fractional. Endow each fractional component of $x|_J$ with 1 token and redistribute the tokens among the constraints in (1-2-3) as follows:

- The 1 token associated with the variable $x_{(c,h,h')}$ is apportioned as follows: $\frac{1}{r_h}$ tokens to each of the constraints $\mathcal{H}_h \cdot x = k_h$ and $\mathcal{H}_{h'} \cdot x = k_{h'}$ (if $h = h'$, then $\mathcal{H}_h \cdot x = k_h$ gets $\frac{2}{r_h}$ tokens) and the remaining $1 - \frac{2}{r_h}$ token assigned to the couple c constraint–that is, $\sum_{h,h'} x_{(c,h,h')} \leq 1$.
- The 1 token associated with the variable $x_{(d,h)}$ is apportioned as follows: $\frac{1}{r_h}$ tokens to the constraints $\mathcal{H}_h \cdot x = k_h$; the remaining $1 - \frac{1}{r_h}$ tokens are allotted to the doctor d constraint–that is, $\sum_h x_{(d,h)} \leq 1$.

It is straightforward to see that the number of tokens allocated to each hospital h is at least

$$\frac{\mathcal{H}_h \cdot (\lceil x \rceil - \lfloor x \rfloor)}{r_h} = 1.$$

Now, consider the number of tokens allocated to a single doctor d constraint. There must be at least two hospitals h and h' such that $x(d,h), x(d,h') > 0$. Hence, the number of tokens

[13] The same conclusion will be reached even if we allow the quantity of tokens to depend on both the hospital and the identity of the doctors.

allocated to this constraint is at least $1 - \frac{1}{r_h} + 1 - \frac{1}{r_{h'}}$. We need this sum to be at least 1. Hence, $r_h, r_{h'} \geq 2$. A similar argument for a couples, c, constraint requires that

$$1 - \frac{2}{r_h} + 1 - \frac{2}{r_{h'}} \geq 1 \ \Rightarrow r_h, r_{h'} \geq 4.$$

Hence, for our token argument to work we need $r_h \geq 4$ for all hospitals h which is precisely what we have assumed.

H Additional Results

H.1 Proof of Theorem 2.2

Let H^R be the set of rural hospitals, to which we assume no couple applies. Let H^U be the remaining (urban) hospitals. The main change in the IR algorithm is that we never drop any constraint corresponding to $h \in H^R$. Thus, at each iteration

$$\mathcal{H}_h x = k_h \text{ for all } h \in H^R.$$

The modified version of the IR algorithm, called IR1, is described in Figure 2.

To show that the IR1 algorithm returns a near-feasible stable matching that does not violate the capacity of $h \in H^R$, we follow the proof of Theorem 2.1. It is enough to show that if IR1 algorithm has not terminated, we can always find an active constraint to delete.

First, because the IR1 algorithm always maintains a solution satisfying the capacity constraints of rural hospitals, the aggregate constraint can be rewritten in terms of urban hospitals only. Namely,

$$\sum_{d,h:h\in H^U} x_{(d,h)} + \sum_{c,h,h':h,h'\in H^U} 2x_{(c,h,h')} \leq \sum_{h\in H^U} k_h.$$

Absent from this constraint is any variable $x_{(c,h,h')}$ where among the pair (h, h'), one is urban and the other is rural because of our assumption that only single doctors apply to rural hospitals.

Step 0 Start from $x := \bar{x}$ a dominating solution satisfying (4) and (5).
Initialize the active constraints to be the constraints:
$\mathcal{H}_h \cdot x = k_h$ for $h \in H^U$ and the aggregate constraint $a \cdot x \leq \sum k_h$

Step 1 If x is integral, stop; otherwise, among the active constraints that bind at the solution x, we eliminate one of them. The rule for selecting the constraint to eliminate is described:

- Choose any binding urban hospital constraint, $\mathcal{H}_h \cdot x = k_h$, such that $\mathcal{H}_h \cdot (\lceil x \rceil - \lfloor x \rfloor) \leq 3$ and eliminate it.
- If no urban hospital constraint can be eliminated, check if there are at most 2 non-binding constraints among (4) such that each contains at least one fractional variable. If so, eliminate the aggregate capacity constraint.

If no constraint can be found to eliminate, stop, x must be integral. If a constraint is eliminated, denote by $\mathcal{A}x \leq b$ the system of remaining (active) constraints in (5).

Step 2 Find an extreme point z to maximize the number of jobs allocated:

$$\begin{aligned} \max a \cdot z : \quad & z_i = x_i \text{ if } x_i \text{ is either 0 or 1} \textit{(fix the integral components)} \\ & \mathcal{D}_0 \cdot z = 1; \mathcal{D}_1 \cdot z \leq 1; z \geq 0 \ \textit{(doctor/couple constraints as in (4))} \\ & \mathcal{H}_h x = k_h \text{ for all } h \in H^R \textit{(rural hospital constraints)} \\ & \mathcal{A}z \leq b \ \ \textit{(active hospital constraints.)} \end{aligned}$$

Step 3 Update x to be the extreme point solution z^* found in step 2. Update $\mathcal{D}_0$ to include the new constraints from (4) that become binding at z^* from step 2. Update $\mathcal{D}_1$ to remove the new constraints from (4) that become binding at z^* from step 2. Return to step 1.

Figure 2: IR1 algorithm

Second, we modify the token distribution scheme by changing how the token associated with $x_{(d,h)}$ for $h \in H^R$ is allocated. Namely, assign $\frac{1}{2}$ a token to the constraint $\mathcal{H}_h \cdot x = k_h$; the remaining 1/2 token is given to the doctor d constraint–that is, $\sum_h x_{(d,h)} \leq 1$. For the other variables, the token distribution remains the same as in Section G.

Each urban hospital constraint receives at least 1 token. To see why, observe that if a hospital constraint contains a non-integral variable, it must contain at least two of them. Each non-integral variable contributes 1/2 a token to the relevant constraint. Thus, the relevant constraint obtains at least 1 token.

Each couple constraint has at least two non-integral variables or none. When none, we can ignore this constraint because it does not affect any non-integral variables. As before, the number of tokens allocated to a couple constraint is at least 1.

Each fractional variable in in a single doctor constraint contributes either 1/2 or 3/4 of a token depending on whether the corresponding hospital is rural or urban. Thus, such a constraint also receives at least 1 token and *strictly* more than that if one of the variables is associated with an urban hospital.

Hence, as in case 1 in Section G, we can always eliminate one active constraint if the IR1 algorithm has not terminated. When there are no active constraints left (as in case 2 of Section G), the remaining constraints and variables are associated with the single doctors and rural hospitals only. This corresponds to the standard linear program of a many-to-one matching *without* couples. An extreme point of this linear program is integral.

H.2 Using different objective functions to prioritize hospitals

The IR algorithm described in Figure 1 uses an objective function, $a \cdot x$, to maximize the number of jobs allocated. Termination of the IR algorithm does not depend on this specific choice of objective function. The IR algorithm works for *any* linear objective function, $c \cdot x$. This can be used to reflect the fact that assigning extra slots to one hospital may be cheaper than allocating them to another.

In particular, replacing $\max a \cdot x$ with any linear objective function $c \cdot x$, the IR algorithm in Figure 1, starting from the fractional stable matching $\bar{x}$, will terminate in a 2-feasible stable matching in which the aggregate capacity does not increase by more than 4. Furthermore,

$c \cdot x^* \geq c \cdot \bar{x}$.

Because the choice of the linear objective function, c is arbitrary, we can round $\bar{x}$ in any "direction". This implies the following result. (See Figure 3 for an illustration.)

Claim H.1 *The fractional stable matching $\bar{x}$ can be expressed as a lottery over 2-feasible stable matchings that do not violate the aggregate constraint by more than* 4.

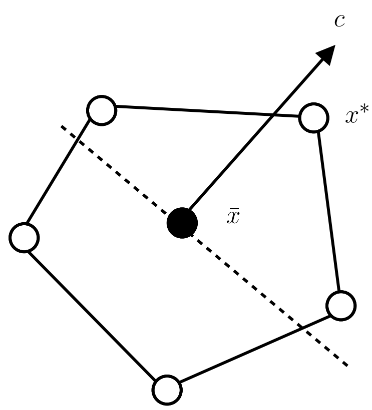

Figure 3: Fractional stable matching can be expressed as a lottery over near-feasible stable matchings

Claim H.1 is true because otherwise, $\bar{x}$ lies outside the convex hull of the near-feasible stable matchings, and therefore we can separate $\bar{x}$ from these near-feasible stable matchings with a linear function.

Claim H.1 provides a randomized algorithm to round $\bar{x}$ so that it is ex-ante feasible (but ex-post is 2-feasible).