Better donors: a non-monetary incentives mechanism to increase kidney market participation

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Ruben Mayer-Hirshfeld
Department of Economics
Stanford University
Stanford, CA, 94305
rmayer99@stanford.edu

Under the direction of
Professor Marcelo Clerici-Arias

ABSTRACT

Patients that need a kidney transplant and have a potential donor that is not compatible often participate in centralized kidney exchanges to find a match for a successful transplant. A significant challenge for kidney matching exchanges involves the over-representation of patients that are not compatible with most donors. The presence of these highly sensitized patients decreases the number of possible exchanges amongst incompatible pairs, hence decreasing total successful transplants. This paper proposes a non-monetary mechanism that would decrease the sensitivity of kidney exchange pools. Specifically, the mechanism would encourage compatible pairs with old, low sensitivity donors to participate in centralized kidney exchanges with the objective of exchanging the old donor's kidney with a kidney from a younger donor, hence improving the health outcomes of the patient. The paper uses Monte Carlo simulations to show that, in a kidney exchange pool with real-world characteristics, very two added compatible pairs lead to an additional kidney transplants. Furthermore, the simulations show that 94% of participating compatible pairs were matched with a younger donor. Given 2016 donor demographics, the introduction of this mechanism could have increased US annual paired kidney donations by up to 10%, or 72 new transplants. If implemented, the proposed a mechanism would lead to both an increase the life expectancy of patients from compatible pairs and a significant increase in total kidney transplants - all without any notable tradeoffs.

Introduction

There are 100,000 patients in the United States that suffer from renal disease and are on the waiting list to receive a kidney transplant. About a third of the transplants that take place each year involve living donors that can donate one of their kidneys without incurring significant risk or loss of quality of life.

It is often the case that a patient finds a living donor, but the donor is not physiologically compatible with her. In the last decade, several centralized kidney exchanges have used algorithms from graph theory to help match these incompatible donor-patient pairs with each other. These matches allow each donor to give his or her kidney to a recipient from another pair so that the patient they know can receive a kidney from a different donor. These matching mechanisms increase the total number of transplants, but the matching process has several characteristics that reduce efficiency. Specifically, the need to conduct kidney transplant surgeries simultaneously (to guarantee that all patients receive a kidney) limits the cycle size of most exchanges to two or three. In addition, some selection issues have led to an over-representation of highly sensitized patients (patients that are less likely to be compatible with any given donor). These two factors lead to a *sparse compatibility graph*, or an exchange pool with few potential trades, and ultimately lead to a smaller number of total transplants.

This paper proposes a mechanism that would incentivize the participation of less sensitized patients (patients that are compatible with more donors) in kidney exchanges. This increase in participation from less sensitized patients would lead to a decrease the sparseness in the patient-donor compatibility graph. Specifically, the mechanism involves giving compatible pairs with low sensitivity recipients and donors over the age of 65 the opportunity to participate in the exchanges in order to find a younger donor for the patient. This mechanism would improve the outcomes for the kidney exchange market by simultaneously increasing the total number of successful transplants and improving the health outcomes of participating patient-donor pairs with old donors.

The first section of this paper surveys the literature that is relevant to this research topic. The second section takes an in-depth look at the market characteristics that led to the proposal of this incentives mechanism. The third section proposes a kidney exchange model and lays out the specific features of the incentives mechanism. The fourth section describes the Monte Carlo simulations and the parameters used to evaluate the potential effectiveness of the proposed matching mechanism. The fifth section describes the results of the simulations. The final section of the paper discusses the limitations and implications of the results.

1 - Literature Review

Since the beginning of the 21st Century, a significant amount of research has been devoted to the problem of kidney transplants, and the potential of kidney exchanges to save the lives of patients incompatible donors. This section surveys the foundational literature of the kidney matching problem, the literature focused on specific participation-related challenges associated with kidney exchanges as well as literature that is directly related with the premise of using incentives to increase participation in kidney exchanges.

1.1 - Foundational Literature

Roth, Sönmez and Ünver (2004) introduced a proposal for a centralized kidney exchange that would increase efficiency in two-way trades between patients with incompatible donors. By using simulations, Roth et al. argued that the welfare gains derived from instituting a kidney exchange program "would be substantial, both in increased number of feasible live donation transplants, and in improved match quality of transplanted kidneys." Roth et al compared the kidney matching problem to the archetypical housing allocation problem, but "with the novel feature that while live donor kidneys can be assigned simultaneously, the cadaver kidneys must be transplanted immediately upon becoming available."

Gentry, Segev, Warren, Reeb and Montgomery (2005) proposed using an optimized version of the Edmonds Algorithm (1965) from graph theory to clear kidney exchanges. Gentry et al. use simulations to argue that a nationalized system based on their algorithm would "result in more transplants (47.7% vs 42.0%, P.001), better HLA concordance (3.0 vs 4.5 mismatched antigens; P.001), more grafts surviving at 5 years (34.9% vs 28.7%; P.001), and a reduction in the number of pairs required to travel (2.9% vs 18.4%; P.001)" (as compared to existing baselines during the time of publication).

Roth, Saidman, Sonmez, Unver and Delmonico (2006) proposed including three-way trades to matching mechanisms to further increase the efficiency of the exchange. Roth et al. formulated the kidney matching problem as an "integer programming problem" and used commercial CPLEX software to maximize "the number of transplants subject to the constraint that the cycle size not exceed the specified exchange size (two-way, three-way, or unrestricted)."

1.2 - Participation-related challenges

Ashlagi, Gamarnik, Rees and Roth (2012) used real-world patient databases from the Alliance for Paired Donation (APD) to show the existence of a “high percentage of highly sensitized patients in the data.” Ashlagi et al. (2012) found that the proportion of highly sensitized patients in the APD database is “higher than the percentage of highly sensitized patients that arise in [previously used] simulations.” The authors further argued that despite the fact that “for sufficiently large pools of patient-donor pairs, (almost) efficient kidney exchange can be achieved by using at most 3-way cycles”, this is not the case “when there are many highly sensitized patients” due to the added “sparsity in the compatibility-graph”. Meaning that in existing kidney exchange programs, highly sensitized patients are often much less likely to receive a kidney. Thus, Ashlagi et al. (2012) proposed a “theoretical framework for studying highly sensitized exchange pools” concluding that longer chains initiated by altruistic donors (people that are willing to donate their kidney without receiving anything in exchange) would increase the efficiency of current exchanges.

Roth and Ashlagi (2014) demonstrated a participation-related problem with in the kidney exchange problem. The authors showed that as hospitals become players, individual rationality leads to the over representation of highly sensitized patients in kidney exchanges. Roth et al. explain that, given the profitability of kidney donation procedures, the revenue lost by submitting patients to a kidney exchange incentivizes hospitals to “enroll only their hard-to-match patient-donor pairs, while conducting easily-arranged exchanges internally.” This subsequently leads to a sparse kidney-compatibility graph and fewer matches amongst highly sensitized patients.

1.3 - Participation incentives

A few articles have proposed incentives systems to increase participation in kidney exchanges Roth et al. (2014) proposed a “bonus mechanism,” similar in spirit to frequent flyer programs, and show that it provides incentives for hospitals to enroll their easy as well as their hard to match patient-donor pairs.” In a similar vein, Dickerson, Hajaj, Hassidim, Sandholm and Sarne (2015) proposed a credit-based model that “incentivizes truthful revelation by lowering the probability that in the future, a transplant center’s disclosed pairs will be included in a global matching, if that center reveals in the present a smaller number of pairs than it is expected to have”.

Despite the existing literature focused on incentivizing hospitals to include their easy-to-match patients in kidney exchanges, not a lot of literature examines patient-level incentives for participating in kidney exchanges. Sönmez and Ünver (2015) proposed a “new incentive scheme that relies on incentivizing participation of compatible pairs in exchange via insurance for the patient for a future renal failure.” However, the financial nature of this incentives mechanism adds third-party costs, and possibly conflicts with US law (it is forbidden to pay potential donors in exchange for their kidney).

Mital and Abdulkadiroglu (2011) suggested incentivizing participation in kidney exchanges for matching pairs by offering “better-matching transplant through kidney exchange.” Mital’s incentives mechanism did not include a financial aspect, and instead focused on improving the “Human Leukocyte Antigen match” (or tissue compatibility) of kidney donor pairs. However, as put by Roth et al. (2004), "the experience of these surgeons suggests… that patient and surgeon preferences over kidneys should be 0-1, i.e. that patients and surgeons should be indifferent among kidneys from healthy donors whose kidneys are compatible with the patient. This is because, in the United States, transplants of compatible live kidneys have about equal graft survival probabilities, regardless of the closeness of tissue types between patient and donor." In other words, an improved HLA match does not lead to improved survival rates for kidney recipients, and therefore, does not serve as a real incentive to enter a kidney matching program. Mital's himself recognized that the two-thirds improvement in HLA match is not a very strong incentive for matching patient-donor pairs to participate in an exchange program, and that altruism would have to play a part in their decision process.

2 - Market Characteristics

As shown in the literature review, a selection bias has led to the overrepresentation of highly sensitized patients in kidney exchanges[1]. This bias is caused by individual hospital incentives, as well as by the higher likelihood that low sensitized patients find a compatible donor without the need to enter an exchange. As a result, kidney exchange clearinghouses face a high representation of patients that are not compatible with many donors. This leads to a sparse donor-patient compatibility graph that prevents an efficient matching. These circumstances have created the need for increased participation amongst low-sensitivity patients. While previous literature has recognized this need, very few non-financial mechanisms have been proposed.

[1] The "sensitivity", or PRA level of a patient refers to a patient's level of percentage reactive antibodies. PRA is measured as a number between 0 and 1, which also represents the probability that any two patients will be incompatible.

Recent literature as well as recent developments suggest that it is possible to institute a non-financial incentives program in kidney exchanges that motivates some matched pairs to enter the exchange. Specifically, Segev et al. (2011) studied the viability of kidney donors over 70 years of age. The authors' findings "support living donation among older adults but highlight the advantages of finding a younger donor, particularly for younger recipients." In other words, Segev et al. found that patients suffering from renal failure are better off if they receive a kidney from a donor that is 70 years of age or older, but that they are even better off if they receive a kidney from a younger donor. Since Segev's paper was published, the total kidney donations provided by donors above 70 years of age has substantially increased[2]. This new development removes the 0-1 preference paradigm for kidney exchanges described by Roth et al. (2004) and introduces the opportunity for a new mechanism that incentivizes donor-patient pairs with old donors to enter kidney exchanges in order to match the patient with a better kidney from a younger donor.

3 - Model and Incentives Mechanism

As stated in the previous section, a new incentives mechanism could encourage the participation of low-sensitivity patients with old donors in centralized kidney exchanges. This mechanism would work by encouraging low sensitivity patients from compatible pairs to enter the exchange with the objective of receiving a kidney from a younger donor. Functionally, this means that the exchange would have to match these patients with with young donors, or not include them in the matching at all.

[2] According to the Organ Procurement and Transplantation Network, There were 112 donors over 65 in 2011, compared with 216 in 2016.

The kidney matching problem can be modeled using graph theory. There are two specific exchanges examined in this paper - the first exchange includes only incompatible donor-patient pairs, and the second exchange incorporates the entry of incentivized compatible pairs that include an old donor. The second exchange has an added requirement that recipients from compatible pairs do not get matched with old donors. Both of these exchanges can be represented by models based off of the work done by Ashlagi et al (2012).

3.1 - Incompatible Pairs Model

An exchange composed exclusively by a set of incompatible donor-patient pairs V can be represented with a compatibility graph, D_V, where each incompatible donor-patient pair is represented by a node $u \in V$. For any two nodes, $u,v \in V$, there is a directed edge from u to v if and only if the donor in u is compatible with the recipient in v.

3.2 Compatible Pairs Model

An exchange that includes both incompatible donor-patient pairs V and compatible donor-patient pairs with old donors V' can be modeled as the set pairs N, where $V, V' \in N$. This set also leads to a directed graph Dn. To incorporate age into the model, we divide the nodes in N into two disjoint sets, O, the set of all pairs with an old donor[3], and Y, the set of all pairs with a young donor. For any node $u \in N$, u is in Y with probability P_Y and u is in O with probability $(1 - P_Y)$.

[3] An old donor is defined as a donor aged 65 or older.

There are three sets of edges in *Dn*. The first set originates and ends in *V*. For any nodes $u,v \in V$, there is a directed edge from *u* to *v* if and only if the donor in *u* is compatible with the recipient in *v*.

The second set includes edges that originate from nodes in *V* and end in nodes in *V'*. Recall that the patient-donor pairs in *V'* entered the exchange in order to conduct an exchange with a young donor. This means that for any two nodes $u \in N$ and $v \in V'$, we add a directed edge from *u* to *v* if and only if the donor from *u* is compatible with the recipient from *v* and if $u \in Y$. Thus, for any two nodes $u \in V$, and $v \in V'$, there is a directed edge from *u* to *v* if and only if the donor in *u* is compatible with the recipient in *v* and $u \in Y$.

The third set originates in *V'* and ends in *V*. For any two nodes $u \in V'$, and $v \in V$ there is a directed edge from *u* to *v* if and only if the donor in *u* is compatible with the recipient in *v*.

Finally, notice that there are no edges that originate and end in *V'*. This is because *V'* is a subset of *O* (given that all the nodes have an old donor), and the age constraint for the recipients in *V'* requires that any edge ending in *V'* originate from a node in *Y*.

3.3 Finding the Optimal Allocation

Kidney exchanges are solved by finding cycles between nodes, where pairs in the cycle exchange kidneys with each other. A *k*-way cycle involves a collection of nodes $v_1, v_2 \ldots v_k$ such that there is a directed edge from v_i to v_{i+1} and there is also an edge from v_k to v_1. As mentioned by Ashlagi et al (2012), in models that only include incompatible donor-patient pairs, logistical constraints prevent any cycles with $k > 3$.

An exchange's optimal allocation is represented by the set *C* of 3-way or 2-way cycles that includes the maximum amount of nodes, adding the constraint that no node *n* can be included in more than one cycle.

3.4 Introducing Blood-Compatibility and Sensitivity Into the Model

In order to determine if any given donor and recipient are compatible, the model takes the blood type compatibility of the pair, and the sensitivity of the recipient into account (these two factors are independent).

For any pair $p \in N$, both the donor and the recipient in the pair have one of four blood types - O, A, B or AB with probabilities P_O, P_A, P_B and P_{AB} respectively. Note that $P_O + P_A + P_B + P_{AB} = 1$ and the blood type of the donor is independent from the blood type of the recipient. For any two nodes $u,v \in N$ the donor in *u* is blood-compatible with the recipient in *v* if their blood types are on the same row on Figure 1.

Donor Blood Type	Can Donate To
O	O, A, B, AB
A	A, AB
B	B, AB
AB	AB

Figure 1 - Blood compatibilities, derived from Roth, Sonmez and Unver (2007)

The model also takes patient sensitivity into account. As previously mentioned, the PRA of a patient is "the probability with which a patient will be immunologically incompatible even with a blood type compatible donor" Ashlagi et al (2012). In order to maintain simplicity, the model assumes that patients either have a high PRA, or a low PRA (this is a standard assumption to make). Hence, the nodes in N can be divided into two disjoint sets, L and H, where L is composed by pairs with low PRA recipients, and H is composed by pairs with high PRA recipients. For any node n, $n \in L$ with probability λ, and $n \in H$ with probability $(1 - \lambda)$.

By combining both stated compatibility factors, we conclude that for any two nodes $u,v \in N$, if the donor from u is blood-compatible with the recipient from v, then there will be a directed node from u to v with probability P_H if $v \in L$ and with probability P_H if $v \in H$, where $P_H < P_L$.

4 - Simulations Setup

We assessed the potential impact of incentivizing compatible donor-patient pairs with old donors to participate in kidney exchanges by using Monte Carlo simulations. The simulations were composed of three phases. The first phase involved selecting parameters that reflect the characteristics of real-world donor patient pools. The second phase involved simulations that used existing matching algorithms to measure a performance baseline for existing exchanges. The final phase involved adding the incentivized compatible pairs to the simulated exchanges in order to assess the impact of the incentives system.

4.1 - Population Parameters

The parameters that determine the characteristics of a participant in a typical simulated population were discussed in the model, and were determined by looking at observations from past research:

Parameter	Symbol	Value	Source
Prevalence of O blood type	P_O	0.4814	Roth et al (2007)
Prevalence of A blood type	P_A	0.3373	Roth et al (2007)
Prevalence of B blood type	P_B	0.1428	Roth et al (2007)
Prevalence of AB blood type	P_{AB}	0.0385	Roth et al (2007)
Prevalence of Low PRA Recipients	λ	0.3728[4]	Ashlagi et al (2012)
Prevalence of High PRA Recipients	$1 - \lambda$	0.6272	Ashlagi et al (2012)
PRA for High Sensitivity Recipients	P_H	0.041	Ashlagi et al (2012)
PRA for Low Sensitivity Recipients	P_L	0.587[5]	Ashlagi et al (2012)
Total pairs in pool	-	138[6]	Ashlagi et al (2012)

Figure 2 - Population parameters as determined by past research

4.2 - Baseline Simulation

In order to establish a baseline for the performance of a kidney exchange with the decided parameters, we constructed a random compatibility graph based on the Incompatible Pairs *Model.* We used integer programing optimization software from Gurobi Optimization, inc. as well as open source code posted by Emile Dupont and Chris Maes to find the optimal allocation for the constructed graph, and measure the number of matched pairs for different population sizes; averaging out the results over 500 simulations. This technique is virtually identical to the

[4] PRA values are derived from real datasets from Alliance for Paired Donation. Value is derived by averaging 0.3436 and 0.402 - the two values from Ashlagi et al.
[5] Ashlagi does not include overall PRA values - only blood type-specific values, but PRA does not vary that much, and simulations with a range of PRA values did not significantly change results.
[6] Population values are derived from real dataset from Alliance for Paired Donation. Value is derived from averaging 131 and 144 - the values from Ashlagi et al.

simulations conducted by Roth et al (2007), but it uses different parameters. Hence, to ensure that the simulation was giving an accurate baseline, we ran the simulation using the original parameters proposed by Roth et al (2007), and compared the results. As shown in Table 3, the total matched pairs derived from running 500 simulations on 25, 50 and 100 pair pools all fell within the margin of error of the total matched pairs in Roth et al's work, thus showing that our software produces accurate results[7].

Total Pairs	**Matched pairs in Roth et al (2007) (Margin of error)**	**Matched Pairs in Simulation**
25	11.272 (4.0003)	11.348
50	30.47 (5.5133)	27.264
100	59.714 (7.432)	59.546

Figure 3 - Performance of our software compared with Roth et al's work.

4.3 - Adding Compatible Pairs

The final stage of the simulations involved adding the incentivized compatible pairs to the previously constructed compatibility graph and constructing a compatibility graph that reflected the *Compatible Pairs Model*. Subsequently, we compared the total matches achieved in this new compatibility graph to the baseline. We also measured the proportion of participating compatible pairs that were actually matched with a younger donor (pairs that were not matched with a younger donor would subsequently have to exchange kidneys with each other, hence

[7] It is important to note that in order to reproduce Roth et al's results, the simulation software was modified to take some factors into account that are not significant for the main models for this paper. Specifically, we tested for compatibility within each patient-donor pair, and removed compatible pairs from the pool. In addition, we used the same PRA values for female patients with a spouse donor as Roth et al.

achieving the same outcome as if they had not participated in the exchange, but suffering a short delay caused by the length of the matching process[8]).

The process of adding compatible patient-donor pairs requires the definition of new parameters. Specifically, it is necessary to define P_Y, the total number of added compatible pairs to the graph and the characteristics of these new patient-donor pairs:

P_Y (prevalence of young donors) -In 2016, 97% of living kidney donors were younger than 65 (OPTN)[9].

Total added compatible pairs - It is quite challenging to estimate the effect that the incentives proposed in this paper might have on compatible pair participation. Hence, once again, we varied this parameter to measure the different potential impact that the incentives system might have based on participation rates. We varied the parameter to range between 1% and 20% of the overall pool size.

Characteristics of compatible pairs - Since the added compatible pairs are not part of self-selecting group as the incompatible donor pairs already in the pool, their PRA and Blood type distributions would be different than the incompatible pairs. To keep things simple, we used the general population parameters established by Roth et al (2007) for blood distributions, but assumed that only pairs with low-sensitivity donors would be allowed to participate in the

[8] Matching process usually takes place every month or every two months (Roth et al 2007)

[9] While Segev et al's (2011) research draws the boundary between old and young donors at 70, public kidney donation data uses 65 as the cutoff point. Given the significant difference in health outcomes for patients with donors over 70 and other patients, there is reason to believe that there would also be a difference in outcomes for patients with donors over 65.

incentives system (this makes sense, given that the goal of the incentives mechanism is to reduce the overall sensitivity of the exchange pool).

5 - Simulation Results

We ran Monte Carlo simulations to quantify the effects that the introduction of low sensitivity compatible pairs would have on the outcomes of centralized kidney exchanges. By averaging out the results of 500 simulations with the parameters defined above, we found that adding low sensitivity donors to the exchange pool would have a significant positive effect on total matches. Figure 4 shows a linear relationship between the number of added compatible pairs and the increase in previously unmatched pairs. Specifically, in an exchange pool with the parameters defined in the section above, regressing the number of added compatible pairs with the increase in unmatched pairs gives a coefficient of 0.48 (standard error of 0.0076). Similarly, regressing the number of added compatible pairs with the percentage decrease in unmatched pairs produces a coefficient of -1.3% (standard error 0.022).

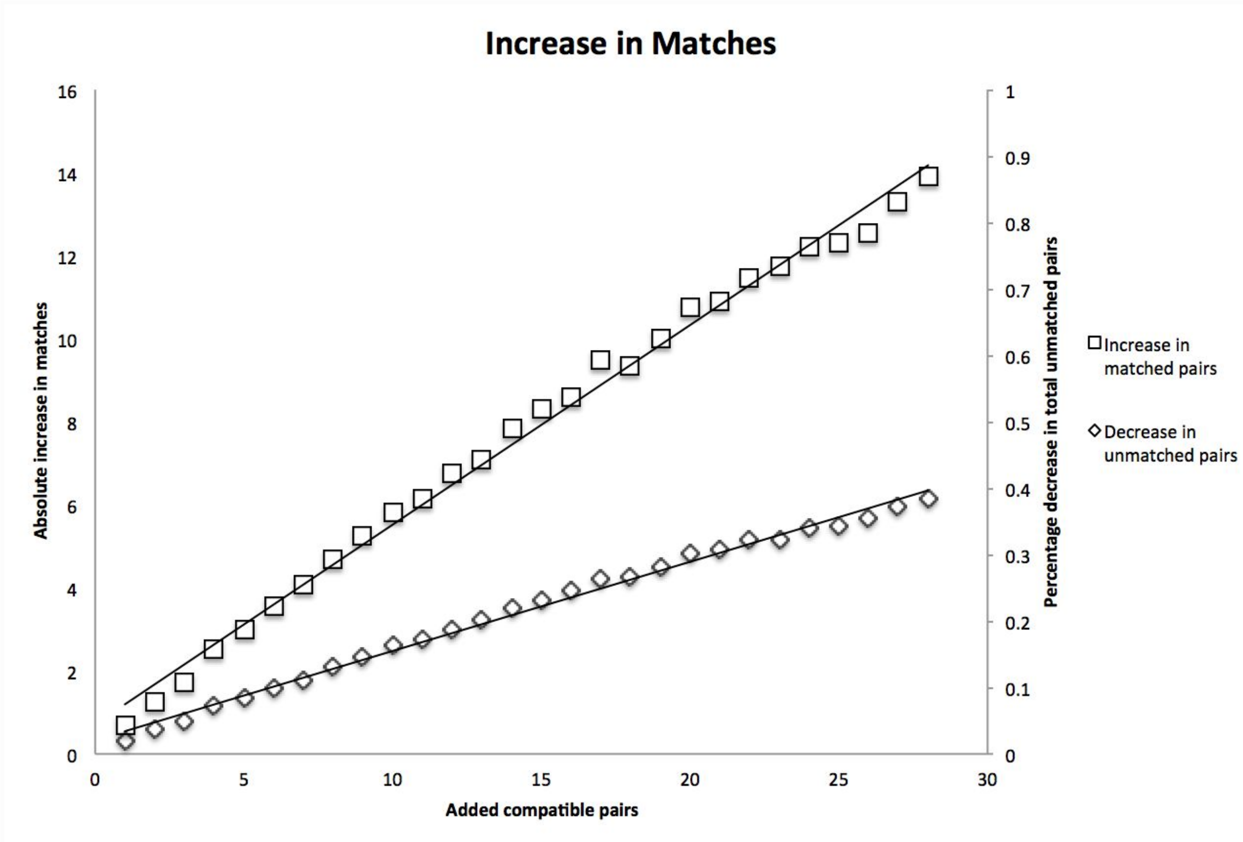

Figure 4 - This graph shows the increase in matches caused by adding compatible pairs to an exchange pool with the characteristics described in section IV.

It is important to note that existing low sensitivity and high sensitivity pairs were almost equally likely to benefit from the inclusion of the new compatible pairs. The ratio of high sensitivity to low sensitivity pairs increased only by average of 0.0048 (standard error 0.0005)[10]. It is important to keep this ratio low in order to prevent any distortions in the pool that would prevent future matches amongst remaining pairs - As mentioned previously in the paper, when the proportion of high-sensitivity pairs in an exchange pool increases, it becomes more difficult to match the pairs.

Finally, as shown in figure five, regressing the percentage of compatible matches that found a match with the total number of added pairs produces a y intercept of 94.4% (standard

[10] For full distribution, see A1 in appendix

error 0.00003) and a slope of (-0.009% standard error 0.008). This means that there are high personal incentives for compatible pairs to donate the exchange, given that they have an extremely high chance of improving the recipient's kidney if they do so. The disincentive for the remaining 5.6% of compatible pairs is also relatively low - while participating in the exchange might cause a delay in their prospective transplant, the old donor would still be able to donate her kidney to the recipient after the matching takes place.

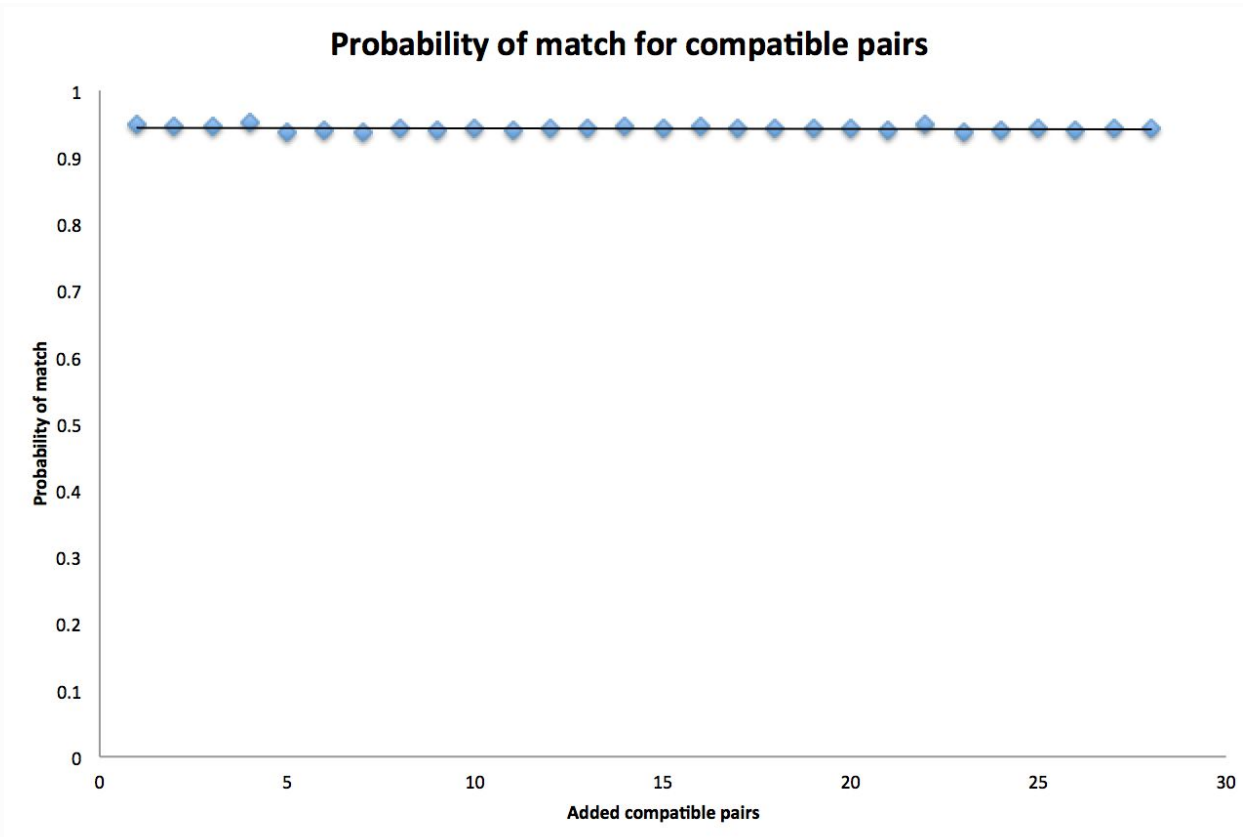

Figure 5 - This graph shows that the probability that a low sensitivity pair with a compatible donor is matched successfully remains consistently around 94% regardless of the total amount of introduced compatible pairs.

While this paper does not attempt to predict the precise amount of compatible pairs that might opt to join an exchange pool, it is important to at least provide a rough estimate in order to evaluate the potential benefits of the paper's proposal. In 2016, there were 214 kidney donors with over 65 years of age. Given that only low-PRA donors could enter an exchange pool, we can use population data to estimate that roughly 70% the 214 pairs would be eligible to join an exchange pool (Roth et al. 2007). By multiplying these parameters with the added matches per compatible pair coefficient (0.48), we conclude that in 2016 there would be an upper limit of 72 additional matches in the US. This would account for an 11% increase in annual kidney paired donations (OPTN). Furthermore, as previously stated, the amount of kidney donors over 65 is increasing year by year, and the incentive mechanism described in this paper would further accelerate this process. While more in-depth analysis is necessary to definitively quantify the potential participation in the program, it is encouraging to see that there is a large enough population to make a significant impact.

5.1 - Robustness

In order to demonstrate the robustness of our results, we varied some of the parameters that we we used in our simulations. In all of the cases, the introduction of compatible pairs still led to a significant increase in total matches, and the probability that compatible pairs were matched successfully remained above 50%. We changed the following parameters:

P_Y - Proportion of young Donors in pool

As mentioned earlier in this paper, the prevalence of older donors has been on the rise, so it would be reasonable to assume that this share might increase, particularly given that people over 65 make up 20% of the population eligible to donate a kidney (Kaiser Foundation). Hence, to increase the robustness of our simulations, we varied P_Y between a range of 97% and 80%[11]. Varying P_Y had a linear effect on patient outcomes over the range that we tested. Each point increase P_Y led to a 0.3 (standard error 0.082) decrease in added matches and to a 0.06 (standard error 0.006) point decrease in the probability that a pair with an old donor would find a better match by entering the exchange. This means that at the worst case scenario seen at $P_Y = 0.80$, an average of 93% (standard error 0.34) of compatible pairs would be matched with a younger donor, and on average, each added compatible pair would lead to an increase in 0.53 (standard error 0.01) additional matched incompatible pairs.

λ - Prevalence of low sensitivity recipients in pool

The prevalence of low sensitivity recipients is also an important parameter that might threaten the robustness of the results. Even though the value for λ used during the simulations was derived from real world data, it is possible that this value could be inaccurate, or that it could change under different circumstances. For this reason we tested the impact of varying the proportion of low sensitivity recipients. We used the same parameters as with the original simulations, but fixed the total compatible pairs at 10% of the size of the pool (rounded up to 14 for a pool of 138).

Varying the value of λ between 0 and 0.5[12] shows that the total increase in matched pairs decreases with the value of λ increases, ranging between 1.26 (standard error 0.012) additional matched pairs per compatible pair at $\lambda = 0$ and 0.33 (standard error 0.009) additional matched pairs per compatible pair at $\lambda = 1$. The proportion of successfully matched compatible pairs

[11] For full distributions, see A2 in appendix
[12] For full distributions, see A3 in appendix

decreased slightly as λ increased, ranging from 95.1% (standard error 0.002) at $\lambda = 0.5$ to 77.3% (standard error 0.005) at $\lambda = 1$.

Size of Pool

The size of the incompatible donor-patient pairs pool could affects the robustness of the results. And, given that different donor-patient pools often vary by size, we ran the simulations with the same parameters as in the original simulation (once again, fixing the total added compatible pairs at 10%). We varied the pool size between 25 pairs and 200 pairs[13].

The results showed that as the pool increases in size, there is a linear increase in the increase in matched pairs - for each additional member of the pool, there is a 0.1 (standard error 0.0004) increase in gained matches. Additionally, as pool size increases, there is also an increase in the proportion of compatible pairs that are successfully matched, ranging from 69% (standard error 0.01) at a pool size of 25, 97% (standard error 0.02) at a pool size of 195, and surpassing 90% at a pool size of 91.

6 - Discussion

6.1 - Limitations

There are several limitations to this paper's results. These include the impreciseness of simulated data, oversimplification and potential errors in the model's parameters and the simplicity in the paper's matching algorithm as compared with real-world matching algorithms.

[13] For full distributions, see A4 in appendix.

The results from this paper are all derived from Monte Carlo simulations with simulated patient and donor pools. While this is a standard practice for research in this area (see Roth et al. 2006), some research has used real-world data to examine the implications of different algorithms or exchange designs. This type of data allows for state of the art results that would lead to an improvement in the results.

The use of simulated data adds an additional level of uncertainty to the results due to potential errors in the model's parameters. While most of the parameters reflect existing exchange pools, there are still some considerations that should be taken into account. Specifically, some of the data used to derived the parameters was flawed, such as the data regarding the proportion of old donors, which has been increasing over time, and uses a different age cutoff than the literature that examines the impact of old donors on patient outcomes (65 instead of 70). Our research accounts for these potential errors by varying the parameter values to increase the robustness of the results, but only one parameter was varied at the same time, meaning that if any errors compounded over several parameters, this would compromise the results. In addition, the paper does not attempt to model any behavioral changes that the proposed incentives mechanism would cause on compatible donor-patient pairs. We simply assume that the improved outcomes for these patients would lead to increased participation, but more robust risk-benefit analysis would be necessary to quantify the participation of compatible donor-patient pairs.

Finally, the integer-programming algorithm that we use to evaluate the impact of our proposed mechanism is not as complex as the real matching mechanisms used by existing exchange programs. Over the past five years, many kidney exchanges have increased the use long donation chains initiated by an altruistic donor to match as many patients as possible. Since our algorithm assessed the impact of the incentives mechanism against a baseline algorithm that only allows for two way or three way exchanges, it is likely that the increase in total added matches would be lower in real life. However, while the presence of donation chains might mitigate the impact of our findings, it does not negate the need for decreased sensitivity in kidney exchange pools, and it does not decrease the incentives for compatible pairs to participate (long chains would make it even more likely that they would find a younger donor).

6.2 - Ethical Issues

There are some ethical issues that should be taken into account before taking any actions that might result from the conclusions of this paper. Specifically, introducing more old donors into kidney exchange pools leads to more recipients receiving a kidney that leads to a lower life expectancy. Furthermore, some patients that might otherwise have received a kidney from a young donor would now receive the kidney from an old donor, meaning that the changes to the system actively harmed them. While these harms would have been offset by gains from other patients, and no specific patient would know how their outcome would have changed under a different system, it is still necessary to grapple with the ethical implications of sacrificing one patient's welfare for the welfare of another one.

6.3 - Policy Implications

There are two areas of policy changes that would be necessary to implement the incentives mechanism described in this paper. The first involves changes to the matching algorithms used by centralized exchanges. The second involves changes in the messaging provided to compatible pairs with old donors by healthcare professionals.

The algorithmic changes needed to implement the incentives system proposed in this paper are quite modest. The most significant change would involve using age of donor as a factor to determine match compatibility between two pairs, where patients from compatible pairs would not be compatible with any donors that are defined as old. In addition, kidney exchanges could improve outcomes by changing their scoring rubric to optimize outcomes for compatible pairs to increase participation incentives.

If the algorithmic changes are implemented by centralized kidney exchanges, it would also be necessary to convey the potential benefits of participating in an exchange to compatible pairs with old donors. This messaging could be implemented by publishing relevant literature for patients, or by encouraging doctors to advise patients on the matter.

Overall, the policy actions required to to implement the finding in this paper are quite modest and have a low cost. Given the clear welfare gains and the lack of potential drawbacks shown by this paper, it follows that subsequent research should be conducted to evaluate the implementation of the proposed incentives mechanism. Specifically, a more compelling case could be made by using real and data and algorithms from kidney exchanges around the country and by making a model that makes a more precise prediction of the amount of compatible pairs that would participate in the program.

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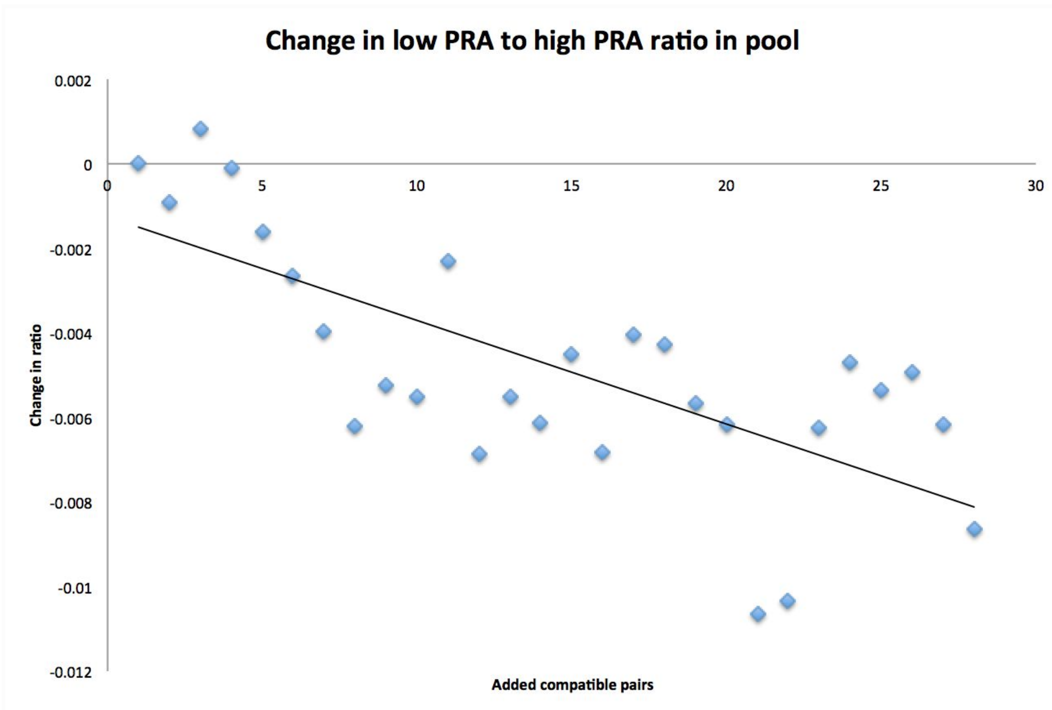
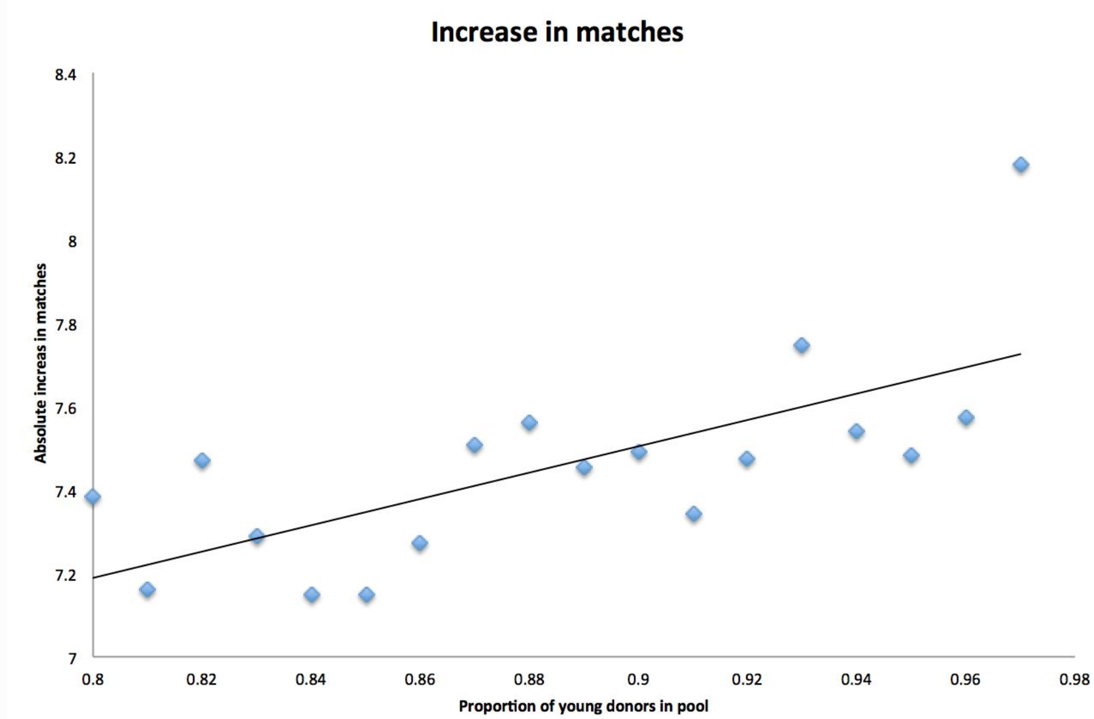
8 - Appendix

Figure A1. Change in low-PRA to high-PRA ratio in exchange pool.



Notes: See main text, section 5.

Figure A2. Exchange outcomes when varying P_Y (Proportion of young donors in pool).



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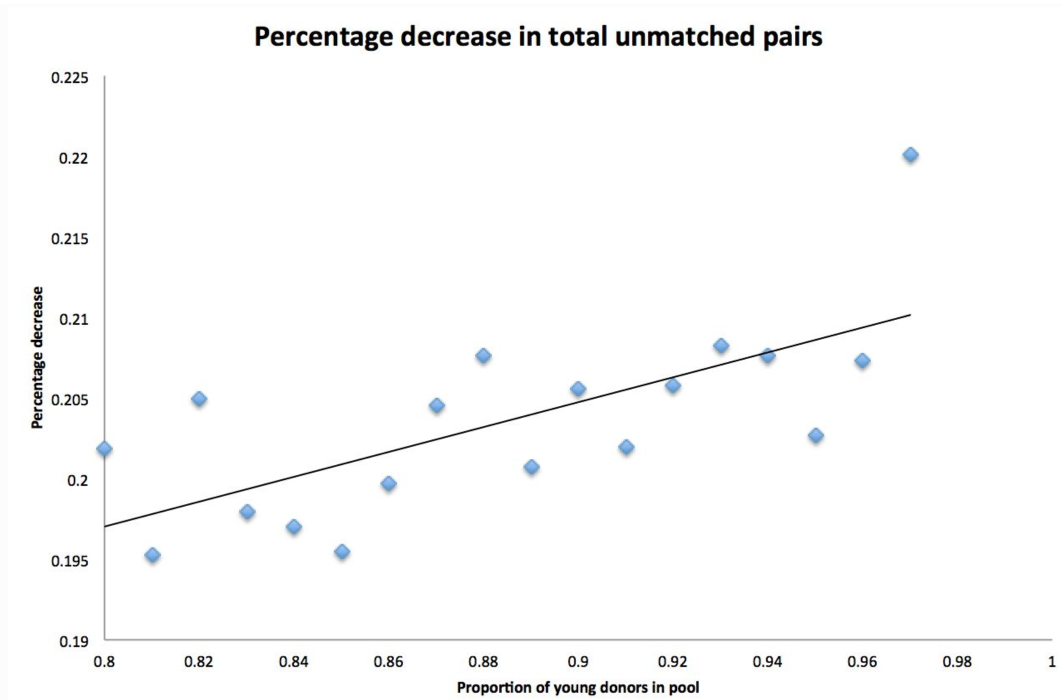

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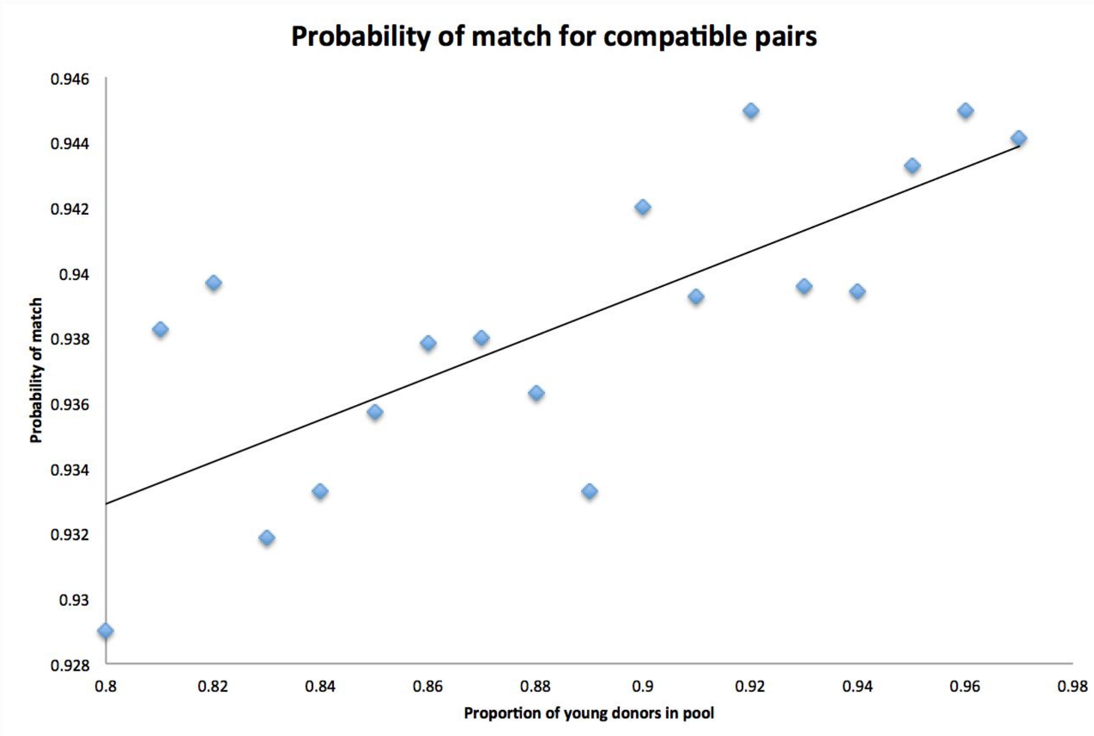
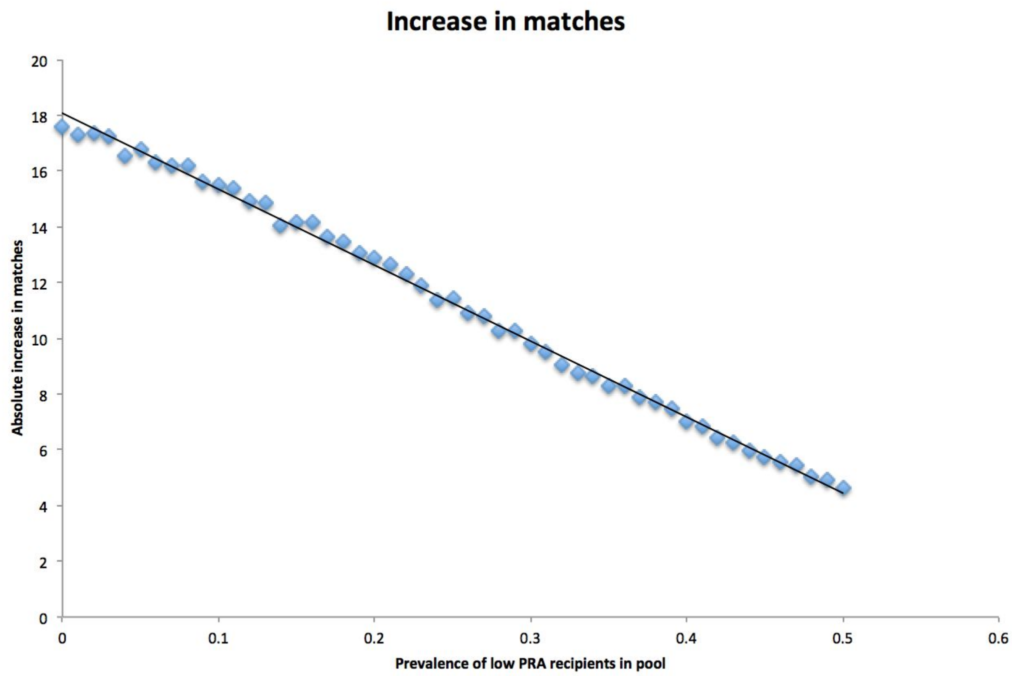


iii.

Notes: See main text, section 5.1.

Figure A3. Exchange outcomes when varying λ (Proportion of low-PRA recipients in pool).



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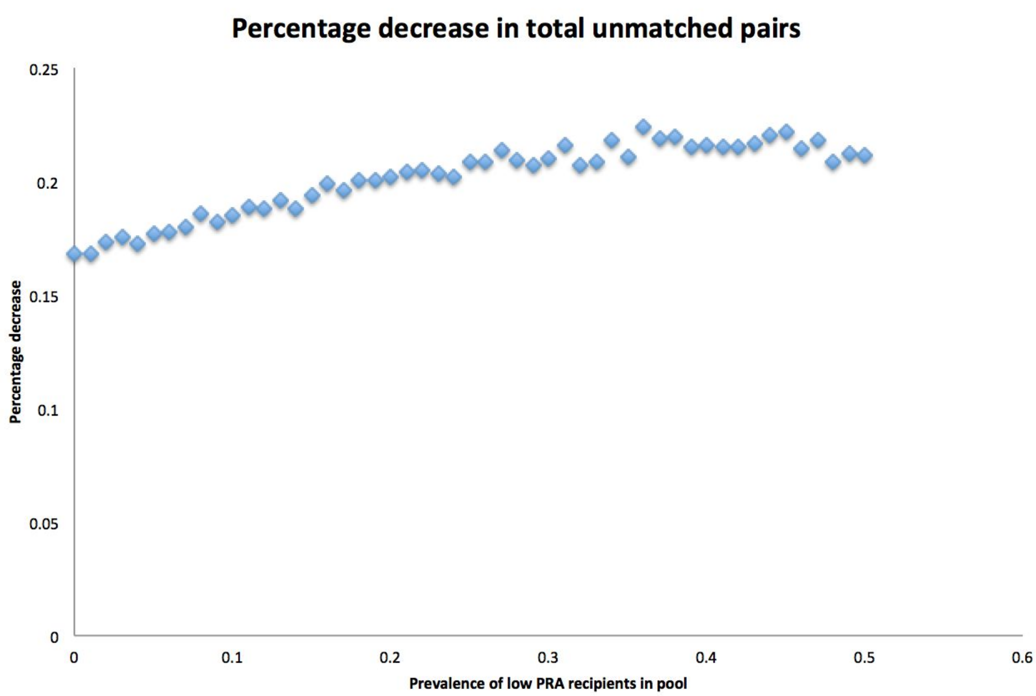

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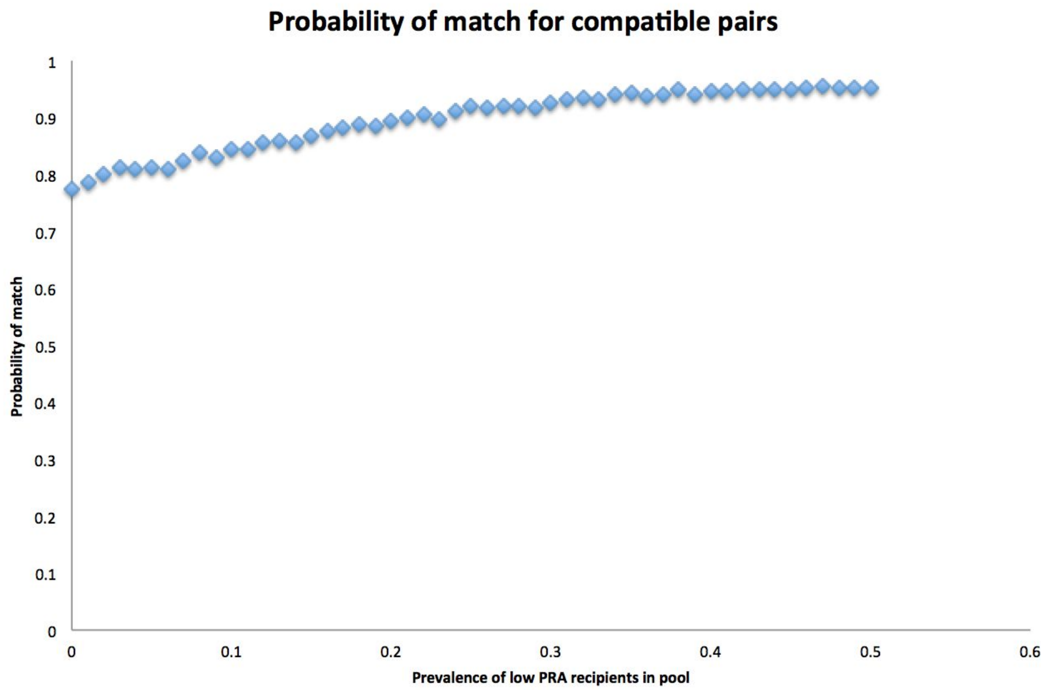
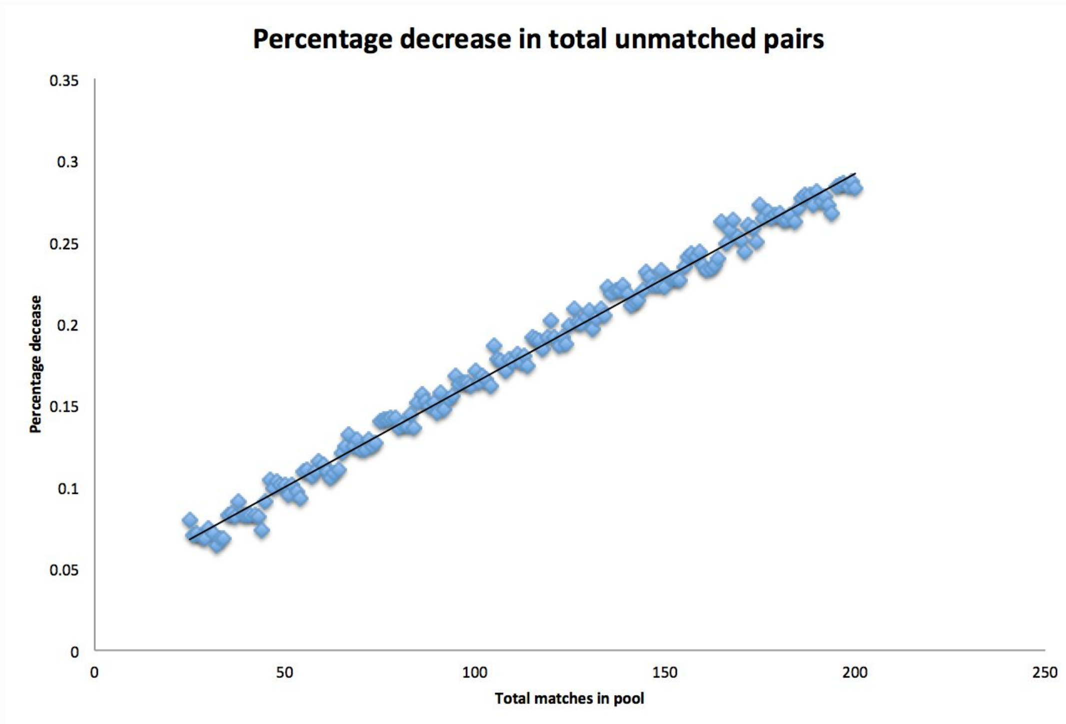


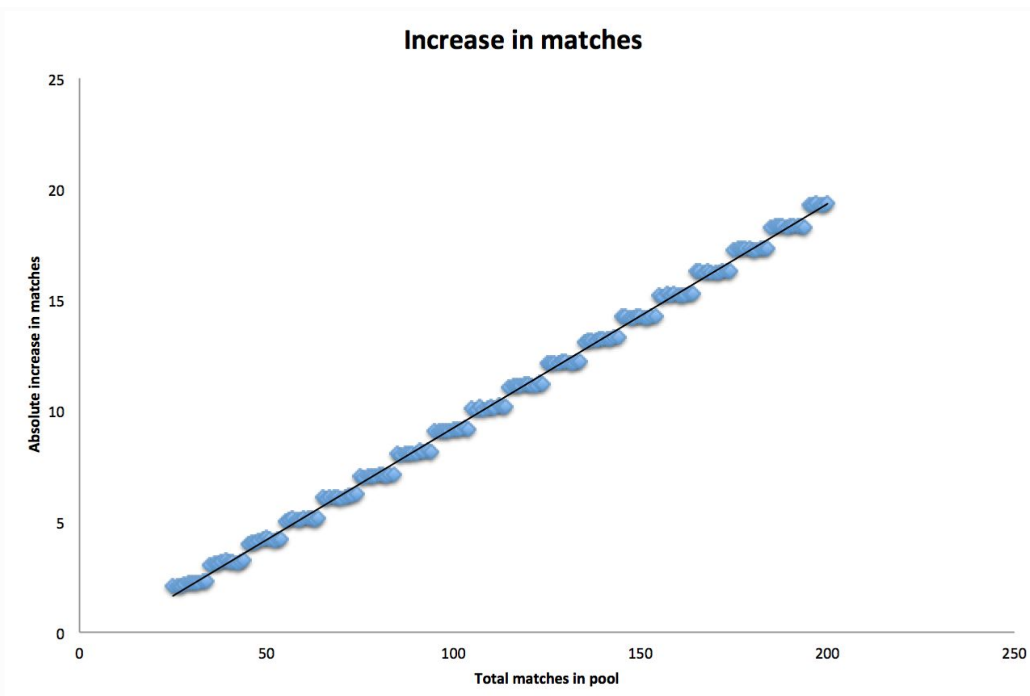
iii.

Notes: See main text, section 5.1.

Figure A4. Exchange outcomes when varying size of pool



i.



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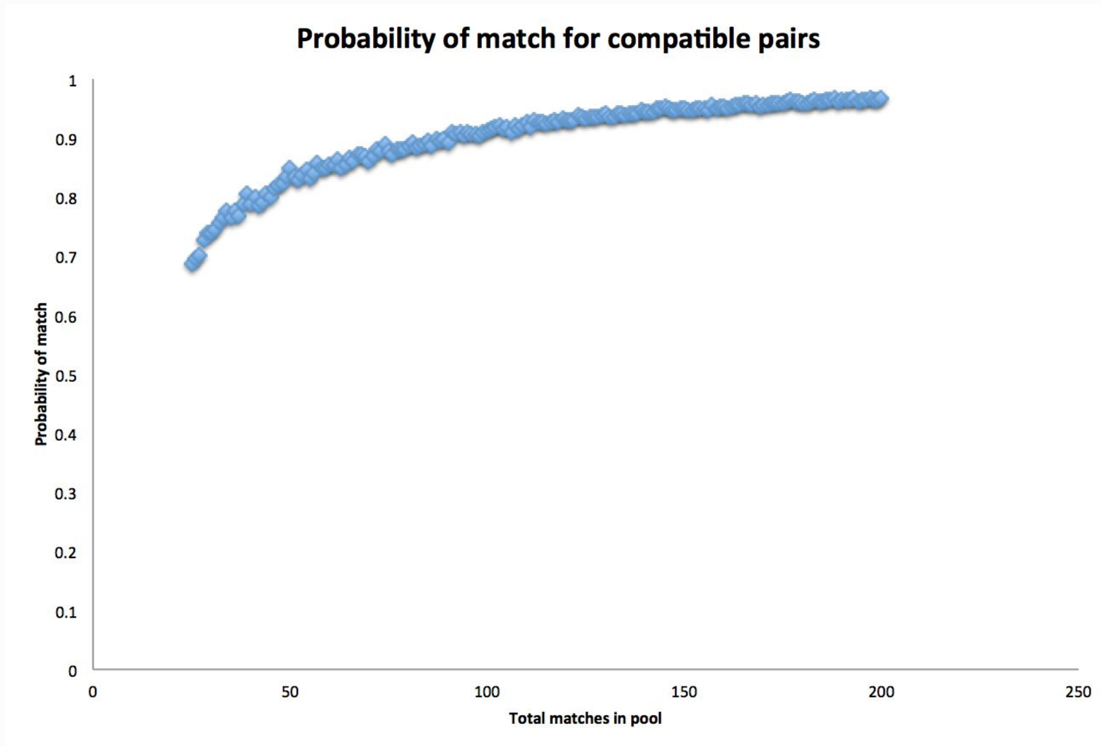

iii.

Notes: See main text, section 5.1

Table A1: Raw data with standard parameters.

Size of pool	Added compatible pairs	Decrease in unmatched pairs	SE	Percentage change in unmatched pairs	SE	Total compatible pairs matched	SE
138	1	0.682	0.0392	0.0191	0.00122	0.95	0.00976
138	2	1.24	0.0586	0.0359	0.00182	1.89	0.0154
138	3	1.73	0.0703	0.0485	0.00206	2.84	0.0181
138	4	2.5	0.0765	0.0717	0.00226	3.8	0.0204
138	5	3	0.0895	0.0835	0.0025	4.69	0.0256
138	6	3.57	0.0993	0.0999	0.00281	5.64	0.026
138	7	4.09	0.104	0.111	0.00277	6.56	0.0291
138	8	4.71	0.106	0.133	0.00305	7.53	0.0321
138	9	5.25	0.111	0.146	0.00305	8.45	0.0329
138	10	5.82	0.125	0.164	0.00352	9.42	0.0337
138	11	6.13	0.119	0.172	0.00342	10.3	0.0389
138	12	6.77	0.13	0.188	0.00346	11.3	0.0404
138	13	7.09	0.14	0.201	0.00401	12.3	0.0425
138	14	7.86	0.147	0.22	0.00402	13.2	0.0391
138	15	8.3	0.152	0.233	0.00413	14.2	0.0416
138	16	8.61	0.152	0.246	0.00438	15.2	0.0456
138	17	9.47	0.164	0.264	0.00412	16	0.0472
138	18	9.33	0.167	0.266	0.00467	17	0.0526

Notes: See section 5.