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The Pennsylvania Adoption Exchange Improves Its Matching Process

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The Pennsylvania Adoption Exchange (PAE) helps caseworkers who represent children in Pennsylvania's child welfare system by recommending prospective families for adoption. We describe PAE's operational challenges using caseworker surveys, and analyze child outcomes through a regression analysis of data collected over multiple years. A match recommendation spreadsheet tool implemented by PAE incorporates insights from this analysis and allows PAE managers to better utilize available information. Using a discrete-event simulation of PAE, we justify the value of a statewide adoption network, and demonstrate the importance of generating better information about family preferences for increasing the percentage of children who are successfully adopted. Finally, we detail a series of simple improvements that PAE achieved by collecting more valuable information and aligning incentives for families to provide useful preference information.

Keywords: community OR; public service; matching; market design.
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According to the most recent report of the Children's Bureau of the U.S. Department of Health and Human Services (2014), approximately 397,000 children in the United States are living in the foster care system, and 102,000 of these children are waiting for adoptive placement. In 2012, although 50,000 children were successfully adopted from foster care, approximately 23,000 were discharged as a result of their emancipation; they reached the age of 18 without receiving a permanent home. As cataloged by Howard and Brazin (2011), numerous studies have shown that children who spend significant time in foster care or age out of foster care without finding a permanent family suffer from alarming levels of unemployment, homelessness, early parenthood, and incarceration. For example, Reilly (2003) reports that 41 percent of respondents between the ages of 18 and 25 who had aged out of the foster care system have spent time in jail.

In response to these trends, state governments, county agencies, and nonprofit organizations have devoted significant resources to providing children in foster care with permanent placements in a timely manner. Federal legislation, such as the Fostering Connections to Success and Increasing Adoptions Act of 2008, has mandated and reinforced these efforts. The state of Pennsylvania funds the Pennsylvania Adoption Exchange (PAE), which was established in 1979 to support county and nonprofit agencies as they attempt to find adoptive families for children who are difficult to place because of attributes such as age or special needs. In addition to listing children on a website and hosting in-person matching events, PAE maintains detailed data on children and the preferences of families that might adopt them. PAE is mandated to provide adoption matching services for children seeking a permanent family. We collaborated with managers at the Pennsylvania Statewide Adoption and Permanency Network (SWAN), a program overseen by the Department of Human Services and responsible for administering PAE on behalf of Pennsylvania, to redesign the match recommendation process.

PAE's match recommendation function has two primary goals. First, it helps overcome geographical and institutional barriers in the adoption search process, given Pennsylvania's 67 counties that are supported by 82 nonprofit organizations. Second, the match recommendation system helps social workers search through extensive data on child characteristics and family preferences. Furthermore, PAE managers believe that caseworkers sometimes have excessively high expectations; that is, they are waiting for the "perfect" family before placing a child. Therefore, the process has an additional goal of promoting a decision-making structure.

In this paper, we evaluate PAE to help increase the success of its match attempts. Our project contributes to an interesting and important public policy area and nonprofit application of market design. We focus on simple changes that address PAE's most significant challenges, and identify key elements of the child adoption market. We worked with PAE to collect additional information from families and children, and created a spreadsheet matching tool that PAE staff members use to recommend families. The concept of a computerized matching tool for ranking families is not new; however, we believe that we are the first to link its effectiveness to an increased rate of successful adoptions through a discrete-event simulation of the adoption network. We are also among the first to note that the matching process may distort incentives for families to truthfully state their preferences; we propose simple remedies to address this.

We organized the remainder of our paper as follows. First, we provide context for the problem of a match recommendation system as it relates to research on the design of matching markets. We then characterize the challenges that PAE faces and assess the current system through caseworker surveys and a regression analysis using child outcome data from 2005 to 2013. We describe how PAE recommends prospective families for children by comparing children's needs with family preferences on a set of approximately 100 attributes using a spreadsheet tool. Based on this understanding of PAE's role in the matching process, we analyze the value of the network and the information available to the network through a discrete-event simulation of PAE's operation. We then discuss our recommendations for the information that PAE collects, the decision rules for match recommendations, and the interaction with system participants. Finally, we conclude by summarizing the improvements implemented and possible future improvements in adoption and other similar domains.

Supplemental material to this paper discusses (1) the Child Registration/Update Form (CY 130), (2) the Resource Family Applicant Registration/Update Form (CY 131), (3) the Pennsylvania Adoption Exchange Case Worker Survey, and (4) Results from Case Worker Survey (available as supplemental material at http://dx.doi.org/10.1287/inte.2015.0828).

Design of Adoption Markets

Despite the growing importance and urgency of finding families for children in state custody, little is known about how to define, analyze, and improve the family-search process. Landes and Posner (1978) were the first to describe the fundamental supply-and-demand imbalance for children of different demographic characteristics by using an economics framework. An empirical study by Baccara et al. (2014) identifies biases in preferences of prospective adoptive families for infant adoption. They show that a child's desirability to prospective families depends heavily on the child's age, gender, and race, with some of the greatest disparities accounted for by the child's race.

We view PAE as a two-sided matching market and rely on the market-design literature to frame our approach to the problem; we use operations research and economics techniques to improve the current recommendation practice. Early market-design work focused on understanding and improving centralized clearinghouses that operate in the absence of prices and face institutional and ethical constraints. The seminal work of Gale and Shapley (1962) introduced the formal two-sided matching framework. This theory was subsequently advanced and adapted to important applications such as the design of the national residency matching program in the United States for matching medical school graduates to internships, residencies, and fellowships at hospitals, as described by Roth and Peranson (1999). This approach was also adapted for other applications such as the assignment of students to public schools (Abdulkadiroğlu and Sönmez 2003) and kidney exchange (Roth et al. 2005).

A recent strand of literature in matching market design has focused on introducing new ideas to improve the functioning of a centralized or decentralized matching market rather than designing new clearinghouses to conduct the matching. For example, Coles et al. (2010) report the introduction of a signaling tool for the academic job market for new economics PhDs. Lee et al. (2011) report on an experiment to measure the effects of the use of signaling devices on online dating. Ata et al. (2012) discuss a new company, OrganJet, which uses private jets to transport patients to overcome the inefficiencies of regionally isolated organ donation networks. A related study by Arikan et al. (2012) shows that broader sharing of the bottom 15 percent of kidneys (in terms of quality) from deceased donors leads to significantly increased procurement rates for those organs.

Child Adoptions in Pennsylvania

SWAN's primary goal is to help find permanent families for children in the custody of Pennsylvania's counties. Children who fail to be placed upon initial attempts at the county level are provided with extra services at the state level, including match recommendations from PAE. County child welfare appropriations in Pennsylvania exceeded $1.5 billion in fiscal year 2014–2015 (Pennsylvania Department of Human Services 2015), and are largely used to support approximately 15,000 children, of which 2,000 children are classified as waiting for adoption (Children's Bureau, U.S. Department of Health and Human Services 2014). Between 2007 and 2012, an average of 239 children per year registered to receive match recommendations from PAE. The Office of Children, Youth and Families (OCYF) of Pennsylvania's Department of Human Services mandates that children without an identified adoptive family must be registered with PAE within 90 days of termination of parental rights (TPR).

PAE managers believe that the best scenario for a child, even for a child who is about to reach the age of majority, is to be placed with a permanent family. For children who are placed, the time during which the child is a legal orphan should be minimized. Furthermore, the suitability of the family for the child is important. In particular, some families are better prepared than others to handle children with special needs, whether medical, behavioral, or psychological.

Prior to TPR, a county caseworker seeks a suitable family for the child. If no clear kinship adoption possibility or potential family is available within the agency's local network, the child and youth services (CYS) worker may contact SWAN and request match suggestions from PAE. The caseworker must register the child with PAE within 90 days after TPR if no report of intent to adopt has been filed. Through working with PAE coordinators, the CYS worker then receives the names of between five and 10 families to consider and pursue. After identifying interested families, the worker arranges an interview and consults with a committee comprised of social workers and other professionals with diverse expertise to choose a family with which to place the child. After a series of successful visits of increasing duration and decreasing supervision, the child is placed with the family. According to Pennsylvania law, an adoption can then be finalized after six months.

In spring 2011, to characterize the challenges facing PAE, we worked with a PAE manager to survey caseworkers for all active children; our objective was to gain a broader understanding of attitudes about PAE across the state. Survey recipients included both county caseworkers and social workers, known as child-specific recruiters, who work for private nonprofit agencies and serve as an additional resource for county caseworkers in finding families for hard-to-place children. The supplemental files include the survey and results.

The caseworkers were first asked to indicate the helpfulness of various avenues of finding families: 65 percent of respondents said that this never or rarely served as the initial source of prospective families for children who are successfully placed. Furthermore, no respondents strongly agreed and only 32 percent agreed with the statement that "PAE does a good job of recommending the most suitable families via electronic matches from the Resource Family Registry for each child." The caseworkers also testified to the difficulty of making placement decisions and caseworker bias. More respondents agreed or strongly agreed (53 percent) than disagreed or strongly disagreed (37 percent) with the statement that they "know of caseworkers who struggle to make placement decisions for children because of emotional attachments to those children." Even more respondents agreed (65 percent) than disagreed

(23 percent) with the statement that they "know of caseworkers whose personal preferences lead to negative perceptions toward some families."

Survey responses demonstrate both the ineffectiveness of the current matching system and the caseworkers' mistrust of match recommendations from PAE. However, caseworkers expressed more positive views about the possible helpfulness of the registration data; more than 60 percent of respondents agreed or strongly agreed that family data are "helpful" for screening and child data are "accurate." This indicates the potential value of a statewide matching network, and motivates efforts to improve PAE's ability to help caseworkers find families for children in county custody.

Analysis of Child Outcomes

We reviewed registration and outcome information about children served by PAE to better understand adoption trends in Pennsylvania and the varying levels of difficulty in trying to find adoptive placements. PAE managers overcame significant challenges related to the decentralized nature of the adoption process in Pennsylvania to prepare this data set for our use. To our knowledge, we are the first to analyze the relationship between child outcomes and child attributes upon registration in Pennsylvania. The results of the analysis have provided insights about which children might require additional adoption resources, and information to share with caseworkers as part of training on best practices.

Between 2005 and 2013, PAE assisted in the family-search process for 1,853 children seeking adoptive families. This set of children was a subset of children in county custody with the goal of adoption; only when the matching process encounters difficulties at the county level does the search process shift to the state level. The mean age of a child upon registration with PAE was 9.41 years, and the median age was 9.63 years. Boys comprised 57.8 percent of all PAE registrants. Of these 1,853 children, outcomes were known for 1,514 children, because 283 were still active cases upon the creation of the data set in May 2013, and outcomes were missing for 56 children. Otherwise, child outcomes are known and grouped into categories, each of which has a value between 0 and 1 which PAE managers provided. The most desirable outcome, a finalized adoption, has a value of 1. Emancipation, which can be referred to as aging out of the system, is the least desirable outcome and has a value of 0. Other positive outcomes include permanent guardianship arrangement (0.8) and living with a relative (0.7), among other scenarios. An outcome of "hold" with a foster care arrangement is considered a neutral outcome and has value of 0.5. Other negative outcomes include placement in a residential facility (0.2) or a goal change such that the child's caseworker is no longer seeking an adoptive placement for the child (0.1).

Of the children for whom outcome data are known, the county caseworker succeeded in finding a finalized adoptive placement for 41.4 percent (627 of 1,514) of children. Another 19.1 percent of children have lesser positive outcomes with values of 0.7 or 0.8. Negative outcomes with values less than or equal to 0.2 are experienced by 26.2 percent of children, with 12.4 percent of children aging out of the system. The remaining portion (13.3 percent) of children have neutral outcomes. Using the values given by PAE managers, the expected outcome value for a child in the data set is 0.64.

Regression Model

We developed a linear regression model and a logistic regression model to analyze the relationship between children's attributes when they were registered with PAE and their outcomes. We created 88 factors from registration data, and used the outcome as the dependent variable. Specifically, we used the outcome value for the linear model and a binary variable with positive outcomes having value 1 and neutral and negative outcomes having value 0 for the logit model. We included the square of the child's age upon registration to represent the increasing importance of age for older children. The date of registration was expressed in the fractional number of years after January 1, 2005. Gender was represented by a binary variable, as was the child's designation as being African-American and (or) Hispanic. Another binary variable represented whether the child had more than one race designation. Eighteen binary variables represented the items under the sections labeled "Educational Status" and "Special Needs" on the CY 130 forms, and an additional variable counted the number of binary variables with positive responses. The last category of variables was 61 questions in the

	Dependent variable			
	Outcome value *Ordinary least squares*	Outcome (binary) *Logistic*	Frequency (%)	Importance
Constant	0.794*** (0.046)	1.516*** (0.372)		
Age upon registration (years)	0.020** (0.009)	0.102 (0.075)		High
(Age upon registration)^2	−0.003*** (0.0005)	−0.017*** (0.004)		High
Registration year (after 2005)	−0.009** (0.004)	−0.059* (0.031)		
Male	0.019 (0.017)	0.100 (0.128)	57.1	High
African-American	−0.034** (0.017)	−0.198 (0.132)	42.5	High
Hispanic	−0.051** (0.024)	−0.303* (0.179)	14.1	High
Special needs				
Mental retardation diagnosis	−0.109*** (0.031)	−0.562** (0.230)	9.0	High
Multiple placement history	−0.035* (0.018)	−0.189 (0.137)	45.6	Medium
Drug exposed infant	−0.020 (0.026)	−0.100 (0.202)	11.6	Medium
Emotional disability	−0.019 (0.022)	−0.071 (0.162)	20.2	Medium
General education	0.064*** (0.019)	0.353** (0.146)	37.1	
Siblings	0.085*** (0.019)	0.465*** (0.143)	47.3	High
Child characteristics				
Blind	−0.164* (0.085)	−0.899 (0.611)	1.0	Medium
Uses foul or bad language	−0.118*** (0.027)	−0.613*** (0.194)	15.0	Medium
History of running away	−0.086** (0.043)	−0.443 (0.321)	4.2	High
Desires contact with siblings	−0.079*** (0.020)	−0.443*** (0.152)	59.4	Low
In contact with former foster family	−0.064*** (0.022)	−0.353** (0.162)	18.8	Low
Rejects father figures	−0.061** (0.031)	−0.345 (0.230)	8.5	Low
Difficulty accepting and obeying rules	−0.061*** (0.022)	−0.337** (0.160)	36.9	Low
In contact with birth parents	−0.058*** (0.020)	−0.327** (0.153)	26.0	Low
No. of characteristics present	0.007*** (0.003)	0.034* (0.020)		
Parent(s) with criminal record	0.017 (0.018)	0.087 (0.138)	51.6	Low
Difficulty relating to others	0.018 (0.022)	0.101 (0.168)	31.0	Low
Speech problems	0.024 (0.024)	0.176 (0.191)	18.4	Low
Previous adoption or disruption	0.038* (0.021)	0.220 (0.155)	24.1	Low
Strong ties to foster family	0.041** (0.018)	0.226* (0.134)	54.2	Low
Vision problems	0.042* (0.023)	0.224 (0.175)	17.1	Low
High achiever	0.054** (0.025)	0.283 (0.190)	13.1	Low
Observations	1,514	1,514		
R^2	0.345			
Adjusted R^2	0.333			
Akaike inf. crit.		1,697		

Table 1: We choose 28 factors from the available 88 factors to model child outcomes using ordinary least squares and logistic regression methods. Age upon registration, which is a negative factor for children six years of age and older, was the most important factor for predicting outcomes.
Notes. **The values in parentheses indicate the standard deviation. Italicized variable names refer to "Characteristics of Child" questions on CY 130 form. Also, $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. "Frequency" refers to an attribute's prevalence among the observation. "Importance" refers to the existing default weight given to the attribute before our analysis.**

CY 130 section labeled "Characteristics of Child"; a binary variable for number of positive responses in the section was also used.

Starting with these 88 variables, we performed a backward stepwise procedure using the Akaike information criterion for both the linear and logit models to select which variables to include in the model. Linear and logit regressions were performed on the union of the variables from these two models (Table 1). To roughly assess model performance for the linear model, rounding the predicted outcome to the nearest outcome value and classifying it as positive, negative, or neutral, the model classifies 60.0 percent into the correct one of three categories. Only 8.1 percent of children had a positive or negative outcome that was errantly predicted as the opposite outcome. All other prediction errors involved the neutral outcome. When we considered binary child outcomes for the logistic models, we correctly predicted 75 percent of outcomes. For children with negative or neutral outcomes, we correctly predicted 59 percent, and 85 percent for children with positive outcomes.

The child's age upon registration plays a significant role in the regression model and confirms that older children become increasingly difficult to place. For the linear model, the predicted likelihood of success decreases by 0.034 per year at age 8, and by 0.087 per year at age 16. The accumulative decrease in the expected outcome compared to a newborn child is then 0.054 for an eight-year-old child and 0.535 for a 16-year-old child. Although PAE managers anticipated this general trend, they found the quantification of this relationship to be very helpful as they instruct caseworkers around the state on best practices. Specifically, they can encourage caseworkers to register children with the PAE as soon as possible in the adoption process and perform a search through PAE in parallel with family reunification or other placement efforts.

Mental retardation, which had a coefficient of −0.109 for the linear model, was the most negative of the significant special needs factors from the "Child's Statuses" section of the CY 130 form for both models. Two special needs factors—having siblings and attending school in a general education setting—had statistically significant positive coefficients for both models. For the "Characteristics of Child" attributes, the result that surprised PAE managers was a linear regression coefficient of −0.118 for children who use foul or bad language, which was also significantly negative for the logit model. PAE managers found this information valuable to share with caseworkers as part of training on how to identify challenges to a successful placement. Other factors that were significantly negative with 95 percent confidence for both models were a difficulty accepting and obeying rules, a desired contact with siblings, contact with birth parents, and contact with a former foster family. The child's gender was revealed not to have a significant effect in either model, but outcome value decreases of 0.034 and 0.051 (for the linear model) were expected for children with African-American and Hispanic designations, respectively, although the logit model did not determine designation as African-American to have a significant effect.

To understand how the regression results compare to managerial intuition about the different factors' relative importance, we compare them to PAE managers' existing classification of the factors' importance. As part of a previous attempt to create a family-ranking tool that had encountered difficulties, managers divided the factors from the CY 130 form based on their perceived importance into groups with 15 factors as high, 18 factors as medium, and 41 factors as low. Of the 10 significant factors with the most negative ordinary least squares (OLS) coefficient, managers had assessed three of the factors (Hispanic, mental retardation diagnosis, and history of running away) as of high importance and two factors (blind and uses foul or bad language) as of medium importance. They classified the remaining five factors as of low importance. These five factors, which include two behavioral traits and three related to a child's social connections, merit closer attention and a higher weight in the matching process to help identify families more suited to a child's needs. As a result of this analysis, they ultimately decided to reclassify almost all significant ($p < 0.1$) factors with a negative OLS coefficient as high importance in the match-assessment tool, which we discuss next. The lone exception to this rule was multiple placement history, which remained at medium priority because of the low magnitude of its coefficient. PAE managers particularly appreciated the suggestion to increase the importance of factors related to a child's social connections, because they identified those connections as frequent obstacles to adoption.

PAE managers identified four other characteristics, which represent some of the most severe behaviors listed on the CY 130 form (e.g., abusing animals), as high-importance factors that did not appear as significant factors. However, increased managerial attention to finding families suitable to these children's needs might have led to their exclusion from the final model for predicting child outcomes; we do not make a recommendation about whether to reduce the emphasis on these child characteristics.

Match-Assessment Tool

PAE is only one of several governmental and nonprofit institutions that have developed tools to assess a

Category	No. of attributes (scoring weight) High (100)	Medium (10)	Low (1)	Child attribute values (family preference values)
Child demographics				
Age	1	0	0	Current age (max/min age)
Race/Ethnicity	6	0	0	Applicable/*not applicable* (preferred/not preferred)
Gender	1	0	0	Male/female (male/female/either)
Child status				
Educational status	0	1	0	Applicable/*not applicable* (approved/not approved)
Special needs	6	7	0	Applicable/*not applicable* (approved/not approved)
Characteristics of child				
Health	0	3	7	Yes/*no*/*unknown* (acceptable/will consider/unacceptable)
Education	0	1	7	Yes/*no*/*unknown* (acceptable/will consider/unacceptable)
Characteristics and behaviors	5	5	11	Yes/*no*/*unknown* (acceptable/will consider/unacceptable)
Connections and history	0	0	14	Yes/*no*/*unknown* (acceptable/will consider/unacceptable)
Contact with birth family	0	0	1	Yes/*no*/*unknown* (acceptable/will consider/unacceptable)

Table 2: PAE managers use data on 76 attributes to recommend families for children. Weights displayed represent weights used in the existing algorithm.
***Note*. Items in italics indicate child attribute values for which the attribute does not count as part of the total matching score.**

possible match between a child and family. Hanna and McRoy (2011) describe the practice of matching in adoption as a means of finding families that have the right capabilities for handling a child's special needs and identifying gaps in a family's capabilities. They emphasize the need for standardization and data collection, point to match-assessment tools as an important part of the family-search process, and review seven tools used in practice by public and private agencies. Although some tools use more attributes (up to 277) than PAE, the design of PAE's existing matching tool surpasses all seven tools in weighting attributes and in its ambition of helping to find families within a statewide network.

According to its intended design, which we formally express in Algorithm 1 in the appendix, PAE's match-assessment tool computes a family's score between 0 and 100 percent for a child based on 78 pairs of child-attribute values and family preferences from CY 130 and CY 131 registration forms (Table 2). PAE managers assigned a number of possible points to each of these pairs—100 for items of high importance, 10 for items of medium importance, and 1 for items of low importance. When a special need or other attribute is not applicable or of an unknown state for a child, no points are either eligible or awarded to each family for that attribute. We note that PAE also does not give preference to families who say that a special need is undesirable when matching a child who does not have that special need. This practice could create incentives for families to hide special needs that they can accommodate if the families want to be considered for children without those special needs. For attributes that are applicable for a child, a positive family response—a child's age within the family's range, a matching gender, and answers of preferred, approved, or acceptable—receives all possible points for the item. An answer of "will consider" receives 50 percent of the possible points. Otherwise, the family's answer receives no points. For a specific child, the family's score is simply the sum of points received for its answers divided by the sum of possible points for the child. The *Matching Tool Spreadsheet* section of the appendix provides an example match score for a child and family.

In recent years, PAE has struggled to make match recommendations that help caseworkers to find and assess families. Specifically, coordinating algorithm design with an information technology contractor and managing data collected over time across Pennsylvania's 67 counties proved difficult for PAE, and child caseworkers received unhelpful or illogical match recommendations as a result of a flawed implementation of Algorithm 1. The automated match recommendations were even abandoned for over two years during which PAE coordinators manually searched through CY 130 and CY 131 forms to provide match suggestions.

Recognizing the shortcomings of the current rules for choosing matches, we worked with the SWAN managers to redesign the matching tool. This resulted in a spreadsheet-based algorithm that uses PAE data about families and children to select matches. For ease of implementation, we focused on policies that had the same form as the PAE's match-assessment tool. In particular, we considered policies that are based on a point system and ranked families according to some compatibility criteria. Rather than making specific assumptions about the relative importance of each criteria, our method offers the PAE managers the flexibility to select their desired weights and any other geographical constraints, as shown in the appendix. To select prospective families for a child, the spreadsheet tool computes a ranked list of families for a child using CY 130 and CY 131 information stored in tables elsewhere in the matching tool.

The matching algorithm that we implemented differs in two aspects from those that have been applied in prominent centralized two-sided matching applications. First, the algorithms studied in that literature, such as Gale and Shapley's deferred acceptance algorithm (Gale and Shapley 1962), produce a set of final matches that are implemented concurrently. However, our algorithm generates a list of mere recommendations that may be implemented in conjunction with the judgment of the professionals. In this sense, our approach is closer to that adopted by the literature on semi-decentralized matching platforms, such as those for online dating and job matching. The literature on these markets focuses almost exclusively on estimating participant preferences as opposed to increasing match success rate and quality, which we pursue here. The second, more subtle difference is that in centralized matching, participants are required to rank list all available options, whereas here such ranking information is impossible to elicit directly because of limitations such as market size and informational asymmetry. One main function of our algorithm can be seen as constructing such preferences from given pieces of information in the CY 130 and CY 131 forms and using them as the basis of recommendations.

Simulation of the Pennsylvania Adoption Exchange

To examine the impact of a simple matching tool's effective use on the network's overall adoption rate, we represent PAE's matching process as a discrete-event simulation. We show the value of a statewide pool of families compared to a decentralized search process, and analyze how the ability of PAE to predict a match's success increases the number of matches. Specifically, we model how different levels of information about child attributes and family preferences affect the number of matches and the number of attempts before a successful match. We rely on the results of the regression analysis from the previous section to identify the most important child attributes for the simulation, and additionally introduce relevant family registration data to model family preferences.

As an alternative to conventional techniques, such as clinical trials, which would require many years to evaluate, discrete-event simulation has long been used to estimate the effects of policy changes, especially organ-allocation policies (cf. Ata et al. 2012). Similarly, our discrete-event simulation model of PAE's operation is modular and based on input parameters that we estimated using real data. Some of the simulation studies on organ allocation use a finite-horizon model, which is necessary because the data are highly time dependent, and reaching steady state is very unlikely unless an alternative therapy for transplant patients exists. However, we assume stationary parameters in our simulation model, which is justified in the context of child adoption because the population characteristics of children and families in the system do not change dramatically over time.

We divide the adoption network into regions that constitute separate adoption networks defined by geographical and (or) institutional barriers. Children may be adopted only by families that reside within the same region. Decreasing the number of regions to increase the size of each region provides each separate network with more prospective families and more children to match. We model the state of the PAE before our project as 20 separate regions because of the ineffectiveness of the central matchmaker. In that case, each region may correspond to a large county or a coalition of smaller counties in Pennsylvania. Because county caseworkers face geographical limitations in matching, we do not expect a perfect centralized matchmaker to operate as a single region. Instead, managerial insights are primarily motivated by two cases: doubling the region size (i.e., dividing the state into 10 regions instead of 20 regions) and a system with four regions corresponding to PAE coordinators who provide match recommendations to county caseworkers.

Children

Children are defined by their age, number of special needs, and region in which they reside. A younger child is generally preferred to an older child, and a child with fewer special needs is generally preferable to a child with more special needs. The age attribute corresponds to the child's age upon registration with PAE. Using available data for the 1,853 children who have been registered with PAE, we fit the data using the input analyzer tool of @Risk and compared alternatives using a q-q chart. We determined that a beta distribution with shape parameters $\hat{\alpha} = 5.7736$ and $\hat{\beta} = 4.8877$ and scaled to be within the interval $[-5.4648, 22.738]$ would produce the best fit (Figure 1(a)). In the simulation, we disregarded any age values outside the interval $[0.0, 19.0]$ and resampled.

The special needs attribute corresponds to a count of the presenting attributes out of the 10 child attributes that had a significant negative coefficient with a value less than -0.05 in the OLS regression analysis. This cutoff is arbitrary and used only in the simulation analysis to designate attributes of high importance.

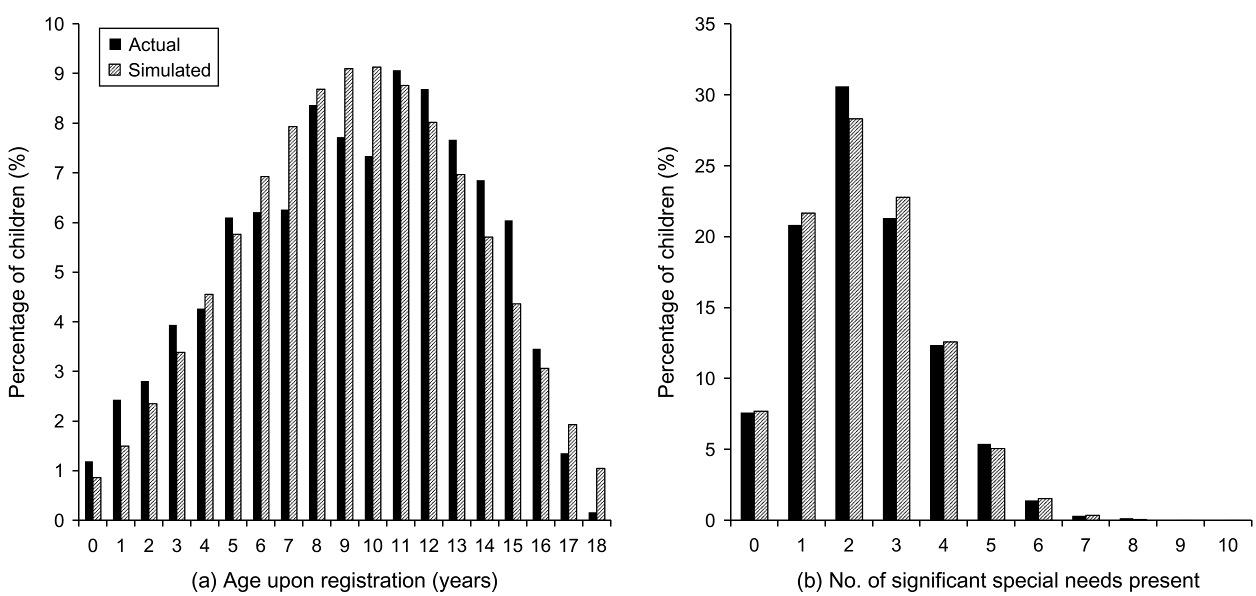

Figure 1: Based on age upon registration data for 1,853 children, we simulate the child's age using a beta distribution and a binomial random variable to simulate the number of significant special needs present for each child.

As with age, we fit the data using @Risk's input analyzer, and modeled the number of special needs present as a binomial random variable with parameters $n = 14$ and $p = 0.16741$ (Figure 1(b)). We discarded any special needs values greater than 10 and resampled.

The registration age and number of significant negative special needs are positively correlated with a correlation coefficient of 0.230. Therefore, we used a normal-to-anything (NORTA) process with two base vectors that have a correlation coefficient of 0.239 that we obtained via a simulation approach. The standard multivariate normal vectors that follow a NORTA distribution are transformed to the age and special needs distributions using the method that Biller and Ghosh (2006) describe.

The value of the child's region attribute is a random variable uniformly distributed over all regions. Children arrive in the system as a Poisson process with a rate of 239 per year, which is the average number of children receiving match recommendations who were registered with PAE annually between 2007 and 2012.

Families

Families are defined by their region of residence and their preferences for an adoptive child's age and maximum number of special needs, as well as the relative weight of the age preference compared to the special needs preference. They arrive at the matching system as a Poisson process with rate of 282 per year, which is the mean number of families to fully register with PAE as approved adoption resources each year between 2007 and 2012. Managers estimate that approximately 1,000 prospective families are available at any point in time, which implies that the expected time in system is 3.55 years by Little's Law. Thus, we model the family's time in the system as an exponential random variable with a mean of 3.55 years, because PAE does not track the distribution of families' time in system. We note that a higher number of families compared to the number of children in the system creates a disparity in the distribution of children available to adopt and the distribution of family preferences, which the PAE system reflects through children who age out of the system without an adoptive placement.

We model the families' behavior as myopic, accepting the first child that they are offered for which their utility of a match with the child is positive. We discuss the model that underlies the family acceptance decision in the *Matching Model and Simulation Details* section of the appendix. Once a family accepts a child, the family leaves the system. The values for a child's minimum age, maximum age, and number of the 10 significantly negative special needs that are designated as "acceptable" are sampled together from the data on 2,194 families (Figure 2). As with children, families are uniformly distributed over the regions.

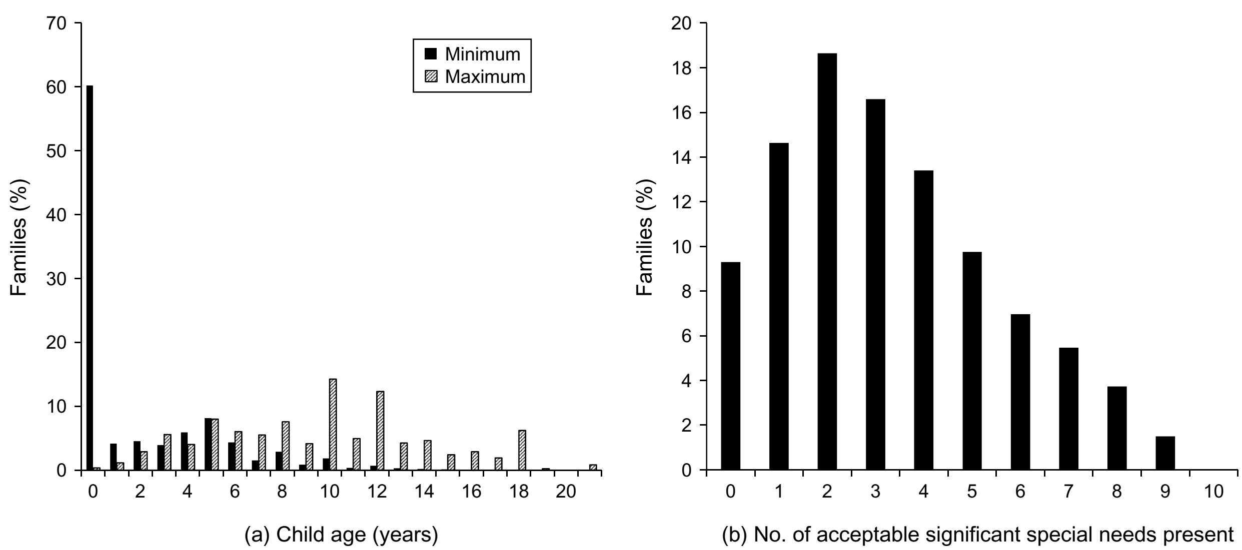

Figure 2: To simulate family preferences, we sample actual preferences from 2,194 registered families.

Matching Process

We represent the matching process as a series of events that take place upon a child's arrival in the system, which PAE managers view as the driver of the matching process. Matches are offered sequentially to families within the child's region. In each system, families are sorted according to criteria that correspond to PAE's operation with different levels of information. The highest-ranking family is selected and offered the child as a match. If a family accepts a match (i.e., its utility for the match is positive), both the family and child leave the system. Whether a family's utility is positive depends on the child's characteristics, the family's preferences, and a random term to represent the uncertainty of attraction. Because data are not available to estimate the randomness of this process, we tested two values of the variability of the error term, which we label as low attraction variability and high attraction variability. If the family rejects the match, the family remains in the system and another match—up to 10 total match attempts—is attempted for the child. For simplicity, we model the matching process as an instantaneous event; however, in practice, time elapses between sequential matching attempts. If no match is found for the child, the child leaves the system. Figure A3 in the *Matching Model and Simulation Details* section of the appendix shows a flowchart that represents this process.

We present three methods for ranking families to investigate the value of information. The three methods and their interpretations are as follows:

(1) Critical attribute (CA) represents a system in which caseworkers can search for families based on either the age or special needs attribute because of constraints on their search time and effort. We represent the matching process before our collaboration with PAE as following the CA policy.

(2) Unknown weight (UW) represents a simple version of a centralized matching system that is limited in its ability to properly incorporate family preference information. Age and special needs attributes are given equal weight in this model.

(3) Full information (FI) represents an improved version of PAE's centralized matching system with families sorted based on a known age preference, special needs preference, and preference weighting term.

Simulation Results

We first compare the simulated mean percentage of children matched over the five-year horizon based on the attraction variability and number of regions for CA, UW, and FI decision rules. The adoption rate increases with the amount of information about the families' preferences utilized in the match recommendation process (Figure 3); that is, CA exhibits a lower adoption

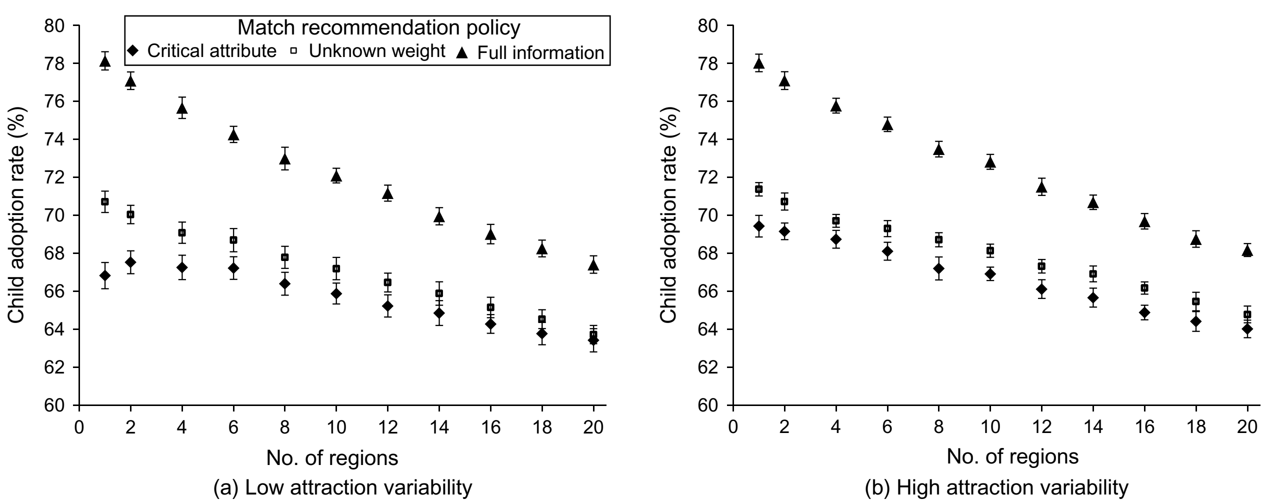

Figure 3: The child adoption rate increases with the quality of information available for matching and decreases with the number of regions (i.e., the segmentation of the network). Bands represent 95 percent confidence intervals.

rate than UW, which in turn has a rate lower than that of FI. The UW policy only slightly improves upon the CA policy with a maximum increase of 3.9 percentage points. However, the FI policy improves on the CA policy by between 4.0 and 11.3 percentage points in the child adoption rate. Whether the attraction variability is low or high appears to have minimal impact on the performance of the policies in terms of the overall adoption rate.

The mean adoption rate always either increases as the number of regions decreases or shows a statistically insignificant decrease. A completely centralized system (i.e., one region) results in an adoption rate that is between 3.4 and 10.7 percentage points higher—depending on the attraction variability and the recommendation rule—than the completely decentralized case with 20 regions. This validates the role of a statewide network. With a larger pool of families, a family that seeks the type of child being matched or can accommodate the child's special needs is more likely to exist.

In addition to an increase in the adoption rate for the UW and FI policies compared to the CA policy, the better use of information also corresponds to a decrease in the mean number of match attempts until a child is adopted successfully (Figure 4). We study this metric as a proxy for two important secondary measures of success for the adoption network: the workload for caseworkers and time in system for the child. Fewer attempts until success means less work for overburdened caseworkers and less time in county custody for a child. Depending on the number of regions, the UW and FI policies result in a decrease in the mean number of match attempts until success of between 32 and 41 percent when attraction variability is low and between 17 and 21 percent when attraction variability is high.

We further investigate the effect of the attraction variability, which represents the unpredictability of attraction between an individual family and a child. When the attraction variability is high, match success is inherently more difficult to predict, which results in an increase in the mean number of attempts per successful adoption of up to 0.81. Comparing the change in the mean adoption rate as the number of regions decreases, the difference between the low and high attraction-variability cases (in relation to the calibration point) is almost always less than one percent. This indicates that the underlying match unpredictability has relatively little impact on the mean adoption rate compared to the matching rule and number of regions. The only exceptions are for the CA policy with one or two regions when high attraction variability results in an adoption rate that is 1.0 to 2.0 percentage points higher

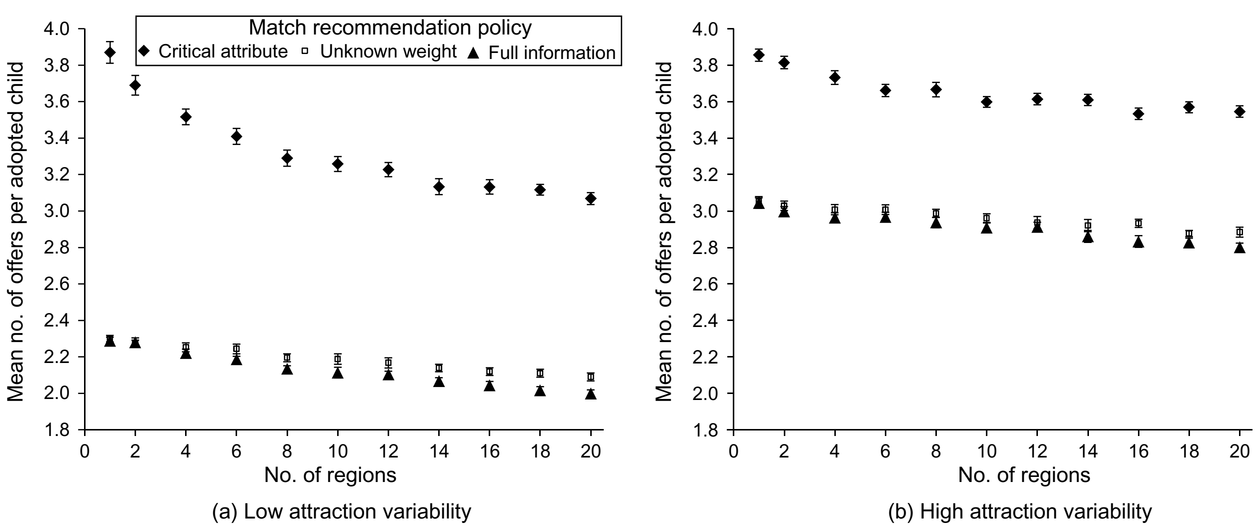

Figure 4: Improving the information available for matching reduces the average number of attempts before a successful adoption. Bands represent 95 percent confidence intervals.

than the adoption rate when the attraction variability is low. In these cases, the lower match-success predictive power of the CA policy for ranking families, the high attraction variability, and the small number of regions mean that families who are offered children later in the sequence of 10 offers are relatively more likely to be stronger candidates.

These results justify the value of a statewide adoption network and show that the quality of information about family preferences is critical to its success. Furthermore, we have shown that better information improves secondary metrics of system performance that can be interpreted as reducing caseworkers' workloads and time in the system for children. If the adoption network can double the size of its regions (i.e., from 10 to 20 regions), while improving how it elicits family preferences for matching (i.e., follow the FI policy), the number of successfully adopted children could increase by approximately 21 children per year. We discuss additional results and managerial insights related to improvements in match quality in the *Matching Model and Simulation Details* section of the appendix.

Process Improvements and Results

To achieve the potential improvement in the adoption rate demonstrated in the simulation, we worked with PAE to improve the information it collects and its family-ranking tool for matching. In this section, we discuss these changes, and the incentives that affect how participants reveal their preferences. A spreadsheet matching tool used by PAE coordinators provides the most tangible evidence of improvements based on our collaboration. Although using a computerized tool for matching is not unique to our project, we are the first to connect the quality of preference information to the overall network adoption rate and show that underlying incentives for how families reveal their preferences can diminish the usefulness of recommendations. We also suggest improvements to the family-ranking algorithm that are novel to the practice of matching in child adoptions.

Registration Information

Through our interviews with child caseworkers and discussions of the simulation results, PAE managers came to recognize new potential for gathering information during the registration process as a driver of the overall network adoption rate. Specifically, our research collaboration has led to the collection of additional information to use in making match recommendations. Although PAE managers believed revising the CY 130 and CY 131 forms to be an arduous process, especially because the forms had been revised recently, they are beginning to collect child and family information through an online survey format that includes a new set of questions. Their intuition about data that would be most valuable for predicting matches informed their selection of these new questions. In particular, these questions focus on the child's positive attributes, such as interests or hobbies, which might predict attraction between children and families. Other questions focus on family attributes that could be compared to child or child-caseworker preferences for families without certain pets or other children in certain age ranges. The questions have received approval from the state for use by PAE and are being implemented.

Furthermore, as a result of our project, PAE managers have begun tracking the results of match recommendations for future analysis. Although the set of information used for match recommendations is currently based on managerial intuition, we have encouraged PAE to maintain data about match attempts and their results to enable us to scientifically evaluate the effect that different questions have on predicting matches. Econometric analysis of child attributes, family preferences, and results of match attempts would allow PAE managers to better estimate the probability of success of a child-family match and assess which questions are more or less important in predicting a match.

Spreadsheet Matching Tool

After several design and feedback iterations, PAE coordinators have begun to use our matching-tool prototype to suggest families to county-level caseworkers. The matching-tool prototype has also allowed them to gain insights into the matching rules and to begin to think about what matching rules help produce the best matches for children. We have supported the addition of features, such as geographical preferences for families, to improve the tool's value to PAE managers.

Compared to the matching tools discussed in Hanna and McRoy (2011), we use the same underlying framework of linearly weighted questions to score a family's suitability for a child, and add three simple innovations.

First, the user can directly specify the weights for each attribute to help determine which attributes are most important for selecting a family for a child. PAE managers and coordinators observed that children are labeled by certain special needs (e.g., fire starter, animal abuser) when the underlying behavior that prompted the label was viewed as innocuous. They felt that having the ability to adjust matching tools weights based on knowledge of the severity of a child's special needs could produce better matches. This feature also allowed the easy changing of default weights for factors identified as important in the regression analysis. Second, the user can state geographical preferences for the family's county of residence, which can be important in assessing the feasibility of a match if continuing community or familial relationships is important for a child. Finally, as Hanna and McRoy (2011) discuss, social workers who assist families can use the tool to identify shortcomings in a family's capabilities to help a child and prepare appropriate support mechanisms. To this end, we have added score summaries by category so that users can more easily identify a family's strengths and challenges, and output reports for use by the matching committee that show how the child and family compare for each attribute.

Information Incentives

We also examined how families and child caseworkers interact with PAE to understand intentional or unintentional behavior patterns that may reduce the effectiveness of the matching process. Through conversations with PAE managers and preliminary runs of the matching system, we noticed that the system is vulnerable to strategic manipulation by families in completing their CY 131 forms. Because rejecting a child is very easy for a family—a telephone hotline is available to review details of and accept or reject an available child for which the family is recommended—families have an incentive to overstate their willingness to accept children with special needs. This allows a family to gain additional information and be considered for other children. Furthermore, this behavior does not necessarily result from conscious manipulation of the PAE system; different families may be inherently more or less strict in how they interpret the difference between responding "acceptable" or "will consider" to a specific special need. The current system gives families the incentive to err on the side of choosing "accept," which makes differentiating between families more difficult for PAE.

We recommended a process change and an algorithmic feature to overcome the challenge of families' overstating their tolerance for children with special needs. First, we recommended that matching should occur in small batches so that the PAE coordinators who use the matching tool can observe if families are chosen too frequently and further investigate the appropriateness of those families as recommended matches. PAE managers initially welcomed this suggestion, and decided that monthly matching meetings would work well with the adoption framework. They also augmented it based on their experiences with a rule that requires PAE coordinators to wait 30 days between successive recommendations of the same family. Second, the family-child match score was adjusted for three criteria—race, age, and gender—to reward families whose preferences more closely fit the child's attributes. For example, a family who indicates a preference for male or female receives a higher score on the gender attribute than a family who indicates a preference of either if the child is of the preferred gender.

Using a matchmaking experiment, we show that the rewarding of narrow preferences more effectively spreads the recommendations over the pool of families. For each active child, we calculated the top five matches (plus ties) from the list of active families using a scorecard with and without rewards for narrow preferences over age, race, and gender. Without rewards for narrow preferences, we noticed that only 7.7 percent of families received at least one match; however, we expect this number to increase in practice because of geographical preference filtering. With rewards for narrow preferences, the number of families who received at least one match increased by 41 percent. We proposed further rewarding narrow preferences based on the number of a child's special needs that the family states is acceptable, and on the acceptable number of all special needs or the 10 special needs identified as significant in the regression analysis.

Another difficulty that PAE managers emphasized is placement decision making by caseworkers representing children. SWAN managers and even caseworkers themselves indicate that some caseworkers struggle with emotional attachment to children to an extent that dispassionately making a placement decision that meets the child's best interests can be challenging. The emotional attachment of some caseworkers can cause them to hold out for the perfect family, when another family likely to be suitable for the child is available. PAE managers have found the spreadsheet matching tool to be valuable as a mechanism to enforce the conceptualization of tradeoffs. In conversations between caseworkers and PAE coordinators who use the matching tool, observing that no family is likely to be a perfect match can lead to discussions about the strengths and weaknesses of a family-child match.

Conclusions

In the collaboration described in this paper, we helped PAE improve the processes for recommending prospective families for children in county custody. We believe that these changes increase PAE's value to caseworkers in their efforts to find families, and will increase the percentage of children who find permanent placements. Furthermore, PAE has begun collecting additional data about the matching process to scientifically compare families' stated preferences to their actual decisions. This will enable future work that would analyze the matching weights and relative value of the registration questions. The challenge of making match recommendations in a two-sided matching market extends beyond the adoption of children in county custody, and insights from this paper may apply to matching for foster care placements.

Acknowledgments

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Appendix

Matching Tool Algorithm

Algorithm 1 (Design of existing algorithm for computing scores for each family for a given child)

Inputs:

(1) Attribute value c_k for each attribute $k = 1, 2, \ldots, K$ corresponding to Table 2 for a single child
(2) Preference value f_{jk} for each family $j = 1, 2, \ldots, F$ and each attribute $k = 1, 2, \ldots, K$
(3) Weight $w_k \geq 0$ for each attribute $k = 1, 2, \ldots, K$

Output: Set of family matching scores $\{y_1, y_2, \ldots, y_F\}$

for $j = 1$ **to** F **do**
  Points possible $x_j^{\text{TOT}} \leftarrow 0$
  Points earned $x_j \leftarrow 0$
  for $k = 1$ **to** K **do**
    if $c_k \notin$ {"not applicable," "unknown," "no"} **then**
      $x_j^{\text{TOT}} \leftarrow x_j^{\text{TOT}} + w_k$
      if $f_{jk} =$ "will consider" **then**
        $x_j \leftarrow x_j + w_k/2$
      else
        if f_{jk} is compatible with c_k (see Table 2) **then**
          $x_j \leftarrow x_j + w_k$.
        end if
      end if
    end if
  end for
  $y_j \leftarrow x_j / x_j^{\text{TOT}}$
end for
return $\{y_1, y_2, \ldots, y_F\}$.

Matching Tool Spreadsheet

To illustrate the match scoring rule used in the matching tool, we provide an example that corresponds to Figures A1 and A2. Based on the child's presenting needs, 425 points are possible for any family matched to the child, including 100 for age, 100 for race, 100 for gender, 60 for special needs, and 65 for characteristics. The family receives 100 points because the child is within the family's stated minimum and maximum ages, 100 points because the family's preference for a white child matches the child's race, and 100 points because the family stated that either gender was acceptable. The family receives 40 out of 60 possible points for the child's special needs, losing points because the family is not approved to adopt a child with "drug-exposed infant" and "abuse-history" designations. For child characteristics, the family is allotted 44 of 65 possible points for a total of 384 out of 425 possible points that translates to a score of 90.35 percent.

Matching Model and Simulation Details

Children are defined by a type $c = \{a, s, r\}$, which reflects that child's desirability on two attributes—age $a \in [0, 19]$ years and number of significantly negative special needs $s \in \{0, \ldots, 10\}$—and a residence region $r \in \{1, \ldots, R\}$, where R is the total number of regions.

Families are defined by their type $f = \{a_{\text{MIN}}, a_{\text{MAX}}, s', r, \alpha\}$, which represents their range of acceptable ages $[a_{\text{MIN}}, a_{\text{MAX}}]$ with $a_{\text{MIN}}, a_{\text{MAX}} \in \{0, \ldots, 19\}$ and $a_{\text{MIN}} < a_{\text{MAX}}$, their tolerance for a child's special needs $s' \in \{0, \ldots, 10\}$, a weight $\alpha \in [0, 1]$ to express the relative importance of age and special needs, and a region attribute $r \in \{1, \ldots, R\}$. We also define a utility function to indicate whether a family will accept an offered child. A child age component and a child special needs component comprise the utility function, and their relative weight is dictated by the weighting term

Match scoring tool for ranking families

				Points Earned	Points Possible
Child ID	(Fictitious)				
Family ID	(Fictitious)				
				384	425
Score	90.35%				
Weight		Child info	Family pref	Points	Pts possible
	Demographic information				
100	Age	13		100	100
	Low age		10		
	High age		14		
100	Race/Ethnicity				
	African American	NA	Not preferred	0	0
	Hispanic	NA	Not preferred	0	0
	White	Applicable	Preferred	100	100
	American Indian/Alaskan native	NA	Not preferred	0	0
	Asian	NA	Not preferred	0	0
	Native Hawaiian/Other Pacific Islander	NA	Not preferred	0	0
100	Child gender	Female	Either	100	100
	Special needs information				
10	Drug exposed infant	Applicable	Not approved	0	10
10	Emotional disability	Applicable	Approved	10	10
100	HIV	NA	Not approved	0	0
10	MH diagnosis	NA	Approved	0	0
100	MR diagnosis	NA	Not approved	0	0
10	Multiple placement history	Applicable	Approved	10	10
100	Physical disability	NA	Approved	0	0
10	Runaway history	NA	Approved	0	0
100	Sexual abuse history	NA	Approved	0	0
100	Siblings	NA	Approved	0	0
10	Special education student	Applicable	Approved	10	10
100	Special medical care	NA	Approved	0	0
10	Abuse history	Applicable	Not approved	0	10
10	Neglect history	Applicable	Approved	10	10

Figure A1: PAE regional coordinators use a spreadsheet with customizable attribute weights that computes scores for all families for a given child. (NA refers to an attribute that is not applicable for a child.)

α. With only limited information about family preferences, we use a uniform distribution for the weighting term, as justified for preference modeling with limited information by Kennan (2006).

We define a family's utility for a match with a child of type c as

$$u(c;f) := \alpha(u^{\mathrm{AGE}}(a, a_{\mathrm{MAX}})) + (1-\alpha)(u^{\mathrm{SN}}(s, s')) + \epsilon, \qquad \text{(A1)}$$

where ϵ is an error term that represents the randomness of a child's attractiveness to a family. We let ϵ be an independent random variable that follows a normal distribution with mean μ and standard deviation σ. The term σ represents families' variability in their attractiveness for individual children. Without data to connect families' stated preferences to their acceptance decisions, we consider cases of $\sigma = 0.1$ and $\sigma = 0.2$; we refer to these cases as low attraction variability and high attraction variability, respectively. Given σ, μ then becomes a tuning parameter for the simulation. The value of ϵ is only revealed when a match is attempted between a family and a child.

Lacking data to directly estimate families' preferences, we instead rely on the analysis of factors related to child outcomes from the previous section to create a model for family preferences. Specifically, we use the resulting coefficients from a linear regression model based on the child's managerially weighted outcome as a response variable and factors of age (linear), age (quadratic), and the number of significant negative special needs. The resulting model is

$$\mathit{Outcome}(c) = 0.8356 + 0.0426a - 0.0045a^2 - 0.0476s, \qquad \text{(A2)}$$

for which the intercept and all three coefficients are significant at a 99.9 percent confidence level. We use these coefficients from this model to estimate the age and special needs components of the utility function. Given a child's age a and a family's preferred minimum age a_{MIN} and maximum

Weight	CHILD CHARACTERISTICS	Child info	Family pref	Points	Pts possible
	1. Does child have significant health issues?	No	Acceptable		
1	2. Does child have allergies or asthma? (may require treatment)	Yes	Acceptable	1	1
10	3. Is child hyperactive? (may require treatment)	Yes	Acceptable	10	10
1	4. Does child have speech problems? (may require treatment)	No	Acceptable		
1	5. Does child have hearing problems? (may require treatment)	No	Acceptable		
1	6. Is child legally deaf?	No	Will consider		
1	7. Does child have vision problems? (may require treatment)	No	Will consider		
10	8. Is child legally blind?	No	Unacceptable		
1	9. Does child have dental problems? (may require treatment)	No	Acceptable		
1	10. Does child have orthopedic problems (special shoes, braces, etc)	No	Acceptable		
10	11. Does child have seizures?	No	Will consider		
1	13. Is child a high achiever in school?	No	Acceptable		
1	14. Does child achieve at grade level in regular classes?	Yes	Acceptable	1	1
1	15. Does child achieve below grade level in regular classes?	No	Acceptable		
1	16. Is child in special education classes?	No	Acceptable		
1	17. Does child have a learning disability?	No	Acceptable		
1	18. Does child need classes for the emotionally or behaviorally handicapped?	Yes	Acceptable	1	1
1	19. Does child need tutoring in one or more subjects?	No	Acceptable		
10	20. Does child have serious behavior problems in school?	Yes	Will consider	5	10
1	21. Is child generally quiet and shy?	No	Acceptable		
1	22. Is child generally outgoing and noisy?	Yes	Acceptable	1	1
1	23. Does child have emotional issues that requires therapy?	Yes	Acceptable	1	1
1	24. Does child tend to reject father figures?	No	Will consider		
1	25. Does child tend to reject mother figures?	No	Will consider		
1	26. Does child have difficulty relating to others and relating to other children?	Yes	Acceptable	1	1
1	27. Does child frequently wet the bed?	No	Acceptable		
1	28. Does child frequently soil him/herself?	No	Will consider		
100	29. Does child masturbate frequently or openly?	No	Unacceptable		
1	30. Does child have poor social skills?	Yes	Acceptable	1	1
10	31. Does child have problem with lying?	Yes	Will consider	5	10
10	32. Does child have problem with stealing?	No	Will consider		
10	33. Does child frequently start physical fights with other children?	Yes	Will consider	5	10
100	34. Does child abuse animals?	No	Unacceptable		
10	35. Is child destructive with clothing, toys, etc.?	Yes	Will consider	5	10
10	36. Does child use foul or bad language?	No	Acceptable		
1	37. Does child have frequent temper tantrums?	Yes	Acceptable	1	1
1	38. Does child have difficulty accepting and obeying rules?	Yes	Acceptable	1	1
100	39. Does child exhibit inappropriate sexual behavior?	No	Will consider		
100	40. Does child have a history of running away?	No	Will consider		
100	41. Does child have history of playing with matches, setting fires?	No	Unacceptable		
1	42. Does child have strong ties to birth family?	Yes	Acceptable	1	1
1	43. Does child have strong ties to foster family?	No	Acceptable		
1	44. Is continued contact with siblings desirable?	No	Acceptable		
1	45.Does child have a previous adoption disruption?	No	Acceptable		
1	46. Was child sexually abused?	No	Will consider		
1	48. Was child exposed to promiscuous sexual behavior?	No	Will consider		
1	49. Was child conceived by rape?	No	Will consider		
1	50. Was child conceived as a result of prostitution?	No	Unacceptable		
1	51. Are one or both parents addicted to alcohol?	Yes	Will consider	0.5	1
1	52. Are one or both parents dependent on substances other than alcohol?	Yes	Acceptable	1	1
1	53. Do one or both parents have a criminal record?	Yes	Acceptable	1	1
1	54. Are one or both parents mentally retarded?	No	Unacceptable		
1	55. Do one or both parents have a mental illness?	Yes	Will consider	0.5	1
1	56. Does agency lack information about one or both parents?	No	Acceptable		
1	57. Is child in contact with birth parents?	Yes	Acceptable	1	1
	58. Is child in contact with siblings?	No			
	59. Is child in contact with extended birth family?	No			
	60. Is child in contact with former foster family?	No			

Figure A2: The spreadsheet tool also includes a section for "Child Characteristics" information.

age a_{MAX}, we define the age component of a family's utility for a child as

$$u^{\text{AGE}}(a, a_{\text{MIN}}, a_{\text{MAX}}) := \begin{cases} 0.0426(a - a_{\text{MAX}}) - 0.0045(a^2 - a_{\text{MAX}}^2) & \text{if } a \geq a_{\text{MIN}}, \\ 0 & \text{if } a < a_{\text{MIN}}, \end{cases}$$

which represents the difference in the effect of age upon outcome between the child's age upon registration and the family's maximum preferred age. For a family that prefers a child between zero and 12 years old, the age component of the utility function is 0.235 for a child of age 4, 0.190 for age 8, and 0 for age 12. For older children, the value is −0.149 for a child of age 14, −0.334 for age 16, and −0.554

for age 18. We note that, because of the quadratic term, the utility component is not strictly decreasing in age for very young children, but we ignore this effect only for simulation purposes because children younger than three represent only about six percent of the population. In general, these children are not difficult to place and are not the focus of PAE. Similarly, the special needs component of the family's utility for a child is defined as

$$u^{\mathrm{SN}}(s, s') := -0.0476(s - s'),$$

which represents the difference in the effect of the number of significant negative special needs and the family's number of corresponding acceptable special needs.

With this model, we can more precisely define the three family ranking methods:

(1) Critical attribute (CA): If $0.0426a - 0.0045a^2 < -0.0476s$, then families are sorted according to $u^{\mathrm{AGE}}(a, a_{\mathrm{MIN}}, a_{\mathrm{MAX}})$. Otherwise, families are sorted according to $u^{\mathrm{SN}}(s, s')$.

(2) Unknown weight (UW): Families are sorted according to their nominal utilities, which disregards the error term, for the child with the two attributes equally weighted (i.e., $\alpha = 0.5$) to represent α unknown.

(3) Full information (FI): Family types are known to the matchmaker, which given a child of type c can rank the families according to their nominal utility $\alpha(u^{\mathrm{AGE}}(a, a_{\mathrm{MAX}})) + (1 - \alpha)(u^{\mathrm{SN}}(s, s'))$.

The simulation is initialized by starting with a pool of 1,000 randomly generated families. The replication length is five years and is preceded by a one-year warm-up period. The family attraction variability tuning parameter is set to $\mu = -0.1875$ for low attraction variability $\sigma = 0.1$ and $\mu = -0.315$ for high attraction variability $\sigma = 0.2$, which corresponds to a 64 percent success rate for the critical attribute rule and matches the expected quality-adjusted outcome value for children in the PAE system between 2005 and 2013. We calibrated the simulation using the CA decision rule to represent the process by which county caseworkers manually searched through families' records focusing on their suitability for a small subset of child attributes, which most accurately describes PAE's functioning before changes were implemented as part of our collaboration. For each scenario—defined by a matching policy and number of regions—we used 25 replications so that we are 95 percent confident that the resulting mean match rate is within one percent of the true mean match rate. We implemented the simulation in Java and relied upon the Java simulation library described in Rossetti (2008) for simulation functions.

Results Related to Match Quality

We additionally consider metrics that provide insights into the quality of matches for children and families. Specifically, we record the percentage of families who adopt a child with

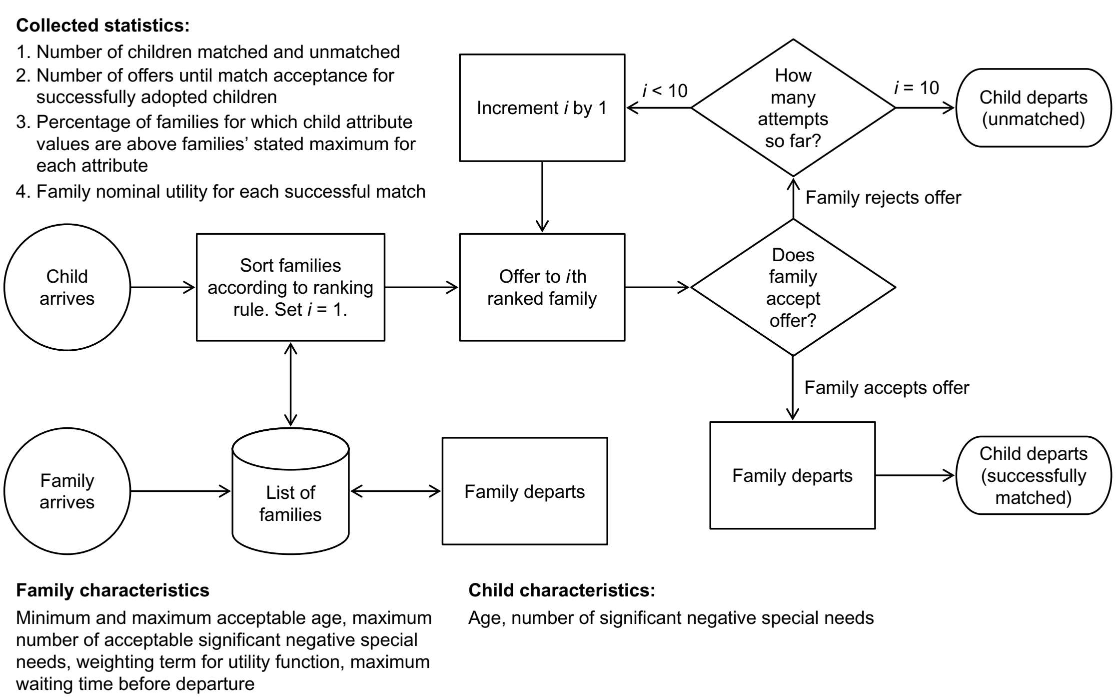

Figure A3: When a child becomes available, we rank prospective families and sequentially make up to 10 match attempts. A child is successfully adopted if at least one family accepts the child. Otherwise, the child is not adopted.

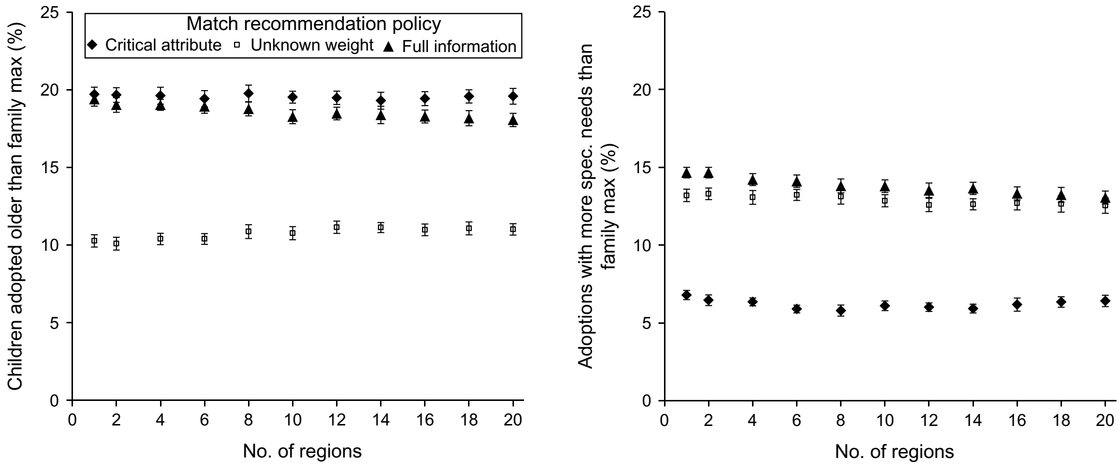

Figure A4: Families' preferences are violated more frequently in adoptions for the critical attribute and full information policies than the unknown weight policy for a system with low attraction variability. Bands represent 95 percent confidence intervals.

attribute values larger than the family's stated maximums (Figure A4). We use these metrics to represent the quality of matches for children, especially in terms of the special needs attribute, because a higher stated tolerance for special needs represents the increased ability of a family to accommodate a child's needs. We also record the average nominal family utility for adoptions, which we use to represent the quality of matches from the perspective of families (Figure A5).

We first examine the UW policy, which assumes that families give equal weight to the age and special needs components of the utility function, and the case of low attraction variability. Under the UW policy, the percentage of families who adopt children with attributes above stated maximums is between 10.1 and 11.1 percent for the age attribute and between 12.5 and 13.3 percent for the special needs attribute, depending on the number of regions and attraction variability. Compared to the UW policy, the CA policy results in matches for which more families adopt children higher than their stated maximums more frequently for the age attribute (19.3–19.8 percent) and less frequently for the special needs attribute (5.8–6.8 percent). Given that the penalty for exceeding a child's age in a utility function is relatively low for children who are younger than teenagers, the difference between the UW and CA policies can be

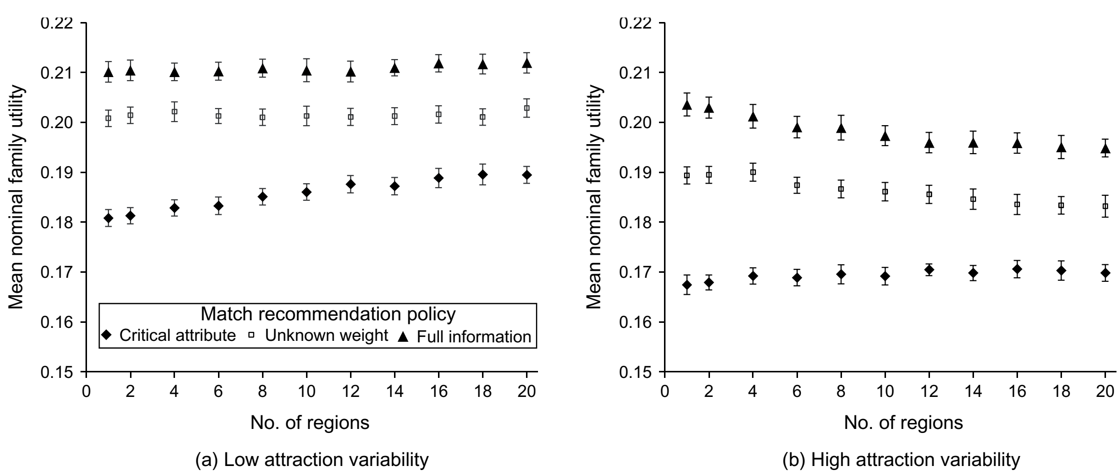

Figure A5: The mean family nominal utility of successful matches increases with the quality of matching information. Bands represent 95 percent confidence intervals.

explained by the practice of the CA policy to ignore the age attribute entirely if it is nominally less important than the special needs attribute.

For the FI policy, the percentage of families who adopt children with attribute values greater than their stated maximums is between 18.0 and 19.4 percent for age, which is almost as high as the CA policy. For the special needs attribute, it is between 13.1 and 14.7 percent, which is higher than the UW policy. This helps to explain the success of the FI policy with respect to the mean adoption rate; it uses knowledge of the weighting term α to violate families' preferences when they are relatively insignificant to propose plausible matches that have a greater chance of success. This explanation is supported by Figure A5, which shows that the mean family utility increases from CA to UW and from UW to FI. We omit a corresponding chart for high attraction variability that shows a similar relationship between the three policies, although in all cases the percentage of families who adopt children with attribute values higher than their stated maximums is higher because of increased attraction variability.

The managerial insight regarding match quality is that improving the matching rate corresponds to more matches that violate families' stated age and special needs preferences when either of those preferences may be relatively less important to families. This highlights the importance of better understanding families' preferences as expressed through registration data and actual match rejection decisions. For example, allowing families to state a preference of "willing to accept training" for individual child special needs questions in registration data could allow PAE to better estimate how families weight questions. Similarly, PAE should expect to offer training more frequently to families on how to handle the special needs of specific children to maintain match quality for children.

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Verification Letter

Jane Johnston, Pennsylvania Adoption Exchange Division Manager, P.O. Box 4469, 471 JPLwick Drive, Harrisburg, PA 17111, writes:

"The purpose of this letter is to summarize the efforts in the partnership between Carnegie Mellon University (CMU) and Pennsylvania Adoption Exchange (PAE). The role of PAE is to find permanent families for children in Pennsylvania's child welfare system. Typically these children are older and have significant emotional or physical needs. Matching these children to waiting families is a challenge. Since 2010 PAE has partnered with CMU's Tepper School of Business to look at innovative methods to match children to families. The research team for this project, Dr. Mustafa Akan, Dr. Onur Kesten, Dr. Utku Unver (Boston College), and Vincent Slaugh, PhD Candidate, have all been instrumental in expanding our view of how to approach matching.

"Utilizing the economic theory of two-sided matching markets we began to develop a new approach to matching children and families. This process took a multiple layered approach implementing the work in phases. A first phase was exposing state officials to this concept and securing approval for thinking about an old process in a new way. We looked at the similarities related to matching children to schools in school choice, medical students to medical schools, specialty labor markets and liver transplant waiting list. CMU developed an algorithm in an Excel format for matching children to families in the first phase of this process has been implemented in test cases. This algorithm will be fully implemented when family data is cleaned and up to date.

"Some of the discriminating work done by CMU included recognizing and evaluating the behaviors of families and case workers in the matching process. They were instrumental in the development and evaluation of surveys completed with both groups. This analysis resulted in recommendations for new and more effective questions to be utilized in the matching process.

"On a routine basis we worked closely with Vincent Slaugh in the development and execution of a customized matching tool that incorporated a complex algorithm that was utilized by Pennsylvania's matching specialists. These staff commented that although the tool developed in Excel was quite complex in consideration of the various aspects of what families want and characteristics children possess it was quite simple to execute.

"The level of expertise supplied by CMU's Tepper School of Business was instrumental in moving the matching efforts of the state to a new level of thinking about how to approach this problem. We are currently reviewing the questions being asked of families and looking to expand the questions that are asked to do matching more effectively. Although we have not fully implemented recommendations provided we are continuing to work to full implementation.

"Our organization has benefited greatly from this private public partnership. More importantly the waiting children of Pennsylvania have gained as a result of this partnership. It is very clear to me and those with whom I work that this change in focus and direction would not have occurred without the efforts of this research team."

Vincent W. Slaugh is a visiting assistant professor of supply chain management at the Smeal College of Business, Penn State University. He received his PhD in operations management from the Tepper School of Business, Carnegie Mellon University, in 2015. He has been a finalist for the INFORMS Doing Good with Good O.R. and Service Science Section student paper competitions. Besides child welfare operations, his research interests include stochastic inventory theory and capacity planning with applications to rental businesses and healthcare staffing.

Mustafa Akan is an associate professor of operations management at the Tepper School of Business, Carnegie Mellon University. His thesis received the Best Dissertation Award of the Aviation Applications Section of INFORMS in 2008. He held the Xerox Faculty Chair in 2009 and served as the Operations Management and Manufacturing PhD program coordinator in 2009–2011. He is the co-recipient of the 2009 INFORMS Best Paper in Service Science, POMS 2012 Healthcare Best Paper awards, and the 2013 Lave-Weil Prize. Dr. Akan won the Gerald L. Thompson Teaching Award in 2014 at Carnegie Mellon University. He received the NSF CAREER Award in 2014. His research interests include pricing and revenue management, mechanism design, liver allocation, matching markets, stochastic modeling, queueing theory, manufacturing and service operations management, and healthcare delivery systems.

Onur Kesten is an associate professor of economics at the Tepper School of Business, Carnegie Mellon University. He received his PhD in economics in 2005 from the University of Rochester and completed his post-doctorate in 2006 at Harvard University. He held the BP Junior Faculty Chair, Faculty Giving Chairs and won Richard Cyert Teaching award as well as the Lave-Weil prize. His research focuses on market design and resource allocation problems with a focus on indivisible goods allocation. He has studied high school and college admissions systems in the United States, China, Turkey, and Saudi Arabia.

M. Utku Ünver is a professor of economics at Boston College. He received his PhD in economics in 2000 from the University of Pittsburgh. He has been a faculty member at Koç University, Istanbul and University of Pittsburgh prior to joining Boston College in 2008. His main research area is theory and practice of market design for allocation, exchange, and matching of indivisible resources. He co-initiated the first live donor paired kidney donations programs that use the principles of mechanism design and optimization, for which he became a Laureate for the Edelman Prize in 2014. He is an elected fellow of the Science Academy in Turkey.