**Online Appendix: *Stopping the Revolving Door***

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## Appendix A: Resource Type Classifier Performance Analysis and Results

Table A1 reports the performance of each classifier. As the need statements are fairly structured with homogeneous writing styles, all three methods have respectable performance, with precision above 80% and recall ranges between 70% and 92%. Among these classifiers, the text regression method has the highest out-of-sample classification accuracy (94% average across categories) with higher precision (96%) and substantially higher recall (92%) than the naïve Bayes and support vector machine classifiers. We therefore use it as our main method of project resource classification.

**Table A1 Resource Type Classification: Comparison of Methods**

| *Resource Category* | Classification Methods | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Naïve Bayes | | | (2) Support Vector Machine | | | (3) Text Regression | | |
| | Precision | Recall | F1-Score | Precision | Recall | F1-Score | Precision | Recall | F1-Score |
| Basic Supplies | 0.82 | 0.89 | 0.86 | 0.86 | 0.94 | 0.90 | 0.93 | 0.96 | 0.94 |
| Classroom Environment | 0.82 | 0.78 | 0.80 | 0.88 | 0.85 | 0.86 | 0.92 | 0.91 | 0.92 |
| Technology | 0.85 | 0.83 | 0.84 | 0.93 | 0.85 | 0.89 | 0.96 | 0.93 | 0.95 |
| Student Experiences | 0.94 | 0.47 | 0.62 | 0.99 | 0.71 | 0.82 | 0.99 | 0.90 | 0.95 |
| Equipment | 0.75 | 0.51 | 0.61 | 0.91 | 0.66 | 0.77 | 0.97 | 0.88 | 0.92 |
| Average | 0.84 | 0.70 | 0.75 | 0.91 | 0.80 | 0.85 | 0.96 | 0.92 | 0.93 |
| Accuracy | | 0.83 | | | 0.88 | | | 0.94 | |

*Notes.* Tagged text sample: 22,920 need statements. Training sample: Statement 1–11,460. Test sample: Statement 11,461–22,920. For each category, precision=true positive (TP)/(TP+false positive (FP)). Recall=TP/(TP+false negative (FN)). F1-Score: Balanced F-score similar to a weighted average of precision and recall. Accuracy=percent of statements classified exactly correctly.

Following Jegadeesh and Wu (2013), for each resource category, we fit a logistic regression of need statements' binary category labels on their word frequencies, using the full sample of 22,920 labelled statements:

$$\text{Category}_i^c = \alpha + \sum_{j=1}^{V} w_j^c F_{i,j} \frac{1}{a_i} + \epsilon_i, \tag{8}$$

where $\text{Category}_i^c$ equals one if the need statement $i$ is tagged as the category $c \in \{\text{supplies, classroom environment}, \dots\}$. We fit five independent regressions as the model assumes independence between labels. Assuming $V$ unique words are used in all need statements, $F_{i,j}$ is the number of times that a word ($j = 1, \dots, V$) is used in statement $i$ and $a_i$ is the total word count of statement $i$. We fit the regression for each category and obtain five sets of word-weight estimates $\hat{w}_j^c$. Then, for each untagged needs statement, we plug in its respective word counts and obtain a predicted likelihood of the statement belonging to each of the resource categories. The category with the highest predicted likelihood is our model-assigned resource type. The final resource classification results are shown in Table A2.

**Table A2 Resource Type Distribution**

| | All Years | | 13/14 to 18/19 | | Project Cost\|Funded |
|---|---|---|---|---|---|
| *Type* | *Freq.* | *Percent* | *Freq.* | *Percent* | *Mean (SD)* |
| Basic Supplies | 30,604 | 51.44 | 10,792 | 50.19 | \$389 (\$195) |
| Classroom Environment | 9,259 | 15.56 | 4,455 | 20.72 | \$454 (\$198) |
| Technology | 15,918 | 26.75 | 4,807 | 22.36 | \$463 (\$221) |
| Student Experiences | 817 | 1.37 | 401 | 1.86 | \$541 (\$230) |
| Equipment | 2,898 | 4.87 | 1,047 | 4.87 | \$446 (\$229) |
| TOTAL | 59,496 | 100.00 | 21,502 | 100 | \$419 (\$207) |

## Appendix B: Illustration of Project Essay Uniqueness Model

This section illustrates our methodology to process the project essays and construct their pairwise similarity measures. Suppose that the entire vocabulary used by the corpus of all project essays consists of eight words: $W = \{w_1, \ldots w_8.\}$ The key intuition of the model—and the key assumption allowing for the quantification of texts into numerical vectors—is that conceptually similar words are conditionally more likely to appear together. For instance, suppose in the above vocabulary $w_1 =$ *"whiteboard"*, $w_4 =$ *"tree"*, $w_5 =$ *"classroom"*. Then intuitively, one would think of the word "whiteboard" as being more closely related to "classroom" than to "tree". Therefore, "whiteboard" is semantically closer to "classroom" in at least one dimension.

Our text processing model executes this exact idea algorithmically and at scale, *embedding* all essay vocabulary words into a multidimensional vector space, with each dimension measuring some aspect of the overall semantic meaning. Words (and essays) with similar semantic meanings would thus have a smaller distance between them in this vector space. In the two-dimensional example, the first three words (highlighted in blue) have similar embeddings, and the same is true for the middle two (green) and the last three (red) words. Each project essay, being a combination of the vocabulary words, can similarly be embedded in the space based on the choice and sequencing of words. In the example, essays 1 and 2 use the first five words more frequently and thus are semantically similar to each other as measured by the smaller cosine angle between their embeddings. The third essay, by contrast, uses the last three words more frequently (or uses the first five words in different sequences), and is thus semantically more unique from the other two essays, as measured by its larger average cosine distance from these essays.

## Appendix C: Example of the Document Preprocessing and One-Hot Encoding

Before fitting the neural network model, the textual features of the documents are first converted into a compatible format in a process called one-hot encoding. To illustrate the specific steps, consider a corpus consisting of a single statement {*"our classroom needs pencils."*} and a prediction window of one word. Ignoring the first word (*"our"*), the model is set up to predict which word would occur (i.e. *"classroom"*, *"needs"*, and *"pencils"*, respectively) given the word before and the word after it ([*"our"*, *"needs"*], [*"classroom"*, *"pencils"*], and [*"needs"*, ∅], respectively). The task is depicted in Panel A of Table C1, structured as a prediction framework with 3 observations, where the context words serve as the "x-variables" and the target words serve as the "y-variable."

We then convert this text-based task into a numerical prediction framework using the process of *one-hot encoding*, which simply casts each observation as a size-$V$ binary vector with $V$ as the number of unique

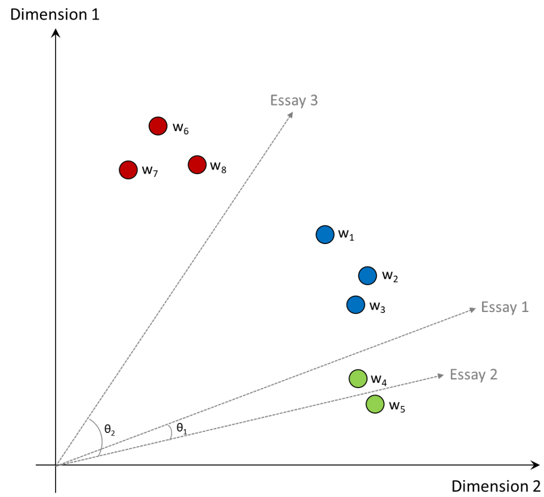


**Figure B1 Illustration of Vector-Based Text Similarity**

**Table C1 Illustration of Training Text Processing**

Training corpus={*"our classroom needs pencils"*}

Panel A. Text processing illustration

| Obs. | Context Words (*"X Variables"*) | Target Word (*"Y Variable"*) | Annotated Example |
|---|---|---|---|
| 1 | (our, needs) | classroom | our classroom needs pencils |
| 2 | (classroom, pencils) | needs | our classroom needs pencils |
| 3 | (needs, ∅) | pencils | our classroom needs pencils |

Panel B. One-hot encoding into vectors

| | v1=our | v2=classroom | v3=needs | v4=pencils |
|---|---|---|---|---|
| our | 1 | 0 | 0 | 0 |
| classroom | 0 | 1 | 0 | 0 |
| needs | 0 | 0 | 1 | 0 |
| pencils | 0 | 0 | 0 | 1 |

Panel C. Training task in vectorized form

| Obs. | Context Vectors (*"X Variables"*) | Context Vectors (*Consolidated*) | Target Vector (*"Y Variable"*) |
|---|---|---|---|
| 1 | ([1,0,0,0],[0,0,1,0]) | [0.5,0,0.5,0] | [0,1,0,0] |
| 2 | ([0,1,0,0],[0,0,0,1]) | [0,0.5,0,0.5] | [0,0,1,0] |
| 3 | ([0,0,1,0],[0,0,0,0]) | [0,0,1,0] | [0,0,0,1] |

words in the vocabulary. The binary vector are "one-hot" as they have a value of 1 for the word that appears in the observation and 0 for all other words. In our example (Panel B), since there are 4 unique words, each observation can be cast as a collection of vectors with 4 binary entries. Since we use a prediction window of 1, each observation has two "x-variables" corresponding to the words before and after the target word. In order to use the neural network, we consolidate them into a single predictor by taking the average of each entry. The resulting consolidated context and target vectors, depicted in Panel C of Table C1, form the main input to the neural network.

## Appendix D: Detailed Description of the Neural Network Model

To illustrate the neural network and the estimation procedure, we consider an example of a three-observation task with $V = 4$ words and estimate the embeddings with a simplified network of $N = 2$ hidden neurons.

As depicted in Figure D1, the network proceeds in an iterative fashion from the (1) input layer, where the "x-variables" are loaded in, to the (2) hidden layer, where the x-variables are related to the hidden neurons using a linear weighting function, then to the (3) output layer, where the hidden neurons are related to the output neurons again in a linear weighting function. The output neurons can then be compared with the actual target words in the data ("y-variables"), and prediction errors computed and minimized by tuning the weights in a fashion conceptually similar to the least-squares regression. In our Table C1 example, the input data have a dimension of $V = 4$ and each of the 3 observations thus has 4 entries (e.g. $x = [0.5, 0, 0.5, 0]$ and $y = [0, 1, 0, 0]$ for the first observation). Consequently, there are four input neurons (denoted as $x_1$ to $x_4$) receiving the values of these entries.

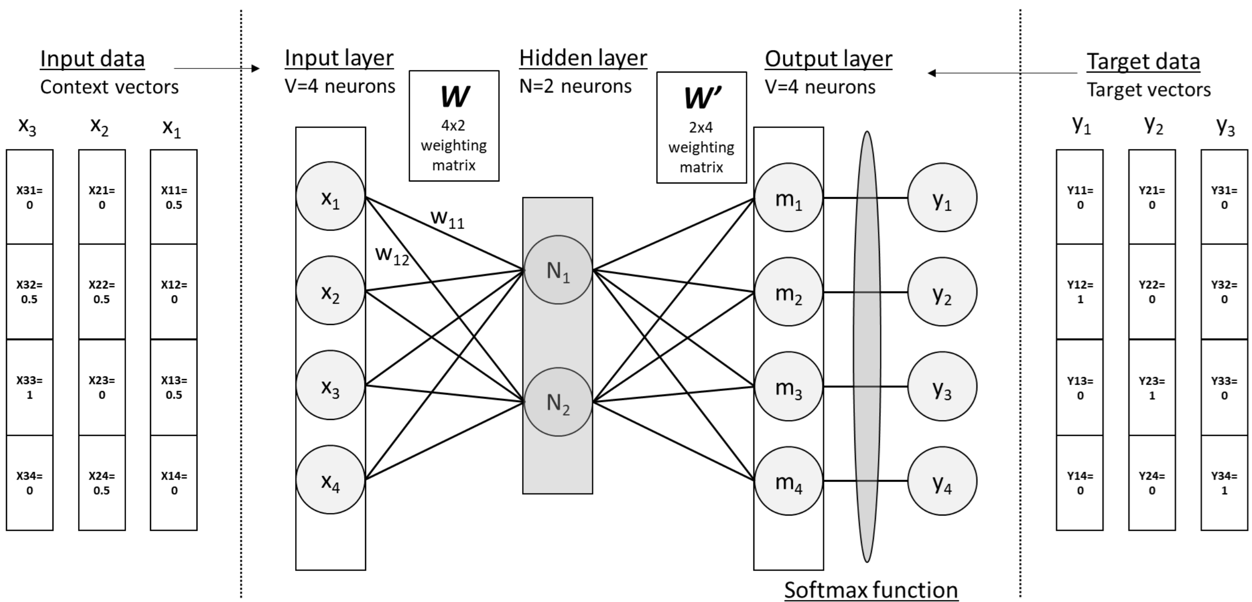


**Figure D1 Illustration of Word Embedding Model**

Once received, the input values are related to the two hidden neurons with a linear weighting function, that is, $N_j = \sum_{k=1}^{4} w_{kj} x_k$ for $j = 1, 2$ and $k = 1, \ldots, 4$. The weights, therefore, form a weighting matrix of size $V \times N$, denoted as $\mathbf{W}$. This weighting matrix, once estimated, are thus the $N$-dimension embeddings of each of the V words in the essay vocabulary. Similarly, the hidden neurons are further related to the output neurons with an $N \times V$ linear weighting matrix, denoted as $\mathbf{W}'$. Finally, the output neurons ($m_1$ to $m_4$) are transformed into the final prediction outputs ($y_1$ to $y_4$) with a softmax function in the form of $y_k = \frac{e^{m_k}}{\sum_{j=1}^{V} e^{m_j}}$.

The model is estimated in a two-pass procedure similar to other statistical estimators. As the first observation is loaded in, the model is initialized with random weights and the output $\hat{y}$ computed—a step referred to as *forward propagation*. This predicted value is then compared with the actual target value $y$ and their difference is encapsulated in an error function of the log form (also referred to as the *loss function*). The loss function is then minimized by updating the weights in $\mathbf{W}$ and $\mathbf{W}'$ using the standard gradient descent method (the *back propagation* step). This process repeats with each new observation until all training data is used (an *epoch*). The model is typically trained with multiple epochs to increase accuracy. In our example with 2 hidden neurons, the procedure estimates the $4\times2$ weighting matrix and thus produces a 2-dimensional embedding for each of the 4 words in the vocabulary. The *doc2vec* algorithm follows this procedure with the addition of another set of inputs corresponding to the document identifier (teacher-school-year in our setting), resulting in statement-level embeddings in the same 2-dimensional space, similar to the arrows depicted in Figure B1.

## Appendix E: Examples of More vs Less Unique Project Essays

**Table E1 More Unique Project Essays**

| |
|---|
| **Example 1:** "When we put on shows, students don't just play or sing. They...stage manage, run lights and sound, usher, participate in the chorus, run concessions, and narrate (in English and Spanish, of course). This year's show is called Barrio Grrrl! The items we've requested are a little diverse (OK, they're all over the place,) but they're exactly what we need to make our All-School Show shine! In our All-School Show, our students do everything. So, our needs are all over the place...The p-bones will be used by multiple students (up to 5 in a day!) who will comprise our newly formed Low Brass Section. (We teach trumpets to every student in the 5th grade, but it gets a little lopsided by 6th grade if you have no bass.) The combination locks - the most boring and utilitarian part of this project - will ensure that we can leave things in the stage area after practice and they will be there when we return. Finally, what good is a great sounding show if you can't see it? This project will allow our All-School Show to be seen, heard, and appreciated..." |
| **Example 2:** "When the going gets tough, attitude helps my students achieve! We live in a very rural area...without opportunities to go on field trips, I feel like my kids aren't getting a great view of the outside world! We happily soldier on, learning about the transcontinental railroad, the rise of big business and labor, and America's involvement on the world stage. Having just had a training on Google Expeditions, I would be excited to share some virtual field trips with my kids! ...Google's free app would expand our horizons beyond our walls and we could even work on creating trips of our own! These VR viewers will make it possible to show students almost a thousand virtual field trips. Beyond the sights of the trip, many are built out with points of interest, audio clips, and questions to build understanding. Even better, colleges and career paths are starting to feature virtual expeditions to show students around campus life or career technologies! My students will also focus on building their own trips, working with multiple levels of curriculum to design, photograph, annotate, and record trips of their own. These kinds of lessons not only take students around the world virtually, but expand their sense of ownership over an exciting project!" |
| **Example 3:** "Be the Change You Want to See in the World! A typical day in my classroom is not only spent on academics, but spent on building relationships and taking risks...When I envision teaching in a...I always see parts of my day where the whole class meets on a carpet as a whole. Unfortunately, the...classrooms are not equipped with carpets. I start each day with a classroom greeting/meeting where we set a positive tone for the day. If I had a carpet, the students could all come to the carpet to sit for this meeting. I also hold a weekly classroom meeting to discuss our bully prevention program. A carpet would be a great gathering place to hold this weekly meeting. The use for this carpet would be endless...during reading time, small group math time, and for social studies when learning about the United States. The map on this carpet would be a great visual for students to look at each day to help them learn the 50 states along with where they are placed within the country. A classroom carpet would greatly enhance learning and classroom community in my...classroom...I feel like having a common place for my class to sit and meet each and everyday will be really effective in providing students with that positive classroom experience that all are in such high need of." |

**Table E2 Less Unique Project Essays**

| |
|---|
| **Example 4:** "Recess is such an important time of day for our...students...We need recess equipment for our entire school. We all share the same equipment, so it gets worn out really quickly. We would like to purchase higher quality equipment that will last for more than a couple of weeks. Please consider helping us equip our kids for this important time of day! Our...students look forward to their recess time everyday. Unfortunately, we are unable to supply them with durable equipment to use during this time. With the balls, jump ropes, hoops, and other recess items, our students will be able to explore many exciting game/activity possibilities. We have very few balls that are not egg-shaped. Most of our balls need to be pumped up everyday because they lose air quickly. Sometimes the last recess kids can't even bounce the balls because they are deflated. None of our...have full coverage anymore, so they cannot be used on wet/damp days. It would be really great to have durable equipment that our students can take pride in caring for." |
| **Example 5:** "I am a...teacher in a large school district...Most of my students are from a low-income household. My students are faced with several challenges both in and out of the classroom. Despite the many challenges they face, I am looking to keep things simple and provide my students with creative and meaningful learning experiences. Many of my students receive backpack food on the weekend. Despite so many hardships, my students are eager to learn and do their best. They want to be in school because they want to learn all they can so they can be successful one day. We would like to get...Kindle Fires for our classroom to help with math and reading skills. My students spend a good portion of their day working at stations and/or small groups. During these stations the students work on math facts and different phonics skills. The students currently use flashcards to practice their math facts and several worksheets/teacher made games to practice phonic skills. I would like to enhance their learning through several...apps that focus on addition/subtraction and phonics/fluency. The apps will keep track of their progress and also reward the students with certifications when completing an activity." |
| **Example 6:** "As a teacher in a low-income school, my students are faced with several challenges both in and out of the classroom. Despite the many difficulties they face, I am looking to keep things simple and provide them with creative and meaningful learning experiences...They are creative and love learning. They love to read and love lots of positive attention." They love to read books and use their imaginations as they turn the pages and go on adventures. My classroom carpet is old and dirty and worn, and not at all a place to sit and allow their minds to run wild as they turn the pages of storybooks. I want to provide them with a bright and cheery place to sit and go on wild rides in the storybooks that they read...and a carpet would help significantly in this setting. Please help my students have a nice place to continue their love for reading." |

## Appendix F: LPM Model Selection

We explain here our choice to use an LPM model. First, when used with fixed effects, nonlinear models such as logit and probit are known to suffer from the *incidental parameter problem* (Neyman and Scott 1948), which has been shown both analytically (e.g., Hsiao 2022) and with simulation (e.g., Katz 2001), particularly when the panel is short as in most education datasets. By contrast, linear panel data models with fixed effects do not suffer from these issues and continue to produce consistent and unbiased estimates. Second, while there exists a special case of a fixed-effects logit model where one can use the conditional likelihood approach to estimate the model parameters (Chamberlain 1984), this approach does not produce estimates of the fixed effects preventing researchers from estimating partial effects and marginal effects properly (Wooldridge 2010). By contrast, linear probability models produce estimates that are directly interpretable as marginal effects.

Third, the fixed effects linear probability model includes all observations in the estimation while the fixed-effects logit model drops observations without variations in the outcome variable, leading to reduced sample sizes. If there is any separation between observations with and without variations in the outcome, it will be exacerbated in the fixed-effects logit models (Li and Wu 2022). In our setting, all teachers who have stayed with a school in our study period will be dropped from the estimation since their outcomes are all zero, which account for 70% of observations. This creates an obviously biased sample to study teacher turnover as the remaining teachers are all teachers who eventually decided to leave their schools. Finally, when the model uses instrumental variables for causal identification as in our case, linear probability models are often preferred over nonlinear ones (such as the probit model) because they offer consistent estimates with minimum assumptions required (Angrist and Pischke 2009). While the main disadvantage of the linear probability model is that it may generate predicted probabilities outside of the [0, 1] range, Angrist and Krueger (2001) provide evidence that the linear probability IV model performs well for estimating causal effects. As such, many studies choose the linear probability model over nonlinear ones, particularly when the model has fixed effects (e.g., Xu et al. 2019, Li and Wu 2022) or uses instruments (e.g., De Giorgi et al. 2010, Song et al. 2020, Belo et al. 2016).

## Appendix G: Logit and Probit Models

This section replicates the main analyses with Logit and Probit models. The results are presented in Table G1. In particular, Columns (1) and (2) estimate the impact of having projects funded through DonorsChoose on teacher turnover—leaving school and leaving the PA public education system, respectively—using the Logit model controlling for the same set of teacher, school, district attributes as in the main analyses. Columns (3) and (4) replicate the same analysis with the Probit model. The last two columns (5 and 6) replicate the analyses using the Probit model while using instruments. All results show that DonorsChoose funded projects reduce teachers attrition at both the school level and the system level. Using marginal analyses, we find that the effect sizes are consistent with what we find in the main analyses, ranging from 1.0 to 2.8 pp across models evaluated at means. Note these models cannot account for teacher-school level fixed effects, due to the extremely large number of fixed effects involved and the need for using instruments. Please refer to the end of Section 4.1 for detailed discussion for why linear models are considered more appropriate models in these settings. Overall, the consistency of the results both in magnitude and in direction demonstrate the robustness of the results—in particular, the results are not driven by the the choice of linear instead of nonlinear models.

**Table G1 Results from Logit and Probit Models**

| | Logit | | Probit | | Probit w/ IV | |
|---|---|---|---|---|---|---|
| | Leave School (1) | Leave PA (2) | Leave School (3) | Leave PA (4) | Leave School (5) | Leave PA (6) |
| Fund | -0.335*** | -0.506*** | -0.183*** | -0.239*** | -0.242*** | -0.312*** |
| | (0.0328) | (0.0524) | (0.0175) | (0.0236) | (0.0340) | (0.0489) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Const | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 759487 | 685748 | 759487 | 685748 | 759487 | 685748 |
| log-Lik | -250419.0 | -115792.1 | -250200.7 | -115640.6 | 334990.1 | 384098.7 |

*Notes.* Controls include the same set of variables as in the main analysis, i.e., time-variant teacher, school, and district-level characteristics. Note neither teacher-school fixed effects nor principal effects are included in these nonlinear models for reasons discussed in Section 4.1. Standard errors are clustered at school level. We use a maximum likelihood estimator approach. ***, $p< 0.01$. **, $p< 0.05$, *, $p< 0.1$.

## Appendix H: Funding Events

DonorsChoose had several funding events throughout the study period. Not all qualified as treatment in our analysis. In Tables H1 and H2, together with Figure H, we show all funding events from 2013–2014 to 2018–2019. We explain whether the event was included because it was not anticipated by teachers or excluded because it was anticipated by teachers.

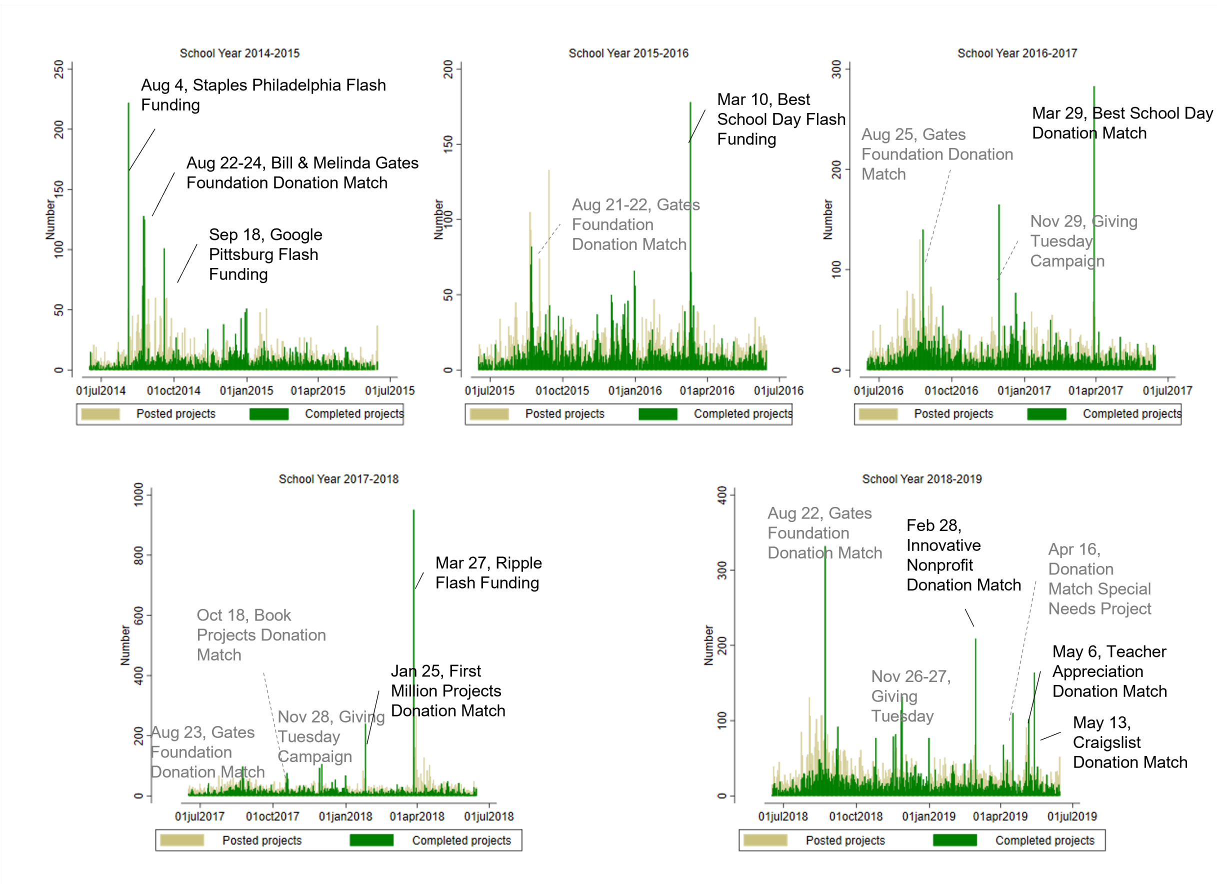


**Figure H1 Funding Events**

*Notes.* This figure displays the number of projects posted and the number of projects funded on DonorsChoose at daily level for academic years from 2014–2015 to 2018–2019. Events that are unanticipated are called out in black, and events that are pre-announced or likely anticipated are called out in gray. Note, there were no flash funding or donation match events during academic year 2013–2014.

**Table H1 Funding Events Summary**

| Date | Event | Location | Anticipated | Include | Twitter |
|---|---|---|---|---|---|
| August 4, 2014 | Staples | Philadelphia | No significant increase in projects posted. | Yes | None |
| August 22–24, 2014 | Gates Foundation | US | No significant increase in projects posted. | Yes | *Through 8/24, we're throwing a back-to-school philanthropic sale! Nearly all projects are half-off–donate today* (August 22, 2014) |
| September 18, 2014 | Google | Pittsburgh | No significant increase in projects posted. | Yes | *Hey, Pittsburgh! @Google just gave over 50,000 and #flashfunded every project in the city!* (September 19, 2014) |
| August 21–22, 2015 | Gates Foundation | US | Yes, a significant increase in projects posted. | No | *Enter JUMPSTART at checkout today, and your donation will be matched by @gatesfoundation!* (August 21 2015) and *Thanks to additional funding from @GatesFoundation we're extending the JUMPSTART promo code for a few more hours!* (August 22, 2015) |
| March 10, 2016 | Best School Day | US | No significant increase in projects posted. | Yes | *50 philanthropists have helped us fully fund 11,000 classrooms today. Happy #BestSchoolDay!* (March 10, 2016) |
| August 25, 2016 | Gates Foundation | US | Yes, a significant increase in projects posted. | No | *Right now, donations to projects on our site are being matched thanks to @gatesfoundation* (August 25, 2016) |
| November 29, 2016 | Giving Tuesday | US | Yes, Twitter post one week prior. | No | *Only one week until #GivingTuesday! Who's made their plan for the big day?* (November 22, 2016) |
| March 29, 2017 | Best School Day | US | No significant increase in projects posted. | Yes | *Tomorrow, your donations will be matched on EVERY project. #BestSchoolDay is back!* (March 28, 2017) |
| August 23, 2017 | Gates Foundation | US | Yes, a significant increase in projects posted. | No | *Help schools get student-ready! All day, claim your #BestSchoolYear match thanks to @gatesfoundation* (August 23, 2017) |
| October 18, 2017 | Fill Every Shelf | US | Yes, a significant increase in projects posted. | No | *Are you ready to #FillEveryShelf? Tomorrow and Thursday, all book projects are matched!* (October 17, 2017) |
| November 28, 2017 | Giving Tuesday | US | Yes, Twitter post one week prior. | No | *It's Black Friday, and you know what that means... Only 4 days until #GivingTuesday!* (November 24, 2017) |
| January 25, 2018 | First Million Projects | US | No significant increase in projects posted. | Yes | *Our community has hit an incredible milestone: you've funded the #FirstMillion classroom projects! To celebrate, donations to every live DonorsChoose project are doubled tomorrow. Here's to the next million!* (January 24, 2018) |
| March 27, 2018 | Ripple | US | No significant increase in projects posted. | Yes | *We can't believe that just happened. With the largest single donation in our history, @Ripple just funded EVERY SINGLE CLASSROOM PROJECT on our site. Happy #BestSchoolDay!* (March 28, 2018) |
| August 22, 2018 | Gates Foundation | US | Yes, a significant increase in projects posted. | No | *All day, we're teaming up with @GatesFoundation to give your donations a back-to-school boost.* (August 22, 2018) |
| November 26-27, 2018 | Giving Tuesday | US | Yes, Twitter post one week prior. | No | *The best part about Black Friday? Only four more days until #GivingTuesday* (November 23, 2018) |

**Table H2 Funding Events Summary Continued**

| Date | Event | Location | Anticipated | Include | Twitter |
|---|---|---|---|---|---|
| February 28, 2019 | Innovative Non-profit | US | No significant increase in projects posted. | Yes | *We were named one of @FastCompany's Most Innovative Companies - so let's celebrate the world's most innovative teachers! All day, we'll boost donations to every classroom project on the site* (February 28, 2019) |
| April 16, 2019 | Every Kid Can Event | US | No, but only for special needs projects. | No | *Today only, donations are doubled to all special needs projects! Let's make sure teachers have the tools they need to make sure #EveryKidCan thrive.* (April 16, 2019) |
| May 6, 2019 | Teacher Appreciation | US | No significant increase in projects posted. | Yes | *TODAY ONLY: To kick off #TeacherAppreciationWeek, @Googleorg is giving every donation a 50% boost!* (May 6, 2019) |
| May 13, 2019 | Craiglist Donation Match | US | No significant increase in projects posted. | Yes | *BREAKING NEWS! Just announced on @GMA...@craignewmark has committed $1 million to match donations to projects on DonorsChoose.org, while funds last! Support a classroom today to have your donation doubled.* (May 13, 2019) |

## Appendix I: Three stage and two stage selection models

In Table I1, we report the results from our selection models, which address the potential selection biases exploiting exogenous variations in posting and funding decisions. The first three columns of the table shows estimates from the three-stage selection model and the last two columns report estimates from the two-stage selection model for robustness. More specifically, Column (1) reports estimates from the posting-stage equation (i.e., Equation 3). As expected, the instrument— *SameSubj-DCTeacher*— positively affects a teachers' propensity to post. Next, the second-stage regression (Eq 3; Column 2) estimates the likelihood of funding with the instrumented posting decision and the funding instrument—projects' eligibility for unanticipated funding events. Here again, intuitively, being eligible for these funding events significantly increases the probability of a teacher's project being funded. The predicted value from the first stage ($\widehat{\text{Post}}_{ist}$) also positively predicts the probability of being funded. Instruments in both stages are strong instruments because the F-statistics are significantly larger than the common critical values from the weak IV tests. In the final stage (Eq 4; Column 3), we estimate the likelihood of teacher turnover with instrumented likelihoods of funding probability on the platform. The size of the effect is consistent with our results from the analyses without instruments (1 pp), although insignificant at p-value=0.1. The two-stage selection model produces almost exactly same results as the three-stage selection model. Both instruments significantly increase funding probability with a first-stage F-statistic substantially greater than critical values in weak IV tests. Because the results from the two-stage and three-stage models are almost identical, we report results from the two-stage model in the main paper.

## Appendix J: Contextual Data for Exploration of Potential Mechanisms

We first leverage the teacher survey data. For each of the four metrics in the survey, we calculate within-year medians. We construct 0/1 variables to indicate whether a Philadelphia teacher in our dataset works at a school with above- or below-median pedagogical control, leadership support and inclusion, peer collaboration, or teacher resources, and then interact these with our Fund variable. As reported in Table J1, we find that

**Table I1 Effects of DonorsChoose Funded Projects on Teacher Turnover (w/ Instruments)**

| | Three Stage Least Square | | | Two Stage Least Square | |
|---|---|---|---|---|---|
| | Eq 2<br>Post<br>(1) | Eq 3<br>Fund<br>(2) | Eq 4<br>Leave<br>(3) | Eq 5<br>Fund<br>(4) | Eq 6<br>Leave<br>(5) |
| Has Same-Subj. DC Tch | 0.005*** | | | 0.003*** | |
| | (0.001) | | | (0.001) | |
| Eligible for Funding Events | | 0.638*** | | 0.638*** | |
| | | (0.009) | | (0.009) | |
| Post | | 0.522*** | | | |
| | | (0.127) | | | |
| Fund | | | -0.016** | | -0.016** |
| | | | (0.008) | | (0.008) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Teacher-School Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Principal Effects | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Const | Yes | Yes | Yes | Yes | Yes |
| N | 715557 | 715557 | 715557 | 715557 | 715557 |
| Adj. Within R-sq | 0.00206 | 0.164 | 0.0603 | 0.164 | 0.0546 |
| Weak IV tests F-statistics | 56.15 | 1.40E+05 | | 6.90E+04 | |
| Stock-Yogo Critical Values | | | | | |
| Maximal 10% size | 16.38 | 16.38 | | 19.93 | |
| Maximal 15% size | 8.96 | 8.96 | | 11.59 | |
| Maximal 20% size | 6.66 | 6.66 | | 8.75 | |
| Maximal 25% size | 5.53 | 5.53 | | 7.25 | |

*Notes.* Tch, teacher. Controls include time-variant teacher, school, principal, and district-level characteristics. Robust standard errors clustered at school level. ***, $p < 0.01$. **, $p < 0.05$, *, $p < 0.1$.

**Table J1 Effect on Retention Based on the Philadelphia District-Wide Teacher Survey**

| | Leave School<br>(1) | Leave PA<br>(2) | Move<br>(3) |
|---|---|---|---|
| Fund | -0.008 | 0.010 | -0.018 |
| | (0.026) | (0.012) | (0.023) |
| Fund × Low Pedagogical Control | -0.017 | -0.006 | -0.008 |
| | (0.025) | (0.014) | (0.021) |
| Fund × Low Leadership Support | -0.040† | -0.027* | -0.015 |
| | (0.025) | (0.014) | (0.019) |
| Fund × Low Peer Collaboration | 0.033 | 0.007 | 0.024 |
| | (0.024) | (0.013) | (0.020) |
| Fund × Low Teacher Resource | -0.003 | -0.013 | 0.007 |
| | (0.029) | (0.014) | (0.025) |
| FE & Controls | Yes | Yes | Yes |
| N | 40598 | 39918 | 40598 |
| Within R-sq | 0.154 | 0.065 | 0.101 |

*Notes.* The same set of controls are included as in the previous table. Fixed effects include year and teacher-school fixed effects. Principal effects are not included as they reduce the amount of variations present in leadership support. Robust standard errors clustered at school level. † t-stat: 1.63, p-value: 0.102. ***, $p < 0.01$. **, $p < 0.05$, *, $p < 0.1$.

DonorsChoose funding has the largest effect on retention when leadership support is low. Recall from Figure 1, leadership approval is nearly always required for teachers' within-the-system supplemental resource requests. Resource access is dependent on leadership support. An interpretation of this result is that DonorsChoose funding helps most where it is the hardest for teachers to access the resources they need. This evidence points to two channels through which crowdfunding affects teachers: (1) the resources secured *and* (2) the ability to secure resources through an external, autonomous procurement process. In fact, because the interaction between DonorsChoose funding and resource level at the school is negative but not significant in Table

J1, this analysis suggests that the autonomous procurement process enabled by crowdfunding may be a particularly important factor driving the crowdfunding effect on teacher retention.

Next, we leverage the teacher interview data (Table J2 and associated Semi-Structured Interview Protocol) to zoom in closer to the teacher experience with DonorsChoose. Our analytical objective with the interviews is to identify detailed examples within the two aforementioned mechanism classes: (1) secured new or more resources, and (2) leveraged an efficient and autonomous procurement process. Specifically, we examine the interviews for evidence of how the procured resources affect teachers and how the crowdfunding process itself affects teachers. We analyze the interview data inductively, that is, we read through the interviews and highlight teacher descriptions of DonorsChoose with this guiding framework in mind. We then triangulate the quotes with the survey, causal estimation and textual data to enrich our initial understanding of potential mechanisms. The next two sections present this integrated evidence. Note that our approach does not identify either mechanism class as dominant. Rather, crowdfunding is an innovation to meet heterogeneous needs, and teachers likely use it for different reasons and benefit from it in different ways.

**Table J2 Teacher Interviews**

| Teacher ID | Type | DonorsChoose | Grade | Subject Area | Experience (yrs) |
|---|---|---|---|---|---|
| 1 | Leaver | Funded | Elementary | General Ed (All Subjects) | 3 |
| 2 | Leaver | Funded | Elementary | Art | 18 |
| 3 | Leaver | Unfunded | High School | English Language Learners (ELLs) | 15 |
| 4 | Stayer | Funded | High School | Spanish | 10 |
| 5 | Stayer | Funded | Elementary | General Ed (All Subjects) | 15 |
| 6 | Stayer | Funded and Unfunded | Elementary | Special Education | 10 |
| 7 | Stayer | Funded | Elementary | General Ed (All Subjects) | 23 |
| 8 | Stayer | Funded and Unfunded | Middle | English Language Learners (ELLs) | 8 |
| 9 | Stayer | Unfunded | Middle | ELA and Social Studies | 9 |
| 10 | Stayer | Unfunded | Middle | ELA and Social Studies | 15 |

**Semi-Structured Interview Protocol**

Part 1: Introduction

· How would you describe your school to a friend?

· How many years have you been a teacher? *If left:* Why did you leave?

· What subject and grade level do you teach?

Part 2: Use of DonorsChoose

· How did you first hear about DonorsChoose?

· What made you decide to complete your first post?

· Do other teachers at your school use DonorsChoose? Does that impact your use of DonorsChoose?

· How many total DonorsChoose projects did you end up posting? Were any funded?

· Have you moved/left your school since you first posted? *If yes:* Are there similar reasons for posting at your old school and your new school? If not, what is different?

Part 3: Impact of DonorsChoose

· How did it affect you when your projects were funded?

· How did it affect you when your projects were NOT funded?

Part 4: Other Resources

· Besides DonorsChoose, are there other ways you get resources for yourself and your students? What are they? - How do these resources affect you and your work?

## Appendix K: Additional Tables and Figures

**Table K1 Additional Sample Summary: Teacher, School, Principal, District Attributes**

| | Posting Teachers | | | Non Posting Teachers | | | Funded Teachers | | | Unfunded Teachers | | | Diff | Diff |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N (1) | Mean (2) | SD (3) | N (4) | Mean (5) | SD (6) | N (7) | Mean (8) | SD (9) | N (10) | Mean (11) | SD (12) | Col 2−5 (13) | Col 8−11 (14) |
| Teacher Attributes | | | | | | | | | | | | | | |
| Leave PA | 16816 | 3.4 | 18.2 | 742950 | 4.6 | 21.0 | 13556 | 3.4 | 18.2 | 3260 | 3.5 | 18.3 | -1.2*** | 0.0 |
| Leave School | 16816 | 11.5 | 31.9 | 742950 | 11.4 | 31.8 | 13556 | 12.0 | 32.5 | 3260 | 9.5 | 29.3 | 0.1 | 2.5*** |
| Female | 16816 | 87.8 | 32.7 | 742950 | 72.7 | 44.5 | 13556 | 88.1 | 32.4 | 3260 | 86.6 | 34.1 | 15.1*** | 1.5** |
| Salary | 16816 | 61.6 | 15.5 | 742827 | 65.9 | 18.0 | 13556 | 61.6 | 15.4 | 3260 | 61.9 | 15.9 | -4.3*** | -0.3 |
| Years in Ed | 16816 | 10.1 | 7.1 | 742950 | 13.6 | 8.5 | 13556 | 10.0 | 7.1 | 3260 | 10.6 | 7.3 | -3.5*** | -0.7*** |
| Full Time | 16816 | 99.8 | 0.0 | 742950 | 98.7 | 0.1 | 13556 | 99.8 | 0.0 | 3260 | 99.7 | 0.1 | 1.1*** | 0.1 |
| % Time | 16816 | 98.7 | 8.3 | 742950 | 92.6 | 20.8 | 13556 | 98.8 | 8.0 | 3260 | 98.4 | 9.4 | 6.1*** | 0.5*** |
| Degree | | | | | | | | | | | | | | |
| Bachelor | 16816 | 63.3 | 48.2 | 742950 | 43.3 | 49.6 | 13556 | 64.6 | 47.8 | 3260 | 58.1 | 49.4 | 20.0*** | 6.5*** |
| Master | 16816 | 36.3 | 48.1 | 742950 | 55.9 | 49.7 | 13556 | 35.1 | 47.7 | 3260 | 41.5 | 49.3 | -19.5*** | -6.4*** |
| Doctor | 16816 | 0.3 | 5.2 | 742950 | 0.5 | 7.3 | 13556 | 0.3 | 5.1 | 3260 | 0.3 | 5.2 | -0.3*** | 0.0 |
| School Attributes | | | | | | | | | | | | | | |
| Enrollments | 16814 | 693.6 | 507.4 | 742722 | 859.8 | 935.9 | 13554 | 693.7 | 505.3 | 3260 | 693.4 | 515.7 | -166.2*** | 0.2 |
| Percent FRPL | 16816 | 71.7 | 31.9 | 742950 | 45.3 | 29.4 | 13556 | 73.6 | 31.5 | 3260 | 63.6 | 32.4 | 26.4*** | 10.0*** |
| Percent Asian | 16816 | 4.5 | 8.2 | 742950 | 3.6 | 5.5 | 13556 | 4.6 | 8.5 | 3260 | 3.8 | 6.7 | 0.9*** | 0.8*** |
| Percent Black | 16816 | 33.0 | 32.8 | 742950 | 13.7 | 22.5 | 13556 | 34.7 | 33.0 | 3260 | 26.1 | 31.1 | 19.3*** | 8.6*** |
| Percent Hispanic | 16816 | 16.2 | 22.1 | 742950 | 10.0 | 16.2 | 13556 | 16.7 | 22.3 | 3260 | 14.2 | 20.9 | 6.2*** | 2.6*** |
| Percent Native | 16816 | 0.2 | 0.3 | 742950 | 0.2 | 0.3 | 13556 | 0.2 | 0.2 | 3260 | 0.2 | 0.3 | 0.0*** | 0.0 |
| Stdnt-Tch Ratio | 16816 | 15.5 | 3.9 | 742950 | 14.8 | 3.3 | 13556 | 15.6 | 4.0 | 3260 | 15.3 | 3.4 | 0.7*** | 0.3*** |
| Charter | 16814 | 12.7 | 33.3 | 741766 | 6.7 | 24.9 | 13554 | 13.0 | 33.7 | 3260 | 11.4 | 31.8 | 6.1*** | 1.6** |
| School Level | | | | | | | | | | | | | | |
| Elementary | 16814 | 73.1 | 44.3 | 741766 | 45.9 | 49.8 | 13554 | 73.8 | 44.0 | 3260 | 70.4 | 45.7 | 27.3*** | 3.4*** |
| Middle | 16814 | 11.3 | 31.6 | 741766 | 20.8 | 40.6 | 13554 | 10.8 | 31.0 | 3260 | 13.3 | 33.9 | -9.5*** | -2.5*** |
| High | 16814 | 11.6 | 32.0 | 741766 | 29.4 | 45.6 | 13554 | 11.1 | 31.5 | 3260 | 13.4 | 34.1 | -17.8*** | -2.3*** |
| Other | 16814 | 4.0 | 19.6 | 741766 | 3.9 | 19.3 | 13554 | 4.3 | 20.2 | 3260 | 2.9 | 16.8 | 0.1 | 1.3*** |
| Principal Attributes | | | | | | | | | | | | | | |
| Female | 16531 | 53.6 | 49.9 | 729054 | 38.8 | 48.7 | 13326 | 54.5 | 49.8 | 3205 | 49.9 | 50.0 | 14.9*** | 4.7*** |
| Salary | 16531 | 108.9 | 29.7 | 729054 | 109.8 | 26.3 | 13326 | 109.0 | 30.0 | 3205 | 108.4 | 28.2 | -1.0*** | 0.5 |
| Years in Ed | 16531 | 14.3 | 8.5 | 729054 | 12.5 | 8.2 | 13326 | 14.5 | 8.5 | 3205 | 13.4 | 8.4 | 1.8*** | 1.1*** |
| Full Time | 16531 | 96.6 | 18.1 | 729054 | 98.8 | 11.1 | 13326 | 96.3 | 18.8 | 3205 | 97.7 | 15.0 | -2.2*** | -1.3*** |
| Degree | | | | | | | | | | | | | | |
| Bachelor | 16531 | 38.4 | 48.6 | 729054 | 12.4 | 33.0 | 13326 | 40.4 | 49.1 | 3205 | 30.3 | 45.9 | 26.0*** | 10.1*** |
| Master | 16531 | 52.5 | 49.9 | 729054 | 74.4 | 43.6 | 13326 | 50.8 | 50.0 | 3205 | 59.5 | 49.1 | -22.0*** | -8.7*** |
| Doctor | 16531 | 8.7 | 28.2 | 729054 | 12.8 | 33.4 | 13326 | 8.4 | 27.8 | 3205 | 10.0 | 29.9 | -4.1*** | -1.5*** |
| No Principal | 16816 | 1.7 | 12.9 | 746210 | 2.3 | 15.0 | 13556 | 1.7 | 12.9 | 3260 | 1.7 | 12.9 | -0.6*** | 0.0 |
| Multi-Principal | 16816 | 5.7 | 23.2 | 746210 | 7.7 | 26.7 | 13556 | 5.5 | 22.9 | 3260 | 6.3 | 24.3 | -2.0*** | -0.8* |
| District Attributes: Annual Expenditure Per Student | | | | | | | | | | | | | | |
| Salary | 16798 | 6.6 | 1.6 | 741521 | 7.2 | 1.6 | 13544 | 6.6 | 1.6 | 3254 | 6.8 | 1.6 | -0.6*** | -0.2*** |
| Supplies | 16798 | 0.6 | 0.2 | 741578 | 0.6 | 0.3 | 13544 | 0.6 | 0.2 | 3254 | 0.6 | 0.2 | -0.0*** | 0.0 |
| Property | 16567 | 0.2 | 0.4 | 734127 | 0.2 | 0.3 | 13352 | 0.2 | 0.4 | 3215 | 0.2 | 0.6 | 0.0*** | -0.0** |

*Notes.* Summary statistics for indicator variables are shown as percentage points. Sample period: AY 2013–2014 to AY 2018–2019. Salary and expenditure are measured in $1000. FRPL: free and reduced-price lunch. ***, p< 0.01. **, p< 0.05, *, p< 0.1.

**Table K2 Summary Results Comparing More versus Less Unique Teacher Projects**

| | More Unique | | | Less Unique | | | Diff |
|---|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD | |
| Teacher Attributes | | | | | | | |
| Leave PA | 8408 | 2.9 | 16.9 | 8408 | 3.9 | 16.9 | -1.0*** |
| Leave School | 8408 | 10.7 | 30.9 | 8408 | 12.3 | 30.9 | -1.7*** |
| Female | 8408 | 89.5 | 30.6 | 8408 | 86 | 30.6 | 3.5*** |
| Salary | 8408 | 61.9 | 15.6 | 8408 | 61.3 | 15.6 | 0.6** |
| Years in LEA | 8408 | 9.5 | 7.1 | 8408 | 9 | 7.1 | 0.5*** |
| Years in Education | 8408 | 10.4 | 7.2 | 8408 | 9.8 | 7.2 | 0.6*** |
| Full Time | 8408 | 99.8 | 4.2 | 8408 | 99.7 | 4.2 | 0.1* |
| % Time Assigned | 8408 | 98.7 | 8.3 | 8408 | 98.7 | 8.3 | 0 |
| Degree | | | | | | | |
| Bachelor | 8408 | 62.5 | 48.4 | 8408 | 64.1 | 48.4 | -1.6** |
| Master | 8408 | 37.2 | 48.3 | 8408 | 35.5 | 48.3 | 1.7** |
| Doctor | 8408 | 0.2 | 4.5 | 8408 | 0.3 | 4.5 | -0.1 |
| School Attributes | | | | | | | |
| Enrollments | 8406 | 689.7 | 504.0 | 8408 | 697.6 | 504.0 | -7.9 |
| Percent FRPL | 8408 | 70.7 | 32.2 | 8408 | 72.7 | 32.2 | -2.0*** |
| Percent Asian | 8408 | 4.3 | 7.7 | 8408 | 4.6 | 7.7 | -0.3** |
| Percent Black | 8408 | 31.3 | 32.6 | 8408 | 34.7 | 32.6 | -3.4*** |
| Percent Hispanic | 8408 | 15.8 | 21.7 | 8408 | 16.7 | 21.7 | -0.8** |
| Percent Native American | 8408 | 0.2 | 0.3 | 8408 | 0.2 | 0.3 | 0 |
| Student Tch Ratio | 8408 | 15.5 | 3.6 | 8408 | 15.6 | 3.6 | -0.2*** |
| Charter | 8406 | 11.9 | 32.4 | 8408 | 13.5 | 32.4 | -1.6*** |
| School Level | | | | | | | |
| Elementary | 8406 | 76.9 | 42.1 | 8408 | 69.4 | 42.1 | 7.6*** |
| Middle | 8406 | 9.9 | 29.8 | 8408 | 12.7 | 29.8 | -2.8*** |
| High | 8406 | 10.1 | 30.1 | 8408 | 13.1 | 30.1 | -3.0*** |
| Other | 8406 | 3.1 | 17.3 | 8408 | 4.9 | 17.3 | -1.8*** |
| Principal Attributes | | | | | | | |
| Female | 8253 | 53.4 | 49.9 | 8278 | 53.9 | 49.9 | -0.6 |
| Salary | 8253 | 109.4 | 29.2 | 8278 | 108.3 | 29.2 | 1.0** |
| Years in Education | 8253 | 14.3 | 8.4 | 8278 | 14.2 | 8.4 | 0.1 |
| Full Time | 8253 | 97.2 | 16.4 | 8278 | 96 | 16.4 | 1.3*** |
| Degree | | | | | | | |
| Bachelor | 8253 | 36.9 | 48.3 | 8278 | 39.9 | 48.3 | -2.9*** |
| Master | 8253 | 53.5 | 49.9 | 8278 | 51.5 | 49.9 | 1.9** |
| Doctor | 8253 | 9.3 | 29.0 | 8278 | 8.2 | 29.0 | 1.1** |
| No Principal | 8408 | 1.8 | 13.5 | 8408 | 1.5 | 13.5 | 0.3 |
| Multi-Principal | 8408 | 5.7 | 23.2 | 8408 | 5.7 | 23.2 | 0 |
| District Attributes: Annual Expenditure Per Student | | | | | | | |
| Salary | 8399 | 6.7 | 1.5 | 8399 | 6.6 | 1.5 | 0.1*** |
| Supplies | 8399 | 0.6 | 0.2 | 8399 | 0.6 | 0.2 | 0.0*** |
| Property | 8283 | 0.2 | 0.4 | 8284 | 0.2 | 0.4 | 0 |
| DonorsChoose Attributes | | | | | | | |
| Num Project Posted | 8408 | 1.5 | 2.2 | 8408 | 2.5 | 2.2 | -1.0*** |
| Num Project Funded | 8408 | 1.1 | 1.7 | 8408 | 1.8 | 1.7 | -0.7*** |

*Notes.* †Conditional on at least one project is posted, because uniqueness measures are derived from posted project essays. Summary statistics for indicator variables are shown as percentage points. Sample period: AY 2013–2014 to AY 2018–2019. Salary and expenditure are measured in $1000. FRPL: free and reduced-price lunch. ***, p< 0.01. **, p< 0.05, *, p< 0.1.

**Table K3 Effects of DonorsChoose Funded Projects on Teacher Turnover**

| | Teacher Attributes<br>(1) | Teacher, School, District Attributes<br>(2) | Teacher, School, Principal, District Attributes & Teacher-School FE, Principal FE<br>(3) |
|---|---|---|---|
| Fund | 0.003 | -0.036*** | -0.012*** |
| | (0.004) | (0.003) | (0.003) |
| Female | 0.004*** | 0.004*** | NA |
| | (0.001) | (0.001) | |
| ln(Salary) | -0.051*** | -0.053*** | -0.094*** |
| | (0.005) | (0.005) | (0.007) |
| Years In Education 6 -10 yrs | -0.052*** | -0.042*** | 0.020*** |
| | (0.002) | (0.002) | (0.002) |
| Years In Education 11 - 15 yrs | -0.067*** | -0.054*** | -0.007** |
| | (0.003) | (0.002) | (0.003) |
| Years In Education 16 - 20 yrs | -0.067*** | -0.054*** | -0.048*** |
| | (0.003) | (0.002) | (0.004) |
| Years In Education 21 - 25 yrs | -0.054*** | -0.038*** | -0.086*** |
| | (0.003) | (0.003) | (0.005) |
| Years In Education 26 - 30 yrs | -0.030*** | -0.014*** | -0.106*** |
| | (0.004) | (0.003) | (0.007) |
| Years In Education 30 yrs | 0.110*** | 0.129*** | -0.036*** |
| | (0.004) | (0.004) | (0.009) |
| Full Time | -0.020*** | -0.027*** | 0.066*** |
| | (0.008) | (0.007) | (0.008) |
| Percent of Time Assigned | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) |
| Bachelor | -0.008 | -0.010 | -0.076*** |
| | (0.011) | (0.010) | (0.030) |
| Master | -0.024** | -0.007 | -0.079*** |
| | (0.011) | (0.010) | (0.029) |
| Doctoral | 0.006 | 0.022* | -0.015 |
| | (0.012) | (0.012) | (0.033) |
| ln(Enrollment) | | -0.019*** | -0.002 |
| | | (0.002) | (0.008) |
| Percent Free and Reduced Lunch Students | | -0.000 | 0.000 |
| | | (0.000) | (0.000) |
| Percent Asian/Pacific Islander | | 0.001*** | -0.004*** |
| | | (0.000) | (0.001) |
| Percent Black | | 0.002*** | -0.001 |
| | | (0.000) | (0.001) |
| Percent Hispanic | | 0.001*** | -0.001 |
| | | (0.000) | (0.001) |
| Percent Native American | | -0.007** | -0.000 |
| | | (0.003) | (0.002) |
| Student Teacher Ratio | | -0.000 | -0.001 |
| | | (0.000) | (0.000) |
| School Closure | | 0.805*** | 0.657*** |
| | | (0.015) | (0.030) |
| District Expnd per Student - Personnel Salary | | -0.005*** | -0.007** |
| | | (0.001) | (0.003) |
| District Expnd per Student - Supplies | | -0.007*** | -0.016** |
| | | (0.002) | (0.007) |
| District Expnd per Student - Property | | -0.000 | -0.004 |
| | | (0.002) | (0.002) |
| Primary Assignment Type | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Principal Characteristics and Fixed Effects | No | No | Yes |
| Teacher-School Fixed Effects | No | No | Yes |
| Const | Yes | Yes | Yes |
| N | 759,766 | 759,766 | 715,557 |
| Adj. R-sq | 0.032 | 0.057 | 0.191 |

*Notes.* LPM, linear probability model. LPM-FE: linear probability model with fixed effects. Years in Education 1-5 yrs is the baseline. Expnd, expenditure. In Column (3), within R-sq is shown. Robust standard errors clustered at school level. ***, p< 0.01. **, p< 0.05, *, p< 0.1.

**Table K4 Pseudo-Treatment Test of Unfunded Projects w/o IV**

| | Leave School (1) | Leave PA (2) | Move (3) |
|---|---|---|---|
| Fund | -0.013** | -0.010*** | -0.004 |
| | (0.005) | (0.003) | (0.004) |
| Year Fixed Effects | Yes | Yes | Yes |
| Teacher-School Fixed Effects | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Const | Yes | Yes | Yes |
| N | 701346 | 634162 | 701346 |
| Adj. Within R-sq | 0.0600 | 0.0345 | 0.0325 |

*Notes.* Robust standard errors clustered at school level. ***, $p < 0.01$. **, $p < 0.05$, *, $p < 0.1$.