Peer Effects in Adoption and Usage of Crowdfunding Platforms: Evidence from United States Public School Teachers

Baek Jung Kim*  Masakazu Ishihara†  Vishal Singh‡

Current Version: August 30, 2018

Abstract

Public school education system in the U.S. displays remarkable inequities in resources, a fact exacerbated by the budget cuts after the Great Recession in 2008. Consequently, schoolteachers have had to find alternative resources to fulfill student needs and have increasingly turned to online crowdfunding. This paper examines the adoption and repeated use of Donorschoose.org (the largest crowdsourcing platform in this domain) by U.S. public school teachers. Our particular focus is on understanding and quantifying the presence and nature of peer effects on short-term adoption and repeated use behavior. Database captures information on approximately 400,000 teachers from 90,000 public schools from 2003 to 2014. We supplement this data with a variety of information capturing attributes of schools (e.g., poverty and ethnic mix of students) as well as the government funding in the school districts. Our key strategy on identifying peer effects relies on time-lag between teachers to resolve a simultaneity (i.e., reflection) problem. Confirming the findings in previous literature, we find strong positive peer effects on adoption decisions indicating the information role played by an experienced colleague. However, peer effects on repeated use are found to be negative, highlighting the common-core nature of this context as teachers compete for limited (primarily local) donors. We quantify “the overall effect of peer adoption and usage” in adoption and repeated use by estimating a dynamic structural model of the teachers’ adoption and repeated use, where teachers’ first-time adoption costs depend on past peer adoption and repeated use decisions are influenced by peer’s usage as well as own and peer success/failure rates in previous solicitation attempts. Model allows us to quantify the economic significance of peer effects in terms of usage (both adoption and repeated use) and welfare (e.g., how much additional money raised due to peer effect). We also discuss implications of our findings for policy makers in education.

*Please direct all correspondence to Baek Jung Kim, Stern School of Business, New York University.
†Stern School of Business, New York University.
‡Stern School of Business, New York University.
Keywords: New Technology Adoption, Public Education Budget, Peer Effects, Online Crowdfunding, Dynamic Demand Models.
1 Introduction

Public school education system in the U.S. displays remarkable inequities in resources across states, among school districts within each state, and even among schools within specific districts. For example, in 2014, the state with the highest average level of public school funding (adjusted for differences in cost of living) was New York, with an annual funding rate of $22,366 per student. Yet as seen in Figure 1, there is large variation in per student spending across school districts within New York. These inequities in resources arise due to the fact that nearly half of public school funding comes from local property taxes, which in turn generates large differences between wealthy and impoverished neighborhoods. Such differences in school funding have important consequences as they have been linked to differences in academic achievement (Card and Payne 2002), dropout rates (Hoxby 2001), and even adult outcomes (Jackson 2012; Heckman et al. 2013; Jackson et al. 2016). Not surprisingly, inequities of educational resources and opportunities has garnered considerable debate among policy makers, academics, and the public at large.

![Figure 1: Public Education Budget (as of 2014)](image)

Although inequalities in education resources have persisted for a long time, the problem has been exacerbated since the austerity measures following the Great Recession in 2008. As discussed in Section 3 below, most states and school districts saw drastic budget cuts following the recession. From a teacher’s perspective, school budgets impact not just their own salary and compensation,
but also school supplies and other necessary teaching resources. A recent survey by the National Center for Education Statistics (2016) finds that a vast majority of public school teachers spent their own money to pay for classroom equipment and supplies, averaging nearly $500 a year. Consequently, schoolteachers have had to find alternative resources to fulfill student needs, with online crowdfunding platforms leading the charge in recent years.

This paper develops an empirical framework to examine the adoption and repeated use of online crowdfunding platforms by the U.S. public school teachers. We analyze the extent to which intrinsic motivation vs. extrinsic factors (education budget cuts in our case) influence adoption and long-term use. Our application uses data from crowdfunding platform Donorschoose.org which is the largest cause-based platform in this domain. Founded in 2000, Donorschoose provides a platform that enables teachers to request classroom supplies (e.g., pens, pencils, or notebooks), books/literacy teaching tools, technology (e.g., computers or projectors), and funding for field trips. According to the latest figures in April 2018, the platform has generated contribution in excess of $640 million reaching 27 million students in public schools across the United States. Our empirical application uses comprehensive information on approximately 400,000 teachers from 90,000 public schools that were active on the platform between 2004 to 2014. We supplement this data with a variety of information capturing attributes of schools (e.g., poverty and ethnic mix of students) as well as the government funding in the school districts.

Like any other technology, teacher’s adoption and repeated use of Donorschoose platform is likely to be governed by a variety of factors such as awareness of its existence, uncertainty regarding expected costs and benefits, availability of alternate local resources, and so forth. In addition, an individual teacher’s behavior is likely to be influenced by actions of her peers. Extensive literature shows that network ties such as friends, family, neighbors, and colleagues serve as convenient and trustworthy source of information, and that social learning from peers can facilitate adoption of new technologies (e.g., Godes and Mayzlin 2009; Nair et al. 2010; Iyengar et al. 2011; Bollinger and Gillingham 2012; Narayanan and Nair 2013; Aral and Walker 2014). In the current context, such peer effects can be even more pronounced (and better measured) since teachers within a school share common working space. Furthermore, such networks are likely to be more evident for ‘close’ peers (e.g. teachers in similar grades or teaching similar subjects). Network ties can exist across schools as well. For example, schools within a district share many resources including a common newsletter which, for instance, could feature a successful fundraising campaign by a teacher thereby providing information to all teachers in that district. In the empirical application, we exploits several aspects of data to explore how peer’s ‘proximity’ influences behavior.

A second important component of our empirical application is that we investigate peer effects
for both adoption and repeated use. Although the information role of a colleague’s adoption on raising awareness and impacting likelihood of adoption on other teacher seems intuitive, its impact on subsequent use (conditional on adoption) is not obvious. In particular, information value from peer’s use is likely to be dominated by teacher’s own experience on the platform in previous cycle. On the contrary, large number of postings by fellow colleagues may lower the probability of getting funded, thereby discouraging use. This may particularly be true in areas where a significant proportion of donations are generated locally. Our empirical analysis isolates peer effects on adoption vs. repeated use in this ‘common-pool resources’ context.

Finally, another important feature of our empirical context is shock to the education budget following the Great recession in 2008. As detailed in Section 4 below, the timing and magnitude of budget cuts varies dramatically across U.S. geographies. We exploit this exogenous variation to examine the important role played by budget shocks on the diffusion process of this platform. More interestingly, this external variation allows us to examine heterogeneity in peer effects in adoption and repeated use decisions. In particular, it allows us to examine how scarcity of resources impact peer effects for initial adoption vs. repeated use, shedding some light on the underlying process.

We examine these issues using data from a variety of sources. As noted above, our primary data comes from the crowdfunding website, “donorschoose.org”. This data provides detailed individual level records on approximately 400,000 teachers that had used this platform at least once up to 2014. These teachers originate from approximately 90,000 schools spanning all 50 states. For each teacher, we observe the time of first use, ID and location of the school, and other attributes such as the grade and subject for which donation is solicited. We supplement this data with extensive information from the Common Core Data (CCD) at the National Center for Education Statistics (NCES); US Census Bureau (for demographic and map shape files); and data from the National Center for Charitable Statistics (NCCS). These data provide details on school finances (e.g., federal-, state-, and local-government funding), metrics on student performance in each school, and demographics (e.g., race, ethnicity, and socioeconomic status) of the population surrounding each school.

Results from descriptive analysis show budget cuts following the recession significantly im-

---

1The term is used for resources that are depletable and to which numerous common users maintain access in a ‘rivalrous’ manner. In general, common goods are “rivalrous” (one person’s use precludes another’s use) and “non-excludable” (it is difficult or impossible to exclude others from using the resource). In this particular context, one teacher’s use of platform of course does not preclude others from posting. However, a vast majority of donations are in fact local suggesting limited donation pool.

2In addition, identifying the causal effect of one’s peers’ behavior on one’s own is notoriously difficult (see, e.g., Manski 1993) but by using unique features of data to control for homophily, unobserved correlates and simultaneity problems, we can identify the casual effect of peers.
pacted the diffusion process of this crowdfunding platform. Teachers from schools that observed a sharp decline in budget were consistently more likely to adopt and use the platform. Consistent with the past literature, we find significant positive peer effects on platform adoption. The magnitude of these peer effects vary systematically based on the ‘proximity’ of peers. For example, peer effects at school level are several magnitudes stronger than district level, and teachers in similar grade within school show larger peer effects. Interestingly, peer effects on repeated use are found to be negative, suggesting crowding out effects in presence of limited local resources. In particular, post-adoption usage is found to be driven by success/failure of peers, and importantly teacher’s own outcome in the previous solicitation. Finally, peer effects for both adoption and repeated use intensify in locations with largest budget cuts. Particularly, schools that experienced major budget cuts display stronger positive peer effects for adoption, while the negative peer effects on repeated use are found to become more negative in these resource constrained locations.

We use the data patterns observed from the reduced form analysis to formulate a dynamic structural model of forward-looking teachers that make adoption and repeated use decisions. Model incorporates teacher’s initial adoption costs, expectation about funding success and future benefits, per-posting transaction costs in the post adoption period, and dynamics effects of own (reputation) and peer effects. Particularly, the dynamics of teachers’ decisions come from the fact that optimal timing of adopting and subsequent posting helps build reputation (i.e., cumulative number of the past funding success) in the market. Estimates from the structural model help us quantify the economic significance of budget cuts, and the short- and long-term multiplier effect of peer influence on the diffusion of this platform. Model estimates are used to simulate the diffusion process (adoption and repeated use) of the platform in the presence/absence of peer effects, and how peer effects change in relation to external shocks similar to those observed after recession.

The rest of the paper is organized as follows. In section 2, we review the literature related to the current work. In section 3, we discuss the data set used in this paper and show summary statistics of our focal variables. In section 4, we examine presence and nature of peer effects by using reduced form analysis and show heterogeneous peer effects by using an external shock from education budget cuts (including the impact of education budget cuts on the use of the platform). In section 5, we propose a dynamic demand model of public school teachers’ decisions (i.e., adoption and repeated use) on the online crowdfunding platform and we discuss identification and estimation strategies for the proposed model. In section 6 and section 7 discuss the estimation results and counterfactual experiments. Section 8 concludes.
2 Literature Review

This paper is related to several streams of the literature: new technology adoption and diffusion, social interaction and peer/network effects, online crowdfunding, a two-sided market, and several topics from the education economics literature on public education regarding the impact of education budget cuts on various outcomes related to students (e.g., academic performance) and teachers (e.g., teachers’ salaries).

**New technology adoption/diffusion and social interaction (peer/network effects):** The diffusion models have been based on the model developed by Bass (1969). This model considered the case of a durable good in a monopoly and investigated the aggregate purchase growth of the category in a single market (e.g., Mahajan et al. 1991). The social network was assumed to be fully connected and homogeneous. An individual in this network adopts the innovation as a result of two types of influences: external influences (i.e., advertising and other communications by the firm) and internal market influences resulting from the interaction between adopters and potential adopters in the social system. These interactions were mostly regarded as based on word-of-mouth and interpersonal communications (Mahajan et al. 1991; Mahajan et al. 2000).\(^3\) This is called an “installed-base” to capture peer effects in the early aggregate diffusion models and in more recent studies using disaggregated data (Sorensen 2006; Manchanda et al. 2008; Narayanan and Nair 2013; Iyengar et al. 2015; Uetake and Yang 2017; Toker-Yildiz et al. 2017).

Specifically, previous studies on peer effects have examined whether the strength of peer effects may differ depending on the peers’ spatial proximity (e.g., Bell and Song 2007; Bollinger and Gillingham 2012; Gardete et al. 2014; Manchanda et al. 2008), intra-group relationships (e.g., Narayan et al. 2011; Yang et al. 2006), and level of opinion leadership or network tie strength (e.g., Aral and Walker 2014; Godes and Mayzlin 2009; Iyengar et al. 2011; Nair et al. 2010).

Our paper contributes to this body of literature by demonstrating *causal* peer effects on not only platform adoption but also on repeated use decisions of public school teachers in the context of online crowdfunding platforms, which are common-pool resources. First, although measurement of causal installed-base effects from behavioral data has proven to be very challenging (Manski 1993; Narayan et al. 2011; Bollinger and Gillingham 2012), we identify causal peer effects by using a unique feature of our data, which is related to the time lag between teachers using the approach proposed by Bollinger and Gillingham (2012). Second, we demonstrate the presence and nature of peer effects in adoption and repeated use. To the best of our knowledge, Iyengar et al. (2015) studied social contagion in a new-product trial and repeated in the context of physicians’

\(^3\)This literature has been surveyed in review papers and books such as Mahajan et al. (1991), Parker (1994), and Mahajan et al. (2000).
prescribing behavior, and they found a positive impact of peer effects on both trial and repeat decisions. However, we found negative peer effects on repeated use (although we did find consistent positive peer effects on adoption), and we propose potential explanations for a negative peer impact in the context of common-pool resources.

**Online crowdfunding and two-sided markets:** This research also contributes to the emerging literature on online crowdfunding. In particular, several papers have provided descriptive evidence about investor behaviors (see, e.g., Kuppuswamy and Bayus 2018; Li et al. 2014; Mollick and Kuppuswamy 2014; Agrawal et al. 2015). For example, Burtch et al. (2013) studied donation-based crowdfunding and found evidence of a crowding-out effect, where contributors become less likely to contribute to a popular project as additional donations are perceived as less important to the recipient. Mollick and Kuppuswamy (2014) offered a description of the underlying dynamics of success and failure among crowdfunding ventures. Kuppuswamy and Bayus (2018) found that backer contributions are smaller in the middle of a funding cycle. Last, Li et al. (2014) examined the dynamics of investors’ backing behaviors in the presence of network externalities and a finite time window. Interestingly, however, none of these papers investigated fund seekers’ behaviors (those who need to get funding); rather, they focused only on the donor side. Thus, in this paper, we study adoption and usage of online crowdfunding platforms by public school teachers using novel data that allows us to investigate fund seekers’ behaviors.

Moreover, because online crowdfunding platforms are two-sided markets, we need to control for endogeneity stemming from indirect network externalities on the donor side to clearly understand teachers’ adoption and repeated use decisions. As discussed by Chu and Manchanda (2016), starting with the seminal work of Rochet and Tirole (2003), there are many studies focusing on platform economies and two-sided markets regarding platform competition, business determination, and pricing structure (e.g., Caillaud and Jullien 2003; Armstrong 2006, Rochet and Tirole 2006). A majority of empirical works on platform markets has studied offline markets, including game consoles (Clements and Ohashi 2005; Dubé et al. 2010), personal digital assistants (Nair et al. 2004), television advertising (Wilbur 2008), har and payment systems (Rysman 2004). However, not many scholars have looked into the factors determining platform evolution and growth among online customer-to-customer (C2C) platforms. Therefore, our paper extends this stream of research by investigating public school teachers’ use of online crowdfunding platforms and explains two potential factors related to platform growth: financial need and peer effects.

**Public Education:** This paper is also related to the public education literature in economics. We will not discuss all the details about the economics and education literature, but there are papers

---

4Please read Jackson (2012) for all details in these fields.
looking into how school funding is related to various educational outcomes such as academic achievement (Card and Payne 2002), dropout rates (Hoxby 2001), and adult outcomes (Heckman et al. 2013; Jackson 2012). In particular, a recent study (Jackson et al. 2018) examined how student performance responded to school spending cuts induced by the Great Recession and found that a 10 percent spending reduction during all four high-school years was associated with a drop by 2.6 percentage points in graduation rates. Given the importance of the association between school funding and student performance, it is surprising that none of the papers investigated how public schools and teachers found alternative resources to compensate for budget cuts after the recession. Thus, we provide empirical evidence for this stream of the literature regarding how teachers behave to increase funding and look into the role of peer effects in this process.

Finally, our paper contributes to structural works on demand models (e.g. Gordon 2009; Goettler and Gordon 2011; Gowrisankaran and Rysman 2012; Lee 2013; Bollinger 2015; Ishihara and Ching 2018; Liu and Ishihara 2017) by incorporating rich features into a model of teachers’ adoption and repeated use decisions about online crowdfunding platforms.

3 Empirical Context and Data

To investigate the impact of education budget cuts and peer effects on the use of online crowdfunding platforms, we assemble three different data sources from Common Core of Data (CCD), National Center for Education Statistics (NCES), and Donorschoose.org. We obtain time-varying school-level characteristics and demographics from the CCD data, time-varying district-level government funding information from the NCES data, and time-varying school-level platform adoption and usage information from the “Donorschoose.org” data. All details of each data source are described in the below.

3.1 Online Crowdfunding Platform “Donorschoose.org” Data

The most important data source is from the U.S. educational cause-based crowdfunding website “Donorschoose.org”. Donorschoose.org, founded in 2000, is an online platform that allows only public school teachers in the U.S. to post requests for funding. Donors, whose gifts are tax-deductible, can easily select projects to which to donate. The platform has raised about $434 million dollars from nearly 2.1 million donors, for over 130,000 teachers in 46,000 schools. A majority of projects request classroom supplies and books/literacy and some projects request some type of technology such as desktops, projects, laptops and etc. for classroom activities.

A teacher selects supplies from lists of approved vendors (no requests for labor or capital
improvements may be submitted). He or she writes several paragraphs regarding student needs and the purpose of the supplies, as well as posting a photograph of the classroom and students. The request’s web page includes information about the school (such as its location and poverty level) and the project (such as its subject matter and the number of students reached). Importantly, the request includes an itemized list of the materials requested, their price and quantity, and any additional charges, such as shipping, sales tax, payment processing fees, fulfillment fees, and optional support for Donorschoose.org; these projects are screened by the organization’s staff. In general, projects expire after five months (prior to 2008, the expiration period was eight months). If a project is funded, Donorschoose purchases the materials and ships them directly to the teacher to ensure quality. If the project expires prior to being funded, donors have the option to have the funds returned to their account (to select another project) or to have Donorschoose select a project for them.

Our data set includes two parts: First it includes all (approximately) 1.5 millions projects that were posted by the public school teachers from its launching in 2003 to 2014 and information specific to these projects, including the target amount, the number of students helped, the location of the school, the primary focus area of the project, the type of resource requested, the date when a project was posted and the date by which it will expire, as well as an essay by the teacher requesting the funds. Second, it includes all 2.1 million donations made from 2003 to 2014 from the donors’ side. Each donation has a donor ID that identifies an individual donor, a basket ID that allows us to link all projects supported at one donation occasion to a single donation basket as well as the date and time the donation was made and the amount contributed. Further, it includes the donor’s location (zip code) and the payment method used to contribute to the project (credit card or credit relating to previous donations that did not hit their target amount).

Although these data sets include individual-level information for both teachers and donors, we aggregate it at the school-level for three reasons. First, because we only observe the teachers who adopt the platform, we cannot study a diffusion of the platform by using the individual-level information; rather, we observe total number of registered teachers for each school so that a school-level aggregation enables us to study a diffusion the process. Second, because the online crowdfunding is a two-sided market, we need to control for indirect network externalities from the donors’ side to estimate unbiased peer effects. We aggregate the donors’ side data at the school-level, meaning that how much money are donated to the projects posted by the teachers from the same school and this enable us to control for the indirect network externalities. Last, we incorporate all school- and district-level fiscal and non-fiscal information from the other data sources with the data of “Donorschoose.org”. Thus, we combine and aggregate these two data sets.
posting of the teachers and donation of the donors to compute for any point in time time-varying adoption and usage information.

3.2 Supplement Data

In addition to “Donorschoose.org” data, we obtain fiscal (e.g., federal-, state-, and local-government funding) and demographic (e.g., race, ethnicity, and socioeconomic status) information on public schools from National Center for Education Statistics (NCES), Common Core Data (CCD) and Census Bureau.

Before explaining all details about the supplement data sets, we first briefly discuss about U.S. Public School Funding system. School funding systems vary by state, but in the typical state, the financing of K-12 education is shared roughly equally by the state and local governments (with the federal government covering less than 10 percent of the cost). On average, school funding comes from 45 percent local money, 45 percent from the state and 10 percent federal. The percentages from each source, of course, differed across the states. For example, the percentages of total revenues coming from federal, state, and local sources in New York were 8 percent, 25 percent, and 67 percent, respectively, while the corresponding total revenues in Utah were 6 percent, 90 percent, and 4 percent.

Then, what is the main source of funding for public schools? States governments rely primarily on income and sales taxes to fund elementary and secondary education. State legislatures generally determine the level and distribution of funding, following different rules and procedures depending on the state. Many states use funding formulas that provide funding based on the number of pupils in a district. Some formulas are weighted based on different factors such as the number of students with disabilities, the number of students living in poverty, or the number of students for whom English is a second language. The allocation for students with different types of needs can vary significantly depending on the funding formula. Additionally, in some states the formula is designed so that higher poverty school districts with less access to local funding receive additional assistance. Thus, there exists larger funding disparities between school districts in the state.

Similarly, property taxes support most of the funding that local government provides for education. Local governments collect taxes from residential and commercial properties as a direct revenue source for the local school district. Wealthier, property-rich localities have the ability to collect more in property taxes. Having more resources to draw from enables the district to keep tax rates low while still providing adequate funding to their local school districts. Poorer communities with less of a property tax base may have higher tax rates, but still raise less funding to support the local school district. This can often mean that children that live in low-income communities
with the highest needs go to schools with the least resources, the least qualified teachers, and substandard school facilities.

Due to the differences in resources, there are large disparities in the amount of funding that schools receive which create differences in educational opportunity. The funding disparities can be broken down into two main areas: interstate- and intrastate-disparity. First, there are significant differences in education funding across different states.\(^5\) Even when adjusted for regional variations in costs, large disparities between states exist. The disparity is caused by a number of factors, including: (1) capacity - how well off a state is based on their economy and resources, and (2) effort - the states willingness to provide funding for education. Wealthier states with a high fiscal capacity, (typically those in the Northeast), have more funding available to spend on education than states with more limited resources (typically those in the South and the West). Additionally, some states spend more of their total available funding on education. Montana, for example, is a low fiscal capacity, but high fiscal effort state. Second, there are large differences in funding among school districts within the same state. Some districts spend significantly more on education than other school districts even if they are within the same state, and sometimes only a few miles apart.\(^6\) When school districts rely on the local property tax as their primary source of funding, schools located in wealthier districts have more resources to draw from than schools in low-income communities.

Moreover, after the Great recession hit in 2008, almost every state reduced its total K-12 funding from the 2007-08 school year to 2014-15 and very few have restored funding to pre-recessions levels (Leachman et al. 2016). While federal stimulus funding helped alleviate some of the spending cuts during the 2009-10 school year, numerous districts around the country still conducted substantial budget cuts and staff layoffs (Goldhaber et al. 2016; Strunk et al. 2015). When states reduce education funding, the burden of these cuts often falls most heavily on the districts that serve greater proportions of students in poverty and emergent bilingual students (Baker et al. 2014). Meanwhile, these higher-need districts face additional costs to provide compensatory educational programs (Darling-Hammond and Lieberman 2013; Duncombe and Yinger 2008; Ladd 2012).\(^7\)

Next, to examine U.S public school funding system with school demographics, we collect data sets from National Center for Education Statistics (NCES), Common Core of Data (CCD), Census Bureau. The NCES data collections include a mixture of universe and sample surveys. Each universe survey is a census of all known entities in the specific universe (e.g., all elementary and secondary public schools or all public school districts in the country). In addition to providing

---

\(^5\) For example, in the 2014 school year, New York spent $22,366 per student while Utah spent only $6,953 per student.

\(^6\) For example, in Illinois, the New Trier Township High School District spent $21,465 per student in 2014 while the Farmington Central Community Unit School District spent only $7,259 per student.

\(^7\) We provide all details of the education budget cuts by states in the subsequent section on summary statistics.
basic descriptive data, the universe surveys frequently serve as sampling frames for cross-sectional and longitudinal sample surveys. One set of universe surveys, the Common Core of Data (CCD), is a comprehensive, annual, national statistical database of all public elementary and secondary schools and school districts, which contains data that are designed to be comparable across states. The objectives of CCD are (1) to provide an official listing of public elementary and secondary schools and school districts in the nation, which can be used to select samples for other National Center for Education Statistics (NCES) surveys, and (2) to provide basic information and descriptive statistics on public elementary and secondary schools and schooling in general. Specifically, there were 18,260 operating LEAs in 2014, including 487 new agencies that opened for the first time. Most operating agencies were regular ones (13,601) that were responsible for educating students residing within their jurisdiction. A total of 1,383 operating agencies were supervisory unions or regional education service agencies that typically provided services to other LEAs. A total of 2,868 were independent charter agencies in which all the associated schools were charter schools. An additional 408 agencies were operated by a state, federal, or other agency. CCD collects the LEA mailing address, telephone number, and type. The survey includes, for the current year, the total number of students enrolled (membership) in prekindergarten through grade 12 (with counts within grade level by race/ethnicity and sex); number of ungraded students; number of English language learner (ELL) students served in appropriate programs; and number of instructional, support, and administrative staff. Moreover, the surveys of the CCD system include data such as enrollment, grades levels, minority population, and poverty level, from all public schools and local education agencies. The CCD also collects school and local education agency finance data, as well as teacher-level data on salaries and compensation. It also includes the number of high school graduates, other completers, and grade 7-12 dropouts.

Last, we assemble all these different data sets to collect information on the detailed school- and district-level time-varying fiscal and non-fiscal variables and also public school teachers’ use of the online crowdfunding platform. Thus, this novel and unique data set enables us to study the impact of education budget cuts and peer effects on the adoption and repeated use of the online crowdfunding platform.

3.3 Summary Statistics

In this section, we provide an overview of patterns in our data sets based on summary statistics of key variables regarding a diffusion and usage process of the online crowdfunding platform. We first explain how to measure the outcome variables - (a) a share of the adoption and (b) a share of the repeated use - and then we show descriptive evidence of the diffusion process.
3.3.1 Use of “Donorschoose.org”

We describe general patterns of U.S. public school teachers’ use of the online crowdfunding platform Donorschoose.org. First, we compute a cumulative share of adoption from 2003 (the initial year of the platform’s launch) to 2014 at the school level as follows:

\[
\text{Cumulative Share of Adopted Teachers}_h = \frac{1}{N_h} \sum_{t=2003}^{2014} \sum_{i \in h} 1(\text{Adoption}_{it}),
\]

where \(i\) denotes teacher, \(h\) denotes school, and \(t\) denotes time unit (i.e., year). \(1(\text{Adoption}_{it})\) is an indicator that is equal to 1 if teacher \(i\) at school \(h\) who adopted the platform at time \(t\) and 0, otherwise. \(N_h\) is the total number of registered teachers at school \(h\). Thus, this metric describes a cumulative total number of teachers at school \(h\) from 2003 to 2014.

![Distribution of Cumulative Share of Adoption](image)

**Figure 2: Distribution of Cumulative Share of the Adoption**

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cum. Share of Adoption Teachers per school (as of 2014)</td>
<td>91,399</td>
<td>0.145</td>
<td>0.231</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Cum. Share of Adopting Schools (as of 2014)</td>
<td>91,399</td>
<td>0.596</td>
<td>0.043</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

**Table 1: Summary Statistics of Cumulative Share of the Adoption**

As shown in Figure 2 and Table 1, as of 2014, on average, 14.5% of public school's teachers, per
school, had used this platform at least once. We look into the status of the school’s adoption of the platform by counting the total number of schools with at least one teacher who has adopted the platform. Also, on average, 59.6% of the U.S. public schools have at least one teacher who has adopted this platform as of 2014. We observe from the above figures and tables that many public school teachers use this online crowdfunding platform to get funding for their classroom activities.

![Map of the United States showing the cumulative share of adopted teachers at the county-level](image)

**Figure 3: Cumulative Share of Adopted Teachers (per school) at the County-level (as of 2014)**

Next, we look at a geographical variation of the cumulative share of the adoption in all states. **Figure 3** shows a geographical variation of the cumulative share of the adoption at the county-level. We observe that teachers located in the southern and western states are more likely to adopt the platform. We will show this in the subsequent section, but it is clear that the schools in the southern and western states receive lower levels of funding from the federal, state, and local governments, and financial needs might lead teachers in those areas to adopt and to use the platform. This platform originated in New York, New York, so at the early stage, many teachers around the New York area started to use this platform, and this area still shows a higher level of adoption compared to other areas. Aside from the New York area, we can also see that the southern and the western states show the highest level of adoption and will explain the reasons for this.

---

8 We have a cumulative share of adoption at the school-level but for the visualization purpose, we show it at the county-level.
3.3.2 Measurements of the Adoption and Repeated Use

In order to measure the adoption, we compute the share of teachers who adopted the platform in school $h$ that had not previously adopted online crowdfunding and decide to adopt on time $t$ as follows:

$$\text{Share of New Adopting Teachers}_{ht} = \frac{1}{N_h} \sum_{i \in h} 1(\text{Adoption}_{it} | \text{non-adoption}_{it-1})$$

(2)

where $i$ denotes the teacher, $h$ denotes the school, and $t$ denotes the time unit (i.e., year). $1(\text{Adoption}_{it} | \text{non-adoption}_{it-1})$ is an indicator that is equal to 1 if teacher $i$ at school $h$ who had not previously adopted the platform by time $t-1$ adopts it at time $t$. $N_h$ is the total number of teachers at school $h$. Thus, this metric describes the fraction of teachers who adopted the platform in school $h$ that had not previously adopted it.

Similarly, we compute the share of teachers who repeatedly used the platform in a school $h$ that had adopted the platform by time $t-1$ and decided to use it again on time $t$ as follows:

$$\text{Share of Repeated-use Teachers}_{ht} = \frac{1}{M_{ht-1}} \sum_{i \in h} 1(\text{Repeat}_{it} | \text{adoption}_{it-1})$$

(3)

where $i$ indicates the teacher, $h$ indicates the school, and $t$ indicates the time unit (i.e., year). $1(\text{Repeat-use}_{it} | \text{adoption}_{it-1})$ is an indicator that is equal to 1 if teacher $i$ at school $h$ who had previously adopted the platform by time $t-1$ repeats use of the platform at time $t$. $M_{ht-1}$ is the total number of teachers who had adopted the platform at school $h$ by time $t-1$.

Figure 4 presents the results of our outcome key variables: share of adoption and share of repeated use. There are two important things to highlight: (1) the share of adoption increases over time, implying that teachers who had not previously adopted the platform are more likely to adopt it over time. Particularly, we observe rapid usage increase after the Great Recession, and as of 2014, on average, 4.6% of the teachers at a given school had adopted the platform in that year. (2) Conversely, the share of repeated use shows a flat pattern at the beginning but turns into an increasing pattern after the recession. For example, as of 2014, on average, 12.5% of the teachers who adopted the platform by 2013 at a given school repeated use the platform. In this section, we only show general patterns of our outcome variables, but in the subsequent sections, we investigate in detail the reasons these variables show such patterns.

We provide all details about a growth patterns for both teachers and donors over time in the appendix.

9

pattern in the subsequent section.
4 Peer Effects

We aim to understand a diffusion process of the platform and one of the key factors is peer effects, meaning that an individual teacher’s behavior is likely to be influenced by actions of her peers. Thus, in this section, we examine causal peer effects on public school teachers’ adoption and repeated use of the online crowdfunding platform. We start by explaining how we define and measure the peer effects. Showing the presence of the causal peer effects is notorious, so we explain all details of our identification strategies to demonstrate the causal peer effects. Next, we show that peer effects play a different role in teachers’ various decisions-platform adoption and repeated use. By using both aggregated and individual-level data sets, we document how peer effects influence the teachers’ adoption and repeated use decisions, show how proximity of peers does matter, and suggest potential mechanisms to explain these effects. Last, we document the existence of heterogeneous peer effects, meaning that the magnitude of peer effects vary across locations and time. By using an exogenous shock (i.e., education budget cuts after the recession) to shift demands of the online crowdfunding platform, we identify how the peer effects are heterogeneous at different times and locations. In short, confirming the findings in previous literature, we find strong positive peer effects on adoption decisions indicating the information role played by an experienced colleague. However, peer effects on repeated use are found to be negative, highlighting the common-core nature of this context as teachers compete for limited (primarily local) donors. Moreover, there is a stronger impact of school-level than district-level peers and similarly, a stronger impact of same grade (within the school) peers, meaning that proximity of peers impacts behavior.
We start with providing preliminary empirical evidence of peer effects. If there are indeed peer effects in the diffusion of the online crowdfunding platform, we would expect to see the new adopters mainly come from the same school where some teachers have already adopted the platform. Below, we present why peer effects might play a role in the diffusion process of the online crowdfunding platform.

Figure 5: Evidence of Peer Effects

Figure 5 presents the growth pattern of Donorschoose.org from 2003 to 2014. The left figure shows the total number of “new teachers” who are first-time adopters each year. We observe a clear growth pattern showing that the total number of new teachers who adopt the platform had increased over time. The right figure illustrates the total number of “new schools” that have a teacher (or teachers) who are first-time adopters of the platform and that had not previously had any teachers adopt the platform, in each year. Interestingly, the total number of “new teachers” constantly increased, whereas the total number of “new schools” increased until 2010 and decreased after that. This result implies that a majority of “new teachers” come from schools where other teachers have already adopted the platform. Of course, this result does not guarantee the presence of peer effects in the diffusion process, but we rigorously investigate the presence and nature of peer effects in the subsequent sections.}

10Moreover, we look into a teacher individual-level data to find evidence of peer effects. Interestingly, we observe 26,658 teachers (approximately 10% of total number of teachers in our data) who transferred from one school to another during the data observation period. Among those teachers, 9,429 (i.e., 30%) were the first teacher who use this platform at the transferred school. We exploit this (exogenous) variation to examine the diffusion process. If network effects is important in the diffusion process, the other teachers at the new school are more likely to adopt this platform after the
4.1 Identification Strategy

Measurement of causal installed-base effects from observational data is very challenging. The three well-known problems that often confound identification of peer effects are endogenous group formation leading to self-selection of peers (homophily), correlated unobservables, and a particular type of simultaneity called “reflection” in which agents’ behaviors affect each other (Manski 1993; Moffitt et al. 2001; Soetevent 2006). Hartmann et al. (2008) discuss some of the different modeling and estimation strategies to avoid these issues. The third issue, reflection, is eliminated by focusing on the effect of the installed base on future adoption and defining the installed base as the set of agents in the relevant peer group who have previously adopted the product, just as in the classical aggregate diffusion models. The other main issues, homophily and correlated unobservables, can be controlled for with sufficient data using a rich set of random or fixed effects. In the case of random effects, misspecification of the distribution can lead to severely biased estimates, and the use of these estimators rely on the questionable assumption that the random effects are independent of the included regressors. Therefore, fixed effects are preferred to random effects because they do not rely on these distributional or independence assumptions. But, as discussed in Narayanan and Nair (2013), the traditional fixed-effects estimator leads to inconsistent estimates when the regressors are either correlated with or direct functions of the lagged dependent variable, as is the case for the installed base (Nickell 1981).

To identify causal peer effects after controlling for the above three issues-homophily, correlated unobservables, and reflection—we follow the approach suggested by Bollinger and Gillingham (2012), which leverages the fact that the decision to install solar panels does not lead to instantaneous installation, due to the time needed to perform the installation. Our data setting is very similar to their setting because the public school teachers’ decision to adopt and to use the platform does not lead to immediate adoption and repeated use; rather, time lags exists between when they make those decisions and when those decisions are executed. This means that a demand shock in the previous time period that leads more people to request a platform adoption and repeated use would not be immediately reflected in the installed base. Thus, our approach leads to consistent estimates of the peer effect even in the presence of correlated unobservables. By using a first-differences estimator with observations at the school and year level, we can avoid a correlation between the experienced teachers came. We present this result in the appendix section. The teachers in the schools which have an experienced (and transferred) teacher are more likely to adopt the online crowdfunding platform within 1 year compared to the other schools which do not have an experienced (and transferred) teacher (i.e., 18.95 new adopters in the schools having an experienced (and transferred) teacher and 7.2 new adopters in the schools not having an experienced teacher. Thus, this is another evidence that peer effects play a key role in the growth of this platform.
first-differenced installed base and the first-differenced unobservables. The specification is as follows:

\[ Y_{ht} = \beta_0 + \beta_1 \text{Installed-base}_{ht} + \beta_2 \text{Installed-base}_{dt} + X_{ht} + \xi_h + \eta_{st} + \epsilon_{ht} \]  

where \( h \) indexes the school, \( d \) indexes the school district, \( s \) indexes the state, and \( t \) indexes the time unit (i.e., year). The dependent variables, \( Y_{ht} \), are (1) the share of public school teachers who decide to adopt, for the first time, the platform at school \( h \) (located in the district \( d \) and the state \( s \)) at time \( t \) and (2) the share of public school teachers who had adopted the platform and decided to re-post the project on the platform at school \( h \) (located in the district \( d \) and the state \( s \)) at time \( t \). The independent variables include the installed-base peer effects; time-varying, school-level characteristics; time-varying, district-level finance information; time-varying, school-level, indirect network externalities; and rich sets of fixed effects.

We have two installed-base peer effects for different reference groups - (1) school and (2) district and these variables are defined as \( \text{Installed-base}^{Adoption}_{ht} = \sum_{\tau=1}^{t-1} \sum_{i \in h} 1(\text{adoption}_{i\tau}) \), describing a total number of teachers who had adopted and completed at school \( h \) and time \( t - 1 \), where \( i \) indexes the teacher and \( 1(\text{adoption}_{i\tau}) \) is an indicator that is equal to 1 if teacher \( i \) in the school \( h \) had adopted and completed the platform at time \( \tau \). Similarly, \( \text{Installed-base}^{Adoption}_{dt} = \sum_{\tau=1}^{t-1} \sum_{i \in d} 1(\text{adoption}_{i\tau}) \), describing a total number of teachers who had adopted and completed at district \( d \) and time \( t - 1 \). Again, we only count teachers who already adopted the platform to deal with a reflection problem.

By using the time lags that exist between when teachers make the adoption decision and when that decision is executed, we could resolve issues driven by the reflection problem. Similarly, when we investigate another dependent variable, posting decision (conditional on the adoption), the installed-base peer effect is defined as \( \text{Installed-base}^{Repeat}_{ht} = \sum_{\tau=1}^{t-1} \sum_{i \in h} 1(\text{Repeat}_{i\tau} | \text{adoption}_{i\tau-1}) \), indicating a total number of teachers “who had adopted and completed to post the project” at school \( h \) and time \( t - 1 \), where \( i \) indexes the teacher and \( 1(\text{Repeat}_{i\tau} | \text{adoption}_{i\tau-1}) \) is an indicator that is equal to 1 if teacher \( i \) in the school \( h \) had adopted and posted the project at time \( \tau \) and we also have the peer effects variable at district level for the repeat use decision.

The other independent variables, \( X_{ht} \), are demographics such as time-varying, school-level characteristics such as poverty and race/ethnicity background, which are measured by a proportion of the free lunch-eligible students and the proportion of nonwhite students at school \( h \) and time \( t \), respectively; time-varying, district-level characteristic measured by per-pupil spending; and time-varying, school-level, indirect network externalities, which are measured by total donation amount of the teachers who adopted the platform at school \( h \) and time \( t - 1 \), which is defined
as \( \text{Donation}_{ht} = \sum_{i \in h} \log(\text{Donation})_{it-1} \), describing the total amount of funding for teacher \( i \) who adopted the platform at school \( h \) and time \( t - 1 \). In other words, this measurement would have potential benefits that the other colleagues who had not previously adopted the crowdfunding platform by the time \( t \) in the school \( h \) would expect when they adopt the platform.

Note that the \( \text{Donation}_{ht} \) (i.e., indirect network externalities) variable is obviously endogenous because an online crowdfunding market is a two-sided market. In other words, the total amount of funding from the colleagues at school \( h \) and time \( t - 1 \) is simultaneously determined by the number of platform adopters at school \( h \) and time \( t - 1 \). To deal with the endogeneity of the indirect network externalities, we exploit the instrument variable approach. We find instruments that are highly correlated with the indirect network externalities but not correlated with the fraction of the adoption, which is the dependent variable, satisfying the exclusion restriction assumption. The instruments are a lagged variable of total donations to the projects posted by the same school teachers and a time-varying “revenue” (including gifts and grants) from the 501(c)(3) public charities and private foundations at the state-year level.\(^{11}\) In fact, approximately 40% of the donations for a certain project come from local donors, meaning that donors are more likely to donate to local projects (which is well known as home bias in the online crowdfunding literature). For this reason, we consider that the revenue from the 501(c)(3) public charities and private foundations is highly correlated with the total donation amount (which might mainly come from local donors) but not correlated with the dependent variable, the fraction of the adopted and repeated use teachers at the school.

Then, we include rich sets of fixed effects such as school and state-year combination. The school-level fixed effects (i.e., \( \xi_h \)) capture cross-sectional variations across schools that might affect the fraction of the adoption. Similarly, the state-year fixed effects (i.e., \( \eta_{st} \)) capture all unobserved demand shocks varying across times within the state. The \( \epsilon_{ht} \) is a mean zero independent and identically distributed random error term.

As we mentioned above, to avoid a correlation between the first-differenced installed base and the first-differenced unobservables, we use a first-differences estimator with the following specification:

\[
\Delta Y_{ht} = \beta_1 \Delta \text{Installed-base}_{ht} + \beta_2 \Delta \text{Installed-base}_{dt} + \Delta X_{ht} + \Delta \eta_{st} + \Delta \epsilon_{ht}.
\]

(5)

Bollinger and Gillingham (2012) show that when the time lag between the adoption (repeated use) decision and the completion of the adoption (repeated use) is greater than the order of

\(^{11}\text{We collect this data from National Center of Charitable Statistics (NCCS). We have only state-year variations and this is the finest unit of analysis from the data.}\)
autocorrelation of $\epsilon$, and the peer effects do not initiate until the adoption is completed, then $\beta_1$ is consistently estimated.\textsuperscript{12} We present the estimation results of Equation 4 and 5 in the next section.

4.2 Peer Effects on the Platform Adoption and the Repeated Use

In this section, we show empirical evidence to understand the role of peer effects in the public school teachers’ decisions on the adoption and repeated use of the online crowdfunding platform. As we described above, we estimate Equation 4 and 5, and the results support our argument that the peer effects play a different role in the platform adoption and repeated use decisions, respectively.

4.2.1 Platform Adoption

\begin{table}[h]
\centering
\begin{tabular}{lll}
\hline
Variables & (1) & (2) \\
 & Model1 & Model2 \\
 & (Fixed Effects) & (First-differenced) \\
\hline
Installed-base (School) & 0.251*** & 0.535*** \\
 & (0.011) & (0.039) \\
Installed-base (District) & 0.038*** & -0.014 \\
 & (0.007) & (0.035) \\
Demographics controls & Yes & Yes \\
Fixed Effects & & \\
School & Yes & No \\
State-year & Yes & Yes \\
Observations & 799,460 & 684,321 \\
R-squared & 0.650 & 0.326 \\
\hline
\end{tabular}
\caption{Results of Peer Effects on the Platform Adoption}
\end{table}

Table 2 shows the estimation results of peer effects on the platform adoption decision. Column (1) contains the estimation results of Equation 4 using traditional mean-differenced school- and time-fixed effects, and column (2) shows the estimation results of Equation 5 using a first-differenced approach.\textsuperscript{13} The key parameter of interest is the $\beta_1$, which is the coefficient of the peer effects at

\textsuperscript{12}The details of the proof are in Bollinger and Gillingham (2012).

\textsuperscript{13}In fact, a time unit of our main analysis is year, but it is hard to test whether the time lag between the adoption (repeated use) decision and completion of the adoption (repeated use) is greater than degrees of autocorrelation of $\epsilon$ because, on average, the time lag is 110.7 days for the adoption and 109.3 days for the repeated use decisions. Thus, for this test, we reconstruct the data with a three-month time unit, so in this new dataset, $t$ is three months. Similar to Bollinger and Gillingham (2012), in the fixed-effects regression, we find positive and statistically significant autocorrelation for the first lag only (i.e., three months), and in the first-differenced regression, we find a negative and
the school-level, and it is positive and significant at the 95% confidence level. This result implies that the peer effects have a positive impact on teachers’ platform adoption decisions, and every additional adoption increases the share of adoption in the same school by 0.251%. In other words, as more colleagues within the same school adopt the platform, the remaining teachers are more likely to adopt the platform in the subsequent time period. Interestingly, we find that the peer effects at the district level also have a positive impact on the adoption but the magnitude of the coefficient is smaller than the school one, indicating that the school-level peer effects have a stronger effects than the district-level so that proximity of peers does matter.\footnote{However, we cannot find significant peer effects at the district level in the first-difference regression. Given this limited result, we claim that peer effects from different reference groups might have different impact on the adoption decision but the magnitude might be downward biased.} Also, note that, consistent with the previous studies (Bollinger and Gilingham 2012; Narayanan and Nair 2012), results of the mean-differenced fixed effects are biased downward, meaning that a magnitude of the peer effects’ coefficient is smaller than that of the first-differenced result.

Moreover, we investigate the teacher individual-level data to show further evidence of proximity of peers.\footnote{Of course, there is a limitation by looking into the individual-level data because we only observe the teachers who adopted the platform so that the analysis sample is a selected one.} We first construct the teacher-level panel data and estimate a linear probability model that the dependent variable is an indicator, \(1\{Adoption_{it}\}\), which is equal to 1 if teacher \(i\) adopts the platform at time \(t\) and 0, otherwise. To see proximity of peers, we run a regression for the teachers from the Pre-K to the 8th grade (within the school) and from the 9th to the 12th grade (within the school), separately. Table 3 presents the results. Column (1) contains the result of the teachers from the Pre-K to the 8th grade and column (2) contains the result of the teachers from the 9th to the 12th grade. Interestingly, the coefficient of the same grade’s installed-base (within the school) variable has a greater magnitude than the different grade’s one (e.g., 0.154 [Pre-K ∼ 8th grade] versus 0.076 [9th ∼ 12th grade] for the teachers from the Pre-K to the 8th grade). In other words, teachers from same grade are more likely to have a stronger positive impact on the adoption decision than different grade’s teachers. Thus, this result demonstrates that proximity of peers impacts behavior.

4.2.2 Repeated Use

Next, we investigate how peer effects affect the repeated use decision of the teachers who adopt the platform. Again, we estimate Equation 4 and 5 by using mean-differenced fixed effects and first-significant correlation for the first lag only (i.e., three months). This demonstrates that the order of autocorrelation is much less than the time lag between adoption (repeated use) and completion.
Table 3: Results of Peer Effects on the Platform Adoption (Individual-level Analysis)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model1</th>
<th>Model2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DV: $\mathbb{I}{Adoption_{ij}}$ (PreK $\sim$ 8)</td>
<td>DV: $\mathbb{I}{Adoption_{ij}}$ (9 $\sim$ 12)</td>
</tr>
<tr>
<td>Installed-base (PreK $\sim$ 8)</td>
<td>0.154*** $(0.004)$</td>
<td>0.020** $(0.009)$</td>
</tr>
<tr>
<td>Installed-base (9 $\sim$ 12)</td>
<td>0.076** $(0.034)$</td>
<td>0.301*** $(0.011)$</td>
</tr>
<tr>
<td>Demographics controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Teacher</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>1,313,512</td>
</tr>
<tr>
<td></td>
<td></td>
<td>255,128</td>
</tr>
<tr>
<td></td>
<td>R-squared</td>
<td>0.681</td>
</tr>
</tbody>
</table>

Note: (1) Demographics controls include time-varying school characteristics such as % of free-lunch students and % of non-white students, time-varying district finance, and time-varying total donation for the projects posted by the same school teachers. (2) School-district-level clustered standard errors in parentheses. (3) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

differenced approach, respectively. Table 4 presents the results. Column (1) contains the result from the fixed effects estimation, and column (2) contains the result from the first-differenced estimation. Our key parameter of interests is the coefficient of peer effects (i.e., $\beta_1$), which is measured by using the total number of teachers who reused and completed the project conditional on the adoption. Interestingly, it shows a negative and significant coefficient, which is opposite to the platform adoption decision. The result is consistent across different approaches. The correct interpretation is that the peer effects have a negative impact on the repeated use decision (conditional on the adoption), and every additional repeated use decreases the share of teachers who repeat to the project in the same school by 0.877%. In other words, as more colleagues who adopted the platform within the same school post the project, the remaining teachers are less likely to post the project in the subsequent period.\footnote{Although the coefficient of peer effects at the district-level is positive and significant, its magnitude is much smaller than the one of peer effects at the school-level. In addition, similar to the platform adoption decision, we investigate the teacher-level panel data to see proximity of peers within the school and find asymmetric peer effects between grades, meaning that teachers from same grade are more likely to have a stronger negative impact on the repeated use decision than different grade’s teachers.}

This negative peer effect on the repeated use of the platform is counter-intuitive because it is opposite to the findings in the previous studies (e.g., Dulleck and Kerschbamer 2006; Nitzan and Libai 2011; Haenlein 2013; Iyengar et al. 2015). These works document the fact that peer influence may positively affect not only trial behavior but also repeat behavior in various contexts. Particularly, Iyengar et al. (2015) found that in the context of new drug prescription behavior by
physicians, positive social contagion exists in both trial and repeat behaviors. They suggest several potential explanations, one of which is that when learning about product quality from personal experience is a slow process, and additional information is necessary, customers may rely on peers as a source of information for not only trial but also repeat decisions. Another explanation is that environmental shocks can raise new doubts about a previously accepted product, making users who had previously used the product again susceptible to informational influence from peers, as suggested by Nair et al. (2010).

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Model1 (Fixed Effects) DV: Share of Repeated Use</th>
<th>(2) Model2 (First-differenced) DV: Share of Repeated Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>Installed-base (School)</td>
<td>-0.877***</td>
<td>-1.511***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Installed-base (District)</td>
<td>0.062***</td>
<td>0.022***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Demographics controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>State-year</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>209,750</td>
<td>201,332</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.519</td>
<td>0.390</td>
</tr>
</tbody>
</table>

Note: (1) Demographics controls include time-varying school characteristics such as % of free-lunch students and % of non-white students, time-varying district finance, and time-varying total donation for the projects posted by the same school teachers. (2) School-district-level clustered standard errors in parentheses. (3) *** p<0.01, ** p<0.05, * p<0.1

Table 4: Results of Peer Effects on the Repeated Use

However, our context is somewhat different from the previous studies in several aspects, and we think these differences explain the positive impact of peer effects on the platform adoption as well as the negative impact of peer effects on the repeated platform use. First, the online crowdfunding platform is easy to learn about, including all of its features and attributes, if teachers adopt it. Thus, conditional on the adoption, peers’ use of the platform does not provide any source of information; rather, teachers’ own adoption experiences might have a bigger impact on the repeated use decision. Second, the probability of getting funding is contingent on the peers’ use (similar to common-pool resources), so the teachers’ repeated use is dependent on the peers’ behavior. For example, teachers might learn from the adoption decision that if too many projects are posted at the same time, the probability of funding is decreased, so peer effects might affect the subsequent project posting through peer pressure. Because teachers might think that the size of the potential donation pool is limited (e.g., again, due to the home bias), they need to optimize their repeated use decision by considering their peers’ usage. Unlike the context of prescription behaviors by physicians, where the repeated use is not contained by others’ behavior and thus peer effects are not necessary to
form any pressure, in our context, peer effects affect the remaining teachers’ usage decisions due to the limited “pie.” Therefore, we speculate that these contextual differences drive the negative impact of peer effects on the repeated use (conditional on the adoption).

Specifically, we claim that a potential explanation of the negative impact of peer effects comes from interactions between teachers’ individual experience and colleagues’ experience regarding success (i.e., whether they get funding or not). On the online crowdfunding platform, the teachers’ reputations (i.e., how many projects they post and how successful they are) is one of the key elements to increase the probability of funding, so teachers tend to choose the optimal timing of repeated use to maximize it. If teachers post too many projects but do not have success, their reputation might be diminished, and the probability of funding for subsequent projects dramatically decreases.\footnote{In general, the donors can see information on the teacher’s posting regarding how many projects he or she has posted and how successful the campaigns have been.} Thus, teachers are more likely to be sensitive not only to their own experience but also peers’ use and experience of the platform. In this case, peer effects do not provide any additional information sources on the platform; rather, they provide peer pressure to the remaining teachers, so we can observe the negative impact of peer effects. In the subsequent section, we test this potential explanation of the negative impact of peer effects by using an individual-level teachers’ repeated use data.

4.3 Potential Mechanism

In the previous section, confirming the findings in previous literature, we find strong positive peer effects on adoption decisions indicating the information role played by an experienced colleague. However, peer effects on repeated use are found to be negative, highlighting the common-core nature of this context as teachers compete for limited (primarily local) donors. Particularly, negative peer effect on the repeated use of the platform is counter-intuitive and a potential explanation of the negative impact of peer effects could come from interactions between teachers’ individual experience and colleagues’ experience regarding success (i.e., whether they get funding or not).

To test whether this potential explanation is valid, we need to control for interactions between the teachers’ individual experience and their colleagues’ experience regarding success. We specifically consider four possible scenarios based on a combination of the status of the teachers’ individual success and the colleagues’ success and see how peer effects are influenced as the following Figure 6. Scenario (D), in which the teacher does not have his or her own successful experience and none of his or her colleagues have had success, is set as a baseline case, and we compare all of the remaining possible cases to it. In scenario (A), wherein teachers are successful
and also observe their colleagues being successful, we anticipate that teachers are more likely to use the platform because they believe that a potential success probability is high from their own and others' previous successful experiences. Next, in scenario (B), in which teachers have success but others do not have success from their adoption decision, we conjecture that the successful teachers are still likely to use the platform because their own experience has a bigger impact on their repeated use decision, so their belief regarding the potential outcome of the project posting is positive. Finally, in scenario (C), in which teachers did not have success but their colleagues were successful, we think that teachers are less likely to use the platform because they might feel uncertainty regarding future potential outcomes due to peer pressure.

<table>
<thead>
<tr>
<th></th>
<th>Peer Success</th>
<th>Peer Non-success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual Success</td>
<td>(A)</td>
<td>(B)</td>
</tr>
<tr>
<td>Individual Non-success</td>
<td>(C)</td>
<td>(D)</td>
</tr>
</tbody>
</table>

Figure 6: Four possible Scenarios

To analyze this situation, we look into the individual, teacher-level data. In this data set, we observe all of the teachers’ repeated posting behaviors (those who already adopted the platform) and the outcomes of their posted projects (i.e., whether they get funding or not) so that we can investigate a potential explanation, as we suggested. In particular, we estimate the following specification:

\[
Y_{it} = \beta_0 + \beta_1 \text{Peer-Effects}_{it} + \beta_2 \mathbb{1}\{\text{Individual-Success}\}_{it} + \beta_3 \mathbb{1}\{\text{Peer-Success}\}_{ht} + \beta_4 \mathbb{1}\{\text{Individual-Success}\}_{it} \times \mathbb{1}\{\text{Peer-Success}\}_{ht} + \beta_5 \text{Controls}_{it} + \mu_t + \kappa_h + \epsilon_{it}
\]  \hspace{1cm} (6)

where \(i\) indicates the teacher, \(h\) indicates the school, and \(t\) indicates the time (i.e., year). The dependent variable \(Y_{it}\) is a binary variable equal to 1 if teacher \(i\) reuses the project at time \(t\) conditional on the adoption by \(t - 1\), and it is 0 otherwise. The independent variables include \(\mathbb{1}\{\text{Individual-Success}\}_{it}\), which is an indicator of whether teacher \(i\) has at least one successful experience by time \(t\) (i.e., indicating whether the teacher is a cumulatively successful teacher by time \(t\)) and \(\mathbb{1}\{\text{Peer-Success}\}_{ht}\), which is also an indicator of whether teacher \(i\)'s school has at least one teacher who has had a successful project by time \(t\) (i.e., an indicator of whether the school has cumulative successful teachers by time \(t\)). We also include other time-varying control variables such as school characteristics and district-level finance information. Last, we control for time- and school-fixed effects to absorb unobserved, time-varying, common factors and permanent.

\(^{18}\)If the public school teachers do not adopt the platform, we cannot observe them in our data set. We only observe teachers who adopt the platform, meaning that they use this platform at least once.
school-level factors that might affect teachers’ repeated posting decisions. Note that we estimate a linear probability model for the repeated use decision, which allows us to circumvent the identical parameters problem that would lead to inconsistency in a probit model with fixed effects (e.g., Angrist 2001).

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Model1</th>
<th>(2) Model2</th>
</tr>
</thead>
<tbody>
<tr>
<td>DV: Repeated Use</td>
<td>DV: Repeated Use</td>
<td></td>
</tr>
<tr>
<td>Peer Effects</td>
<td>-0.263***</td>
<td>-0.268***</td>
</tr>
<tr>
<td>0.019</td>
<td>0.020</td>
<td></td>
</tr>
<tr>
<td>Individual-Success $_{it}$</td>
<td>0.102***</td>
<td>0.036***</td>
</tr>
<tr>
<td>0.002</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>Peer-Success $_{ht}$</td>
<td>0.051***</td>
<td>-0.010***</td>
</tr>
<tr>
<td>0.003</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>Individual-Success $<em>{it}$ × Peer-Success $</em>{ht}$</td>
<td>0.097***</td>
<td></td>
</tr>
<tr>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographics controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year</td>
<td>Yes</td>
</tr>
<tr>
<td>School</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>744,690</td>
<td>744,690</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.198</td>
<td>0.201</td>
</tr>
</tbody>
</table>

Note: (1) Demographics controls include time-varying school characteristics such as % of free-lunch students and % of non-white students, time-varying district finance, and time-varying total donation for the projects posted by the same school teachers. (2) School-district-level clustered standard errors in parentheses. (3) *** p<0.01, ** p<0.05, * p<0.1

Table 5: Teacher-level Regressions after Controlling for Individual- and Peer-Success

Table 5 presents the results (and Figure 7 visualize its effects). Our key parameters of interest are the coefficients of the two indicators of individual and peer success and their interaction term (i.e., $\beta_2$, $\beta_3$, and $\beta_4$, respectively). We emphasize several interesting results: First, we obtain consistent results with the estimation of the aggregated-level data that peer effects have a negative impact on repeated use decisions. In other words, as more colleagues within the same school use the crowdfunding website, the other teachers (who already adopted the platform) are less likely to post a new project. Second, the individual-success indicator (i.e., $\beta_2$) shows a positive and significant coefficient, implying that when teachers have their own past successful experience, they are more likely to use the platform again. This is consistent with our explanation of scenario (B) in Figure 6, meaning that an individual successful experience has a bigger impact on the repeated use decisions because teachers’ expectation of the market potential would be positive (despite observation that their colleagues did not have success). Third, on the contrary, the coefficient of the peer-success indicator (i.e., $\beta_3$) is negative and significant, meaning that if teachers do not have their own successful experience and observe the peers’ success, they are less likely to post the project. This is consistent with our explanation of scenario (C) in Figure 6 that, due to their own negative experience, teachers are uncertain about the potential benefit of using the platform. At the same
Figure 7: Marginal Effects between Individual- and Peer-Success

time, all peers’ usage plays a role as *pressure* rather than information sources. Therefore, the peers’ success has a negative impact on the repeated use decision. Finally, the coefficient of the interaction term between the two indicators of individual and peer success (i.e., $\beta_4$) is positive and significant, implying that teachers who have their own success and observe the colleagues’ success might have a stronger belief in the market potential and, thus, are more likely to repeat use of the platform. Particularly, the magnitude of this parameter is much greater than the parameters of the individual and peer success (i.e., the marginal effects of this term are greater than those of the other two). This means that a combination of individual and peer success leads the teachers to anticipate that the market potential is large, so they tend to use the platform, which is consistent with our explanation of scenario (A).

### 4.4 Heterogeneous Peer Effects

In the previous sections, we demonstrate causal peer effects and their different roles with regard to platform adoption and repeated use. The main finding is that peer effects have a positive impact on platform adoption and a negative impact on repeated use. Based on this finding, in this section, we additionally investigate heterogeneous peer effects on our focal dependent variables - platform adoption and repeated use. Particularly, we exploit education budget cuts after the recession as an exogenous shock to identify heterogeneous peer effects, meaning that we look into interaction effects between education budget cuts and peer effects. Note that budget cuts create a unique situation similar to resource scarcity. It is not straightforward to answer the question with regard to
how the impact of peer effects changes in scarcity. Do peer effects become salient (or less prominent) when resources are scarce? The previous literature on scarcity finds equivocal patterns that people could be both cooperative and competitive when resources are scarce. The idea is that people are likely to cooperate with each other to overcome the constraints, but at the same time, people tend to compete with each other for limited resources. In our context, the education budget cuts after the recession naturally created a scarcity situation, and we use this external shock to identify how peer effects are changed by this scarcity situation.

4.4.1 Impact of Recession and Budget Cuts

Before analyzing heterogeneous peer effects, we first provide empirical evidence for the education budget cuts across states and times and how this policy change affects teachers’ behavior to find alternative resources to compensate for lack of funding by measuring the overall effect of the education budget cuts after the Great Recession on public school teachers’ adoption and usage of the online crowdfunding platform. By using the school-level aggregated data, we document that online crowdfunding platforms, in fact, could be one of the potential alternative resources to compensate for drastic budget cuts.

When the Great Recession hit, property values fell sharply, making it hard for school districts to raise local property taxes—schools’ primary local funding source—without raising rates, which is politically challenging even in good times. As a result, local funding for schools fell after the recession took hold, worsening the already sharp drop in state funding. Local funding still had not recovered in 2014, leaving total state and local funding for schools per student still well below prerecession levels as of the 2014 school year (i.e., the latest year for which these data are available in most states).

Figure 8 presents the result of education budget cuts at the national level. The x-axis indicates time (i.e., year), and the y-axis indicates per-pupil spending, which measures the average general government expenditure (current, capital, and transfers) per student in a given level of education, expressed as a percentage of GDP per capita. We set the amount of per-pupil spending in 2008 as a reference point and compare its change over time to specifically isolate the difference before and after the recession in 2008. We clearly observe that there are drastic education budget cuts after 2008, and this reduction had not been restored by 2014.

Next, we investigate state-level budget changes after the recession hit, combining both cross-section and time variation. Figure 9 illustrates how much the education budget changed from 2008 to 2010 by state. As shown, some states dramatically cut the budget for what period (e.g., Florida, -21.4%), whereas some states slightly increased (or flat) the budget during the same period (e.g.,
Illinois, 3.6%). Consistent with the previous survey from Leachman et al. (2016), we find that after adjusting for inflation, in 31 states, total state funding per student was lower in the 2014 school year than in the 2008 school year, before the recession took hold. In particular, in 19 states, the cuts in state funding per student exceeded 10%, including Arizona, Florida and Alabama, which were already among the deepest-cutting states since the recession hit from 2008 to 2014. Conversely, in 19 states, per-student funding increased during the same period. Thus, we use this policy change of education budget cuts as an exogenous variation to see how public school teachers find alternative resources to make up the lack of funding and how this external shock affects peer effects. We will explain in detail how to identify the causal effect of education budget cuts on the use of the platform in the subsequent section, but in short, we use those thirty states where drastic budget cuts occurred as a treated group and the other twenty states where budgets increased as a control group.

Last, we aim to measure the overall effect of drastic education budget cuts on public school teachers’ adoption and usage of the online crowdfunding platform. We first show growth patterns of the platform between budget cuts states and not-cuts states and then, demonstrate these results by using a regression-based difference-in-differences analysis.

As shown in Figure 10, we observe that after the recession, public school teachers in the states where drastic budget cuts happened are more likely to adopt and use the platform than public school teachers in the states where the budget was sustained throughout the recession.

Next, we support our findings by using a regression-based difference-in-differences analysis.
Figure 9: Example of Education Budget Changes between 2008 and 2010 by States

Figure 10: Share of Adoption and Share of Repeated use by Budget Cuts States
The specification is shown in Equation 7 as follows:

\[
Y_{ht} = \beta_0 + \beta_1 \cdot 1\{\text{Budget-cuts States}_s\} \times 1\{\text{Recession}_t\} + \sum_{h} X_{ht} + \mu_t + \xi_h + \epsilon_{ht} \tag{7}
\]

where \(h\) denotes the school, \(d\) denotes the district, \(s\) denotes the state, and \(t\) denotes the year. The dependent variable \(Y_{ht}\) is a share of adoption at school \(h\) and time \(t\), measuring the fraction of teachers who adopt the platform at time \(t\) in the school \(h\) that had not previously adopted the online crowdfunding platform. Similarly, another dependent variable is a share of posting at school \(h\) and time \(t\), indicating the fraction of teachers who post the project on the platform in the school \(h\) that had previously adopted the online crowdfunding platform and decide to post the project at time \(t\). The independent variables include an interaction term between the state budget cuts and the treated time period (i.e., \(1\{\text{Budget-cuts States}_s\} \times 1\{\text{Recession}_t\}\)) and the other demographics control variables, \(X_{ht}\), including school-level time varying characteristics (i.e., School-characteristics\(_{ht}\)) such as a percentage of non-white students and a percentage of free-lunch eligible students at school \(h\) and time \(t\), district-level time varying financial information (i.e., log(Finance)\(_{dt}\)) measured by per-pupil spending at school district \(d\) and time \(t\), and school-level time varying total donation amount (i.e., Indirect-network externalities), which are measured by total donation amount of the teachers who adopted the platform at school \(h\) and time \(t - 1\), which is defined as Donation\(_{ht}\) = log(\(\sum_{i \in h} \text{Donation}_{it - 1}\)), describing the total amount of funding for teacher \(i\) who adopted the platform at school \(h\) and time \(t - 1\). Finally, we control for unobserved common factors such as time-fixed effects and school-fixed effects that absorb all permanent school features (i.e., \(\mu_t, \xi_h\)). \(\epsilon_{ht}\) is an independent and identically distributed mean zero random error term.

Our primary parameter of interest is \(\beta_1\), which captures the average treatment effects of education budget cuts on teachers’ platform adoption and usage behaviors\(^{21}\) and Table 6 shows the

\(^{19}\)For the robustness check, we create the treated group at the school-district level by using percentage change of the district-level budget changes. In other words, we create an indicator at the school-district level that is equal to 1 if the district decreased the budget after the recession and 0 otherwise. We can replicate the same results as the state-level definition, so we report the results from the state-level definition.

\(^{20}\)Given features of the two-sided market, indirect network externalities are endogenous. We deal with the endogeneity by using an instrument variable approach. For detailed discussion on this, please refer the subsequent section.

\(^{21}\)The identifying assumptions of this parameter in the difference-in-differences analysis are: (1) recoverability, which means that the use of online crowdfunding platforms by public school teachers in the states where drastic budget cuts occurred is a valid counterfactual for their use by public school teachers in the states where there were no drastic budget cuts, and (2) parallel trend assumption, which explains that the trend in behavior of the public school teachers in the states where drastic budget cuts did not happen is similar to the trend for the states where far-reaching budget cuts happened.
results. Standard error is clustered at the school-level. Column 1 of Table 6 shows the result of the platform adoption decision, and column 2 shows the result of the platform usage conditional on the adoption. For most of the variable interest in both regressions, a coefficient of the interaction term between indicators of the treated states and the treated time period are positive and significant, implying that after the recession, public school teachers in the states where drastic budget cuts happened are more likely to adopt and use the platform than public school teachers in the states where the budget was sustained throughout the recession. In other words, the drastic budget cuts motivate the public school teachers to adopt and use the online crowdfunding platform to compensate for the budget decrease. Thus, this result demonstrates that online crowdfunding platforms, in fact, could be a potential alternative funding resource.

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Model1 DV: Share of Adoption</th>
<th>(2) Model2 DV: Share of Repeated Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 {Budget-cuts States_t} \times</td>
<td>0.0037***</td>
<td>0.121***</td>
</tr>
<tr>
<td>1 {Recession_t}</td>
<td>(0.0002)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Demographics controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>School</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>799,460</td>
<td>209,750</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.590</td>
<td>0.375</td>
</tr>
</tbody>
</table>

Note: (1) Demographics controls include time-varying school characteristics such as % of free-lunch students and % of non-white students, time-varying district finance, and time-varying total donation for the projects posted by the same school teachers. (2) School-district-level clustered standard errors in parentheses. (3) *** p < 0.01, ** p < 0.05, * p < 0.1

Table 6: Results of Difference-in-Differences Analysis

In short, by running a series of regression-based difference-in-differences, we document the causal effects of education budget cuts on the use of crowdfunding platforms and, thus, conclude that online crowdfunding platforms, in fact, could be a potential alternative funding resource.

4.4.2 Heterogeneous Peer Effects

By using an exogenous shock (i.e., education budget cuts after the recession) to shift demands of the online crowdfunding platform, we identify how the peer effects are heterogeneous at different times and locations. To conduct this analysis, we estimate the following equation:

in absence of the policy change shock. We discuss all details in the appendix.
\[ Y_{ht} = \beta_0 + \beta_1 \text{Installed-base}_{ht} + \beta_2 \cdot 1 \{ \text{Budget-cuts States}_s \} \times \text{Installed-base}_{ht} \\
+ \beta_3 \cdot 1 \{ \text{Recession}_t \} \times \text{Installed-base}_{ht} + \beta_4 \cdot 1 \{ \text{Budget-cuts States}_s \} \times 1 \{ \text{Recession}_t \} \\
+ \beta_5 \cdot 1 \{ \text{Budget-cuts States}_s \} \times 1 \{ \text{Recession}_t \} \times \text{Installed-base}_{ht} \\
+ X_{ht} + \mu_t + \xi_h + \epsilon_{ht} \]  

(8)

where \( h \) denotes the school, \( d \) denotes the district, \( s \) denotes the state, and \( t \) denotes the year. As in the previous equations, the dependent variables (i.e., \( Y_{ht} \)) are (1) a share of adoption at school \( h \) and time \( t \), measuring the fraction of teachers who adopt the platform at time \( t \) in the school \( h \) that had not previously adopted the online crowdfunding platform and (2) a share of posting at school \( h \) and time \( t \), indicating that the fraction of teachers who post the project on the platform in the school \( h \) that had previously adopted the online crowdfunding platform and who decide to post the project at time \( t \).

The independent variables, \( X_{ht} \), include time-varying, school-level peer effects (i.e., \( \text{Installed-base}_{Adoption}^{ht} \) and \( \text{Installed-base}_{Repeat}^{ht} \) for each dependent variable); rich sets of the control variables, including time-varying, school-level characteristics (i.e., \( \text{School-characteristics}^{ht} \)), such as the percentage of non-white students and the percentage of free lunch-eligible students at school \( h \) and time \( t \); time-varying, district-level financial information (i.e., \( \text{log(Finance)}_{dt} \)) measured by per-pupil spending at school district \( d \) and time \( t \); and time-varying, school-level donation (i.e., \( \text{log(donation)}_{ht} \)) measured by total donation to the projects posted by teachers at school \( h \) and time \( t - 1 \).

Note that we include a three-way interaction term between an indicator of the budget cuts states, an indicator of the postrecession time periods, and time-varying, school-level peer effects (i.e., \( 1 \{ \text{Budget-cuts States}_s \} \times 1 \{ \text{Recession}_t \} \times \text{Installed-base}_{ht} \)). This three-way interaction term captures how the school-level peer effects on platform adoption vary among the states and the times that drastic budget cuts occurred. We take policy change (i.e., education budget cuts) as an external variation to identify the heterogeneous peer effects on the use of crowdfunding platforms. Moreover, to complete the three-way interaction analysis, we include the other interaction terms generated by different combinations of our focal variables, including (i) an interaction between an indicator of the states with budget cuts and the peer effects (i.e., \( 1 \{ \text{Budget-cuts States}_s \} \times \text{Installed-base}_{ht} \)), (ii) an interaction between an indicator of the postrecession time periods and the peer effects (i.e., \( 1 \{ \text{Recession}_t \} \times \text{Installed-base}_{ht} \)), and (iii) an interaction between an indicator of the postrecession time periods and an indicator of the states with budget cuts (i.e., \( 1 \{ \text{Budget-cuts States}_s \} \times 1 \{ \text{Recession}_t \} \)). The first interaction term shows heterogeneous peer effects driven by cross-sectional variation between the states with budget cuts and the
states without them, and the second interaction term shows heterogeneous peer effects captured by time variation before and after the recession period. Last, the third interaction term shows causal effects of education budget cuts on the use of online crowdfunding platform as same as in the previous section.

Finally, we control for unobserved common factors, such as time-fixed effects and school-fixed effects, that absorb all permanent school features (i.e., $\mu_{it}, \xi_{ih}$). $\epsilon_{ht}$ is an independent and identically distributed mean zero random error term).

Table 7: Heterogeneous Peer Effects

Table 7 presents the results. Column (1) contains the results of the regression that the dependent variable is a share of adoption, and column (2) contains the results of the regression that the dependent variable is a share of posting. Our key parameter of interest is the coefficient of the three-way interaction term in both regressions (i.e., $\beta_5$). This parameter captures how the peer effects vary by cross section (across states) and time variations (before and after the recession) of education budget cuts. Because education budget cuts create a unique situation of resource scarcity, we examine how peer effects on the use of online crowdfunding platforms change in this situation.

There are several interesting results that we want to highlight. First, the coefficient of peer effects in both decisions show consistent results with the previous analysis, meaning that peer effects (i.e., # of cumulative completed teachers) have a positive and significant impact on teachers’ adoption decision whereas, have a negative impact on the repeated use decision (conditional on the adoption). Second, the coefficients of interaction terms between the indicator of the states
with budget cuts and the indicator of the postrecession periods in both decisions are consistent with the previous analysis (i.e., positive and significant). Last, regarding the adoption decision, as shown in column (1), the coefficient of the three-way interaction term is positive and significant, implying that peer effects become salient and have a positive impact on the adoption for the states and times when drastic budget cuts occurred compared to the ones in which they did not. In other words, the positive impact of peer effects on adoption becomes salient at the places and times with high financial needs. Similarly, regarding the repeated use decision, as shown in column (2), the parameter of the three-way interaction term is negative and significant, meaning that the negative impact of peer effects on the repeated use become even worse for the states and times when budget cuts happened compared to the others in which they did not. Thus, we demonstrate heterogeneous peer effects by exploiting an exogenous variation of education budget cuts and it becomes salient for the states and times when budget cuts occurred.

To summarize, from the reduced-form analyses, we show empirical evidences to see the impact of education budget cut and presence and nature of peer effects on the adoption and the repeated use of the online crowdfunding platform. We also demonstrate heterogeneous peer effects by using an exogenous variation of the education budget changes. We will incorporate these findings into our model.

5 Model

In this section, given the above findings, we build and estimate a dynamic demand model of forward-looking public school teachers’ decisions on platform adoption and repeated use. Recall that teacher’s platform adoption decision is different from repeated use because of an uncertainty on both benefit and cost. Since teachers have to submit an application to join the platform and post a project, the first adoption decision incurs a cost. As we explained, an uncertainty of future benefits is arguably greater than the repeated use decision; therefore, peer effects would play a bigger role. On the contrary, repeated use decision after teachers adopt the platform has relatively low adoption cost due to the teacher’s past experience and reputation. Also, conditional on the adoption, teachers could know that the probability of getting funding is contingent on the peers’ use (similar to common-pool resources), so the teachers’ repeated use is dependent on the peers’ performance. Thus, peer effects in repeated use decision would be different from the adoption.

Let $i$ index public school teacher, $h$ index school, $d$ index district, and $t$ index time (i.e., year).

---

22Teachers should fill out an application form and describe all details of reason why they need to get funding to support classroom activities. According to the interview with users of Donorschoose.org, this process requires some time, effort, and cognitive resources to go through.
We allow discrete teacher types to capture teacher heterogeneity. Figure 11 illustrates how teachers make the decisions at each time period. At the beginning of the initial period $t = 1$ (i.e., the time in which the platform is launched), no teachers have adopted the platform and repeated use. Thus, teachers’ decision problem at time $t = 1$ is to decide whether to adopt the platform or not. In period $t > 1$, teachers who have not adopted the platform decide whether to adopt the platform or not after observing peers who have adopted the platform up to $t - 1$, school characteristics, and financial status, and teachers who have adopted the platform decide whether to repeat use the platform or not. Let $j \in \{0, 1\}$ indicates no adoption and adoption, respectively and let $k \in \{0, 1\}$ indicates no repeated use and repeated use, respectively. Because we observe the platform, “Donorschoose”, for 12 years (from 2003 to 2014) and teachers will eventually not use the platform later at some time\(^{23}\), we assume a terminal time period $t = T$ after which teachers can neither adopt nor reuse the platform.

In short, motivated by the platform features and reduced-form findings, this model includes all of features as follows: (1) public school teachers’ adoption and repeated use decisions, (2) peer effects on the both adoption and repeated use decisions, (3) teachers; expectation about future peer effects, funding amount from the platform, indirect network externalities, and fiscal/demographic

\(^{23}\)This assumption comes from our empirical finding that on average, teachers are likely to be engaged to the platform for 6 - 7 years.
of the schools, (4) the cost of platform adoption and repeated use, and (5) reputation effects -
how teachers’ past performance of funding would affect subsequent project’s funding status.
Particularly, the dynamics of teachers’ decisions stem from the fact that an optimal timing of
adopting and repeating the platform is important for the teachers to build a good reputation (i.e.,
total number of the past funding success) in the market, so our model captures how this reputation
affects the teachers’ decisions. Moreover, we control for endogeneity coming from indirect network
externalities which is a typical feature in the two-sided market.24 We will describe all details of our
model below.

5.1 Expected Utility Function of Platform Adoption and Repeated Use

We define the expected single period utility that a teacher obtains from platform adoption and
repeated use. Again, in each period, teachers decide whether to adopt the platform or not and conditional on adoption, they decide whether to repeat to use it or not. The single period expected utility consists of four main components: (1) peer effects, (2) expected benefits and adoption/repeated-use cost, (3) indirect network externalities (i.e., the donor side), and (4) other controls including time varying school-level characteristics and district-level finance. Note that teachers are imperfectly informed and hence uncertain about future funding status of their posted project at the time period when they make the decisions. Therefore, the teacher’s expected utility incorporates uncertainty about success of the posted project and the probability of funding depends on reputation.

5.1.1 Platform Adoption

Teacher $i$’s single period expected utility for the platform adoption (i.e., $j \in \{1, 0\}$) at time $t$ is as follows:

$$E_{\tau}[u_{ijht}] = E_{\tau}[\bar{u}_{ijht}] + \epsilon_{ijht},$$

where $A$ denotes a notation of the variables and parameters related to the adoption decision. $\epsilon_{ijht}$ are idiosyncratic errors, known to the teacher but unobservable to the econometrician. These error terms are independent and identically distributed across teachers, schools, and time and follow a Type 1 extreme value distribution. $E[\cdot]$ is the mathematical expectation operator and $p_\tau$ indicates a probability of funding conditional on the past performance, $\tau$, which is the total number of success projects that teacher $i$ has posted by the time $t$. $\tau$ ranges from 0 to 5 (i.e., $\tau \in \{0, 1, ..., 5\}$ and $\tau$ is

[24] Similar to the reduced-form analysis, we use instrument variables to control for the endogeneity of the indirect network externalities from the donor side.
always equal to 0 when teachers make an adoption. Due to the uncertainty of future success, teachers have expected utility over this funding probability \( p_{\tau} \) at the time when they adopt the platform. Last, \( \bar{u}_{ijht}^A \) is the other per period utility terms that we will define all details in below.

Then, if teacher \( i \) decides to adopt the platform at time \( t \) (i.e., \( j = 1 \)), then teacher \( i \)'s single period utility is,

\[
E_{p_{\tau}}[u_{ijht}^A] = \alpha^A N_{ht}^A + g\left(E_{p_{\tau}}[T_{ht}^A]; \lambda_{1i}^A, \lambda_2^A \right) + \pi_i^A IN_{ht}^A + X_{ht}^A + \epsilon_{ijht}^A,
\]

where \( N_{ht}^A = \sum_{i=1}^{t-1} \sum_{i \in I_h} 1(\text{adoption}_{ii}) \), describing a total number of teachers who had adopted and completed at school \( h \) and time \( t - 1 \), where \( i \) indexes the teacher, \( I_h \) is set of teachers at school \( h \), and \( 1(\text{adoption}_{ii}) \) is an indicator that is equal to 1 if teacher \( i \) in the school \( h \) had adopted and completed the platform at time \( t \). Similar to the previous section, this term captures the peer effects.

The second term, \( g\left(E_{p_{\tau}}[T_{ht}^A]; \lambda_{1i}^A, \lambda_2^A \right) \) is the expected benefit (e.g., target funding amount that teacher will receive if the project gets funding) and one-time cost that teachers incur when adopting the platform (e.g., time, efforts, and any other types of cognitive resources to join the platform). An empirical specification of the function \( g \) is given by,

\[
g\left(E_{p_{\tau}}[T_{ht}^A]; \lambda_{1i}^A, \lambda_2^A \right) = -\lambda_{1i}^A + \lambda_2^A \cdot p_{\tau} \cdot T_{ht}^A,
\]

where \( T_{ht}^A \) is an average target amount of projects posted by teachers at school \( h \) and time \( t \). \( \lambda_{1i}^A \) captures any unobserved costs associated to the platform adoption. For example, teachers have to submit an application to join the platform and they need to wait for some time to get an approval. Also, teachers may have some uncertainty to make them hesitate to adopt the platform. Any psychological costs related to complete the application process (e.g., submitting information), opportunity costs incur while they wait for an approval (e.g., waiting), and uncertainty to adopt. We allow the \( \lambda_{1i}^A \) to be heterogeneous by teacher, which is motivated by the reviews about the platform, describing teachers' complaints about the complicated application process and long

---

25 We set a maximum of \( \tau \) is equal to 5 because according to our analysis, on average, a funding probability is indifferent between teachers who made 5 success and those who made success more than 5.

26 As we described in the previous section, we only count the teachers who "completed" the project for the identification purpose similar to Bollinger and Gillingham (2012).
approval time. These reviews imply that there are some teachers, having high (unobserved) costs to adopt the platform.

The third term, $IN_{ht}$, is time-varying school-level indirect network externalities such as the total amount of donation to the projects posted by the teachers at school $h$ by time $t - 1$. Note that teachers can ask acquaintance or students’ parents to contribute to their posted projects and this amount of referred donation varies across teachers (e.g., some teachers have more acquaintance or friends than others, so they are more likely to expect more amount of donation) and thus, we allow the coefficient of the indirect network externalities to be heterogeneous by teacher.

Finally, $X_{ht}$ is a vector of control variables including time-varying school characteristics, $C_{ht}$, such as total number of students who are eligible to the title 1 program (i.e., the federal government program, aiming to help students in poverty), free-lunch, and non-white students and time-varying district fiscal information, $F_{dt}$, such as per-pupil spending from government subsidy. $\xi^A_{ht}$ is the unobserved demand shocks to the demand for platform adoption.

If teachers decide not to adopt the platform at time $t$ (i.e., $j=0$), then the expected utility function is as follows:

$$E_{pt}[u^A_{i0ht}] = \epsilon^A_{i0ht}. \quad (10)$$

5.1.2 Repeated Use

Next, we consider teachers’ repeated use decision (i.e., $k \in \{1, 0\}$) conditional on adoption. Suppose that teacher $i$ has adopted the platform in the previous time periods (i.e., $\sim < t$). At time $t$, teacher needs to decide whether to repeat to use the platform or not. Similar to the adoption decision, teacher $i$’s utility for the repeated use decision at time $t$ is given by,

$$E_{pt}[u^R_{ikht}] = E_{pt}[\bar{u}^R_{ikht}] + \epsilon^R_{ikht},$$

where $R$ denotes a notation of the variables and parameters related to the repeated use decision. $\epsilon^R_{ijst}$ are idiosyncratic errors, known to the teacher but unobservable to the econometricians. These error terms are $i.i.d$ across teachers, schools and time and follow a Type 1 extreme value distribution. $\bar{u}^R_{ikht}$ is the other parts of per period utility terms that we will define all details in below. All others are same as the adoption decision utility function.

Then, if teacher $i$ decides to repeat to use the platform at time $t$ (i.e., $k = 1$), teacher $i$’s single period expected utility is,
\[ E_{pr} [ u_{ikht} ] = \alpha_R N_{ht}^R + g \left( E_{pr} \left[ T_{ht}^R \right]; \lambda_{1i}, \lambda_{2i} \right) + \kappa_R^{IN} N_{ht} + \sum_{i=1}^{t-1} \sum_{h} 1 \left( \text{Repeated-use}_{ii} | \text{Adoption}_{ii-1} \right), \]

where \( N_{ht}^R = \sum_{i=1}^{t-1} \sum_{h} 1 \left( \text{Repeated-use}_{ii} | \text{Adoption}_{ii-1} \right) \), indicating a total number of teachers “who had adopted and completed to post the project” at school \( h \) by time \( t - 1 \), where \( i \) indexes the teacher and \( 1 \left( \text{Repeated-use}_{ii} | \text{Adoption}_{ii-1} \right) \) is an indicator that is equal to 1 if teacher \( i \) in the school \( h \) (who had adopted by time \( t - 1 \)) and posted the project at time \( t \).\(^{27}\) Similar to the adoption decision, this term capture the peer effects.

Next, \( g \left( E_{pr} \left[ T_{ht}^R \right]; \lambda_{1i}, \lambda_{2i} \right) \) is the expected benefit (e.g., target funding amount that teacher will receive if the project gets funding) and one-time cost that teachers incur when reusing the platform (e.g., time, efforts, and any other types of cognitive resources to reuse the platform).\(^{28}\) An empirical specification of the function \( g \) is given by,

\[ g \left( E_{pr} \left[ T_{ht}^R \right]; \lambda_{1i}, \lambda_{2i} \right) = -\lambda_{1i} + \lambda_{2i} \cdot p_T \cdot T_{ht}^R, \]

where \( T_{ht}^R \) is an average target amount of projects posted by repeated use teachers at school \( h \) and time \( t \). Again, \( \lambda_{1i} \) captures any unobserved costs associated to the repeated use decision and this parameter is allowed to be heterogeneous by teacher.

Last, \( \kappa_R^{IN} N_{ht} \) is time-varying school-level indirect network externalities and \( X_{ht} \) is a vector of control variables, including time-varying school characteristics and district fiscal information. \( \epsilon_{ikht} \) is the unobserved demand shocks to the demand for platform repeated use.

If teachers decide not to reuse the platform at time \( t \) (i.e., \( k=0 \)), then the expected utility function is,

\[ E_{pr} [ u_{i0ht} ] = \epsilon_{i0ht}. \]

\(^{27}\)We still count the teachers who completed the projects for the identification purpose.

\(^{28}\)We assume that still repeated use cost incurs even after adopting the platform because teachers anyway need to submit an application form to the platform to post the project and depending on the adoption decision, teachers might have different skills to make their application better.
5.2 Value Functions

As presented in Figure 11, the teacher’s dynamic repeated use decision is nested within the dynamic platform adoption decision through the expected future payoff. We first start with describing the teacher’s dynamic repeated use decision and then describe the dynamic platform adoption decision.

5.2.1 Dynamic repeated use decision

Let \( \omega_{R_{i,t,\tau}} \) be the vector of state variables related to the repeated use decision for teacher \( i \) who has made \( \tau \) successful projects by time \( t \) where

\[
\eta_{Rh}^{R_{i}} = \kappa_{Rh}^{R_{i}} N_{ht} + \varepsilon_{Rh}^{R_{i}}, \quad (13)
\]

The other state variables related to the platform adoption decision, such as \( N_{A_{ht}}^{R_{i}}, T_{A_{ht}}^{R_{i}}, \) and \( \xi_{A_{ht}}^{R_{i}} \), are not included here. Let \( V_{R_{i}}^{\tau} (\omega_{R_{i,t,\tau}}) \) be the integrated value function (i.e., Emax function, which \( \epsilon_{R_{ikht}}^{R_{i}} \) are integrated out) of the repeated use decision by teacher \( i \) and \( V_{ik}^{R_{i,t,\tau}} (\omega_{R_{i,t,\tau}}) \) be the choice specific value function of action \( k \). Then, the Bellman equation is,

\[
V_{R_{i}}^{\tau} (\omega_{R_{i,t,\tau}}) = E_{\tau} \max_{k \in \{0,1\}} \left\{ V_{ik}^{R_{i,t,\tau}} (\omega_{R_{i,t,\tau}}) + \epsilon_{R_{ikht}}^{R_{i}} \right\} = \ln \left\{ \sum_{k \in \{0,1\}} \exp \left( V_{ik}^{R_{i,t,\tau}} (\omega_{R_{i,t,\tau}}) \right) \right\}, \quad (14)
\]

and teacher \( i \)'s choice specific value function on the repeated use decision is,

\[
V_{ik}^{R_{i,t,\tau}} (\omega_{R_{i,t,\tau}}) = \begin{cases} E_{\tau} \left[ \bar{a}_{R_{iht}}^{R} \right] + \beta \left[ p_{R} V_{i,t+\tau+1}^{R_{i}} (\omega_{R_{i,t+\tau+1}}) | (\omega_{R_{i,t,\tau}}) \right] + (1 - p_{R}) E_{\tau} \left[ \bar{a}_{R_{iht}}^{R} \right] \left[ V_{i,t+\tau+1}^{R_{i}} (\omega_{R_{i,t+\tau+1}}) | (\omega_{R_{i,t,\tau}}) \right] & \text{Repeated use } (k = 1), \\
\beta E_{\tau} \left[ \bar{a}_{R_{iht}}^{R} \right] \left[ V_{i,t}^{R_{i}} (\omega_{R_{i,t+1,\tau}}) | (\omega_{R_{i,t,\tau}}) \right] & \text{No repeated use } (k = 0).
\end{cases} \quad (15)
\]

where \( \beta \) is a discount factor.\(^{29}\) Then, the choice probability of repeated use by teacher \( i \) at time \( t \) with state \( \omega_{R_{i,t,\tau}} \) is,

\[
\Pr(k = 1 | \omega_{R_{i,t,\tau}}; i) = \frac{\exp \left( V_{i1}^{R_{i,t}} (\omega_{R_{i,t,\tau}}) \right)}{\sum_{k} \exp \left( V_{ik}^{R_{i,t}} (\omega_{R_{i,t,\tau}}) \right)}. \quad (16)
\]

\(^{29}\)We do experiment to find the best value of the beta and will discuss this in the estimation section
5.2.2 Dynamic platform adoption decision

Next, we consider dynamic teacher platform adoption decision. Let $\omega_{i,t}^A = (N_{ht}^A, N_{ht}^R, F_{dt}, C_{ht}, I_{N_{ht}}, T_{ht}^A, T_{ht}^R, \eta_{ht}^A, \eta_{ht}^R)$ be the vector of state variables on the platform adoption decision, where $\eta_{ijt}$ is defined as,

$$\eta_{iht}^A = \kappa^A IN_{ht} + \zeta_{ht}^A. \quad (17)$$

Similar to the repeated use decision, let $V_{ij}^A(\omega_{i,t}^A)$ be the integrated value function (i.e., $\text{Emax}$ function, which $\epsilon_{ijdt}$ are integrated out) of the platform adoption of teacher $i$ and $V_{ij}^A(\omega_{i,t}^A)$ be the choice specific value function of action $j$ (i.e., adoption or not). Then, the Bellman equation is,

$$V_{ij}^A(\omega_{i,t}^A) = E_{\epsilon} \max_{j \in \{0,1\}} \left\{ V_{ij}^A(\omega_{i,t}^A) + \epsilon_{ijdt} \right\} = \ln \left\{ \sum_{j \in \{0,1\}} \exp \left( V_{ij}^A(\omega_{i,t}^A) \right) \right\}, \quad (18)$$

and teacher $i$’s choice specific value function on the adoption decision is,

$$V_{ij}^A(\omega_{i,t}^A) = \begin{cases} E_{p_t} \left[ \tilde{u}_{i,t}^A \right] + \beta \left[ p_t E_{w_{i,j+1,t+1}} \left[ V_{i}^R(\omega_{i,t+1,j+1}) \right] (\omega_{i,t}^A) \right] + (1 - p_t) E_{w_{i,j+1,t}} \left[ V_{i}^R(\omega_{i,t+1,j+1}) \right] (\omega_{i,t}^A) \right] & \text{Adoption} (j = 1), \\ \beta E_{w_{i,j+1}} \left[ V_{i}^A(\omega_{i,j+1}) \right] (\omega_{i,t}^A) & \text{No adoption} (j = 0). \end{cases} \quad (19)$$

Then, the choice probability of the platform adoption by teacher $i$ at time $t$ with state $\omega_{i,t}^A$ is,

$$\Pr(j = 1|\omega_{i,t}^A; i) = \frac{\exp \left( V_{ij}^A(\omega_{i,t}^A) \right)}{\sum_{j'} \exp \left( V_{ij'}^A(\omega_{i,t}^A) \right)}. \quad (20)$$

We compute the value functions for both adoption and repeated use decisions by using backward induction from the terminal period $T$ based on the finite-horizon assumption. In our estimation, we set $T$ is equal to 20 (i.e., 20 years). We also simply assume that after the terminal period $T$, teachers cannot adopt and reuse the platform.

5.3 Teacher Expectation Process

In this section, we briefly explain how teacher expectation process evolves. Because $\tau$ is determined by peer effects, school characteristics, finance, and total donation amount, we estimate it from outside of the model. Then, the remaining state variables are $(\eta_{iht}, \eta_{ht}, N_{ht}^A, N_{ht}^R, F_{dt}, C_{ht}, I_{N_{ht}}, T_{ht}^A, T_{ht}^R)$. We assume that teachers perceive that these state variables follow a first-order Markov process.
Specifically, we model \( \eta^A_{ht} \) and \( \eta^R_{ht} \) as a function of constant, its lagged value, lagged peer effects, current and lagged school characteristics, district finance, and indirect network externalities as follows:

\[
\begin{align*}
\eta^A_{ht+1} & = \pi^A_{\eta_1} + \pi^A_{\eta_2} \eta^A_{ht} + \pi^A_{\eta_3} N^A_{ht} + \pi^A_{\eta_4} C^A_{ht+1} + \pi^A_{\eta_5} F^A_{dt+1} + \pi^A_{\eta_6} I N^A_{ht+1} + \pi^A_{\eta_7} I N^A_{ht} + \nu^A_{\eta_{ht+1}}, \\
\eta^R_{ht+1} & = \pi^R_{\eta_1} + \pi^R_{\eta_2} \eta^R_{ht} + \pi^R_{\eta_3} N^R_{ht} + \pi^R_{\eta_4} C^R_{ht+1} + \pi^R_{\eta_5} F^R_{dt+1} + \pi^R_{\eta_6} I N^R_{ht+1} + \pi^R_{\eta_7} I N^R_{ht} + \nu^R_{\eta_{ht+1}}.
\end{align*}
\]  

(21)

where \( \nu^A_{\eta_{ht+1}} \) and \( \nu^R_{\eta_{ht+1}} \) are mean zero stochastic error terms. For the peer effects \( (N^A_{ht} \) and \( N^R_{ht} \)), we model it as a function of a constant, its lagged value, current and lagged school characteristics, district-level finance, and indirect network externalities as follows:

\[
\begin{align*}
N^A_{ht+1} & = \pi^A_{N_1} + \pi^A_{N_2} N^A_{ht} + \pi^A_{N_3} C^A_{ht+1} + \pi^A_{N_4} F^A_{dt+1} + \pi^A_{N_5} F^A_{dt} + \pi^A_{N_6} I N^A_{ht+1} + \pi^A_{N_7} I N^A_{ht} + \nu^A_{N_{ht+1}}, \\
N^R_{ht+1} & = \pi^R_{N_1} + \pi^R_{N_2} N^R_{ht} + \pi^R_{N_3} C^R_{ht+1} + \pi^R_{N_4} F^R_{dt+1} + \pi^R_{N_5} F^R_{dt} + \pi^R_{N_6} I N^R_{ht+1} + \pi^R_{N_7} I N^R_{ht} + \nu^R_{N_{ht+1}}.
\end{align*}
\]  

(22)

where again \( \nu^A_{N_{ht+1}} \) and \( \nu^R_{N_{ht+1}} \) are mean zero stochastic error terms. Last, we assume that the process of school-level characteristics, district-level Finance, target funding amount of both adoption and repeated use, and indirect network externalities \( (F^A_{dt}, C^A_{ht}, I N^A_{ht}, T^A_{ht}, T^R_{ht}) \) in a similar manner as \( \eta^A_{ht}, \eta^R_{ht}, N^A_{ht}, \) and \( N^R_{ht} \) by using the following process:

\[
\begin{align*}
C^A_{ht+1} & = \pi^A_{C_1} + \pi^A_{C_2} C^A_{ht} + \nu^A_{C_{ht+1}}, \\
F^A_{dt+1} & = \pi^A_{F_1} + \pi^A_{F_2} F^A_{ht} + \pi^A_{F_3} C^A_{ht} + \nu^A_{F_{ht+1}}, \\
I N^A_{ht+1} & = \pi^A_{I N_1} + \pi^A_{I N_2} I N^A_{ht} + \nu^A_{I N_{ht+1}}, \\
T^A_{dt+1} & = \pi^A_{T_1} + \pi^A_{T_2} T^A_{ht} + \pi^A_{T_3} C^A_{ht} + \pi^A_{T_4} F^A_{ht} + \nu^A_{T_{ht+1}}, \\
T^R_{dt+1} & = \pi^R_{T_1} + \pi^R_{T_2} T^R_{ht} + \pi^R_{T_3} C^R_{ht} + \pi^R_{T_4} F^R_{ht} + \nu^R_{T_{ht+1}}.
\end{align*}
\]  

(23)

where \( \nu^A_{C_{ht+1}}, \nu^A_{F_{ht+1}}, \nu^A_{I N_{ht+1}}, \nu^A_{T_{ht+1}}, \) and \( \nu^A_{T_{ht+1}} \) are all mean zero stochastic error terms. For more details including list of variables in each of these processes, we present the results of estimation in Table 9.
5.4 Teacher Types, Aggregate Demands of Platform Adoption and Repeated Use, and Evolution of Potential Adopters and Repeated Users

In this section, we consider how the size of teacher types evolves to compute the aggregate demand for the platform adoption and the repeated use. We model teacher heterogeneity by \( L \) discrete types. Let \( q_i \) be a proportion of \( i \) type teachers and \( \sum_i q_i = 1 \). We first set the evolution of the size of each teacher type to derive aggregate demand for the platform adoption and repeated use. Let \( M^A_{lht} \) be the size of \( l \) type teachers who have not adopted the platform in school \( h \) at time \( t \). Then, the evolution of \( M^A_{lht} \) is as follows:

\[
M^A_{lht+1} = M^A_{lht}(1 - \Pr(j = 1|\omega^A_{l,t}; l)), \tag{24}
\]

Next, let \( M^R_{lht}(\tau) \) be the size of type \( l \) teachers who have adopted the platform in school \( h \) at time \( t \) with \( \tau \) success and it evolves as,

- For \( \tau = 0 \)

\[
M^R_{lht+1}(\tau = 0) = M^A_{lht} \cdot \Pr(j = 1|\omega^A_{l,t}; l) \cdot (1 - \Pr(\tau = 0)) + M^R_{lht}(\tau = 0) \cdot \Pr(k = 1|\omega^R_{l,t,\tau=0}; l) \cdot (1 - \Pr(\tau = 0)),
\]

- For \( \tau = 1 \)

\[
M^R_{lht+1}(\tau = 1) = M^A_{lht} \cdot \Pr(j = 1|\omega^A_{l,t}; l) \cdot \Pr(\tau = 0) + M^R_{lht}(\tau = 0) \cdot \Pr(k = 1|\omega^R_{l,t,\tau=0}; l) \cdot \Pr(\tau = 0) + M^R_{lht}(\tau = 1) \cdot \Pr(k = 0|\omega^R_{l,t,\tau=1}; l) + M^R_{lht}(\tau = 1) \cdot \Pr(k = 1|\omega^R_{l,t,\tau=1}; l) \cdot (1 - \Pr(\tau = 1)),
\]

- For \( \tau \geq 2 \)

\[
M^R_{lht+1}(\tau) = M^R_{lht}(\tau - 1) \cdot \Pr(k = 1|\omega^R_{l,t,\tau-1}; l) \cdot \Pr(\tau - 1) + M^R_{lht}(\tau) \cdot \Pr(k = 0|\omega^R_{l,t,\tau}; l) + M^R_{lht}(\tau) \cdot \Pr(k = 1|\omega^R_{l,t,\tau}; l) \cdot (1 - \Pr(\tau)),
\]

Then, the aggregate demand of the platform adoption for option \( j \) at state \( \omega^A_{l,t} \) is,

\[
Q^A(\omega^A_{l,t}) = \sum_l M^A_{lht} \Pr(j = 1|\omega^A_{l,t}; l), \tag{25}
\]

46
and the aggregate demand of the repeated use for option $k$ at $\omega_{i,t,\tau}$ is,

$$Q^R(\omega_{i,t,\tau}) = \sum_{l} M^R_{iht}(\tau) \Pr(k = 1|\omega_{i,t,\tau}; l). \quad (26)$$

6 Estimation

We use a GMM approach to estimate the demand model parameters which is similar to Lee (2013) and Ishihara and Ching (2018). We first describe the moment conditions and discuss the identification strategy and the set of instruments.

6.1 Moment Conditions

Unobserved shocks to adoption and repeated use decisions (i.e., $\xi^A_{ht}$ and $\xi^R_{ht}$) are assumed to follow a first-order Markov process, where the errors are mean zero and independent. To allow for a possibility that some unobserved demand shocks could be correlated over time, we use the specification is as follows:

$$\nu^A_{ht} = \xi^A_{ht} - \rho_1 \xi^A_{ht-1},$$

$$\nu^R_{ht} = \xi^R_{ht} - \rho_2 \xi^R_{ht-1}. \quad (27)$$

Next, to create moment condition, we do not directly use $\xi^A_{ht}$ and $\xi^R_{ht}$; rather create moment condition based on $(\nu^A_{ht}, \nu^R_{ht})$. The vector of instruments is $(Z^A_{ht}, Z^R_{ht}, Z^A_{ht,\Delta}, Z^R_{ht,\Delta})$ and we assume that,

$$E\left[Z^A_{ht}\nu^A_{ht}\right] = 0, \quad E\left[Z^A_{ht,\Delta}\Delta \nu^A_{ht}\right] = 0,$$

$$E\left[Z^R_{ht}\nu^R_{ht}\right] = 0, \quad E\left[Z^R_{ht,\Delta}\Delta \nu^R_{ht}\right] = 0. \quad (28)$$

where $\Delta \nu^A_{ht} = \nu^A_{ht} - \nu^A_{ht-1}, \Delta \nu^R_{ht} = \nu^R_{ht} - \nu^R_{ht-1}$. Following Lee (2013) and Ishihara and Ching (2018), as shown to be helpful in the previous literature on the dynamic linear panel estimation literature (e.g., Blundell and Bond 1998; Arellano and Bond 1991), we use both levels and first differences of $(\nu^A_{ht}, \nu^R_{ht})$.

6.2 Inversion of the Demand Systems

Let $\theta \in \Theta$ is a vector of the demand parameters. We set an initial guess of unobserved demand shocks ($\xi^A_{ht,0}, \xi^R_{ht,0}$) for each candidate parameter vector and in the $n$-th iteration for the inversion of the demand systems, given ($\xi^A_{ht,n}, \xi^R_{ht,n}$), we estimate the teacher expectation process for $\eta^A_{liht}, \eta^R_{liht}$
for each teacher type \( l \). Next, we compute the value functions, \( V^A_l(\omega^A_l) \) and \( V^R_l(\omega^R_{l,t}) \), by using backward induction and then compute the predicted number of teachers who adopt and repeat to use the platform (i.e., \( Q^A, Q^R \), respectively. After that, we update the vector of \( (\xi^A_{ht}, \xi^R_{ht}) \) by using the formula as follows:

\[
\begin{align*}
\xi^A_{ht+1} &= \xi^A_{ht} + \ln(\bar{Q}^A_{ht}) - \ln(Q^A_{ht}(\xi^A_{ht}, \xi^R_{ht}, \theta)), \\
\xi^R_{ht+1} &= \xi^R_{ht} + \ln(\bar{Q}^R_{ht}) - \ln(Q^R_{ht}(\xi^A_{ht}, \xi^R_{ht}, \theta)).
\end{align*}
\tag{29}
\]

where \( \bar{Q}^A_{ht} \) and \( \bar{Q}^R_{ht} \) indicate observed total number of teachers who adopt and repeat to use the platform for school \( h \) at time \( t \), respectively. We repeat the above process until convergence by using the updated vector of unobserved shocks.

6.3 Identification

We first provide an informal discussion for the identification in case which there is no heterogeneity in the cost of adoption and repeated use and sensitivity of indirect network externalities (i.e., \( \lambda^A_{1l} = \lambda^A_{2l}, \lambda^R_{1l} = \lambda^R_{2l}, \kappa^A_l = \kappa^A, and \kappa^R_l = \kappa^R \)) and then, followed by discussion on what data variation helps us identify teacher heterogeneity in those parameters.

First, regarding sensitivity of the peer effects (i.e., \( \alpha^A, \alpha^R \)), the impact of district-finance (i.e., \( \gamma^A, \gamma^R \)), school-characteristics (i.e., \( \delta^A_1, \delta^A_2, \delta^A_3, \delta^R_1, \delta^R_2, \delta^R_3 \)), and indirect network externalities (i.e., \( \kappa^A, \kappa^R \)) on the adoption and repeated use decisions, we can identify these parameters by using a variation in time-varying school-level total number of adopters (repeated users) of public school teacher, the variation in time-varying school-level total number of teachers who have previously adopted (re-used) the platform, time-varying district-level government finance changes, and time-varying school-level demographics changes such as proportion of non-white students, free-lunch eligible students, and poverty students, respectively. Moreover, we can identify the cost of adoption (repeated use) (i.e, \( \lambda^A_{1l}(\lambda^R_{1l}) \)) by exploiting a variation in the total number of teachers who adopted (repeated to use the platform over time across schools. The impact of potential benefit of adoption (repeated to use) (i.e., \( \lambda^A_{2l}(\lambda^R_{2l}) \)) is identified by time-varying school-level average target amount of the projects posted by teachers from the same school.

Next, we discuss how the heterogeneity parameters (i.e., \( \lambda^A_{1l}, \lambda^R_{1l}, \kappa^A_l, and \kappa^R_l \)) and the proportion of each type of teachers are identified. Our identification argument is similar to that of Ishihara and Ching (2018), which identifies consumer heterogeneity in price sensitivity and transaction costs.
when they purchase or sell new and used copies of video games. Let us consider a two-period case first. Then, we need total four types of teachers: (1) teachers who adopt the platform in period 1 and repeat to post the project in period 2, (2) teachers who adopt the platform in period 1 and do not repeat to post the project in period 2, (3) teachers who do not adopt the platform in period 1 and adopt the platform in period 2, and (4) teachers who do not adopt the platform in neither period 1 nor 2. We can identify the proportion of teachers that fall into the type 1 category by observing the number of teachers who repeat to use of the platform in period 2. Given the proportion of type 1, we can identify the proportion of type 2 teachers because we observe the proportion of teachers who adopt the platform in period 1 but do not repeat to use it in period 2. The proportion of type 3 can be identified by observing teachers who first adopt the platform in period 2.

Last, the variance in teacher preferences for indirect network externalities and adoption/repeated-use cost is identified by observing the variation in donation trends to the projects that have been posted by the teachers from the same school as well as the potential benefit of the platform adoption and repeated use. Additionally, the panel data also provide another source of identification through the shift in the distribution of teacher valuations of the platform over time. Similar to Lee (2013)’s argument on heterogeneity in consumer preference parameters, if teacher heterogeneity in both indirect network externalities and adoption/repeated-use cost is substantial, then teacher responses over time to changes in potential benefits and cost will be different.

### 6.4 Instruments

Because the online crowdfunding platform is a two-sided market, the indirect network externalities (i.e., \( IN_{ht} \)) are endogenous. Recall that our moment conditions are as follows:

\[
E[Z^A_{ht} v^A_{ht}] = 0, \quad E[Z^A_{ht} \Delta v^A_{ht}] = 0, \\
E[Z^R_{ht} v^R_{ht}] = 0, \quad E[Z^R_{ht} \Delta v^R_{ht}] = 0.
\]

Regarding the elements in \( Z^A_{ht} \) and \( Z^R_{ht} \), which are instruments used for endogeneity of \( IN_{ht} \) in both platform adoption and repeated use decisions, we first include an exogenous shifter of internal network externalities (i.e., total donation amount from the donors). For the estimates to be valid, the exclusion restriction must hold that instruments affect the donation behaviors but are plausibly uncorrelated with the platform adoption and repeated use decisions of public school teachers. We include “revenue” (including gifts and grants) from the 501(c)(3) public charities and private foundations, which vary by state and time (i.e., year) in a set of instruments.\(^{30}\) It is

\(^{30}\text{Again, we collect this data from the National Center of Charitable Statistics (NCCS) and observe only state-year}\)
clear that charitable contribution deductions are related to donors’ behavior but have no direct
impact on platform adoption and repeated use decisions because donations to qualified charities
are considered tax-deductible expenses so that donors can reduce their taxable income, lowering
the tax bill. Given the existence of home bias, state-year level tax deductions from charitable giving
are good instruments, satisfying the exclusion restriction.

Next, we consider that the endogeneity of $IN_{ht}$ in both decisions, adoption and repeated use,
comes from a potential correlation with $\nu_{ht}^A$ ($\nu_{ht}^R$) if donors observe teachers’ adoption behavior
(repeated use) and change their donation behavior based on that. If donors cannot predict $\nu_{ht}^A$ ($\nu_{ht}^R$),
lagged values of $IN_{ht}$ will not be correlated. Given the fact that donors rarely forecast unobserved
demand shocks (e.g., school-level unobservable driving forces of adoption and repeated use), we
consider exploiting these as instruments meaning that we include one-period lagged values of
$IN_{ht}$ in $Z_{ht}^A$ ($Z_{ht}^R$). Moreover, we expect that peer effect, $N^A$ ($N^R$), is possibly uncorrelated with
$\nu_{ht}^A$ ($\nu_{ht}^R$) because to control for the simultaneity issue, we only count the total number of adopted
(reused) teachers who already “completed” the project. Therefore, we include the current-period
and one-lagged values of peer effects of adoption (repeated use) in a set of instruments.

Based on a similar argument, we include four additional sets of instruments. Specifically, we include
the one- and two-lagged values of school characteristics and school district finance, including a
proportion of nonwhite students, free-lunch available students, and district-fiscal information,
respectively. We expect that donors are likely to select projects posted by teachers at schools located
in highest-, high-, moderate-, and low-poverty areas. In other words, they do not pay attention to
“changes” in school characteristics and school district finance by time (i.e., time variation); rather,
they choose projects by levels of poverty that schools are located in (i.e., cross-section variation).
Thus, one- and two-lagged values of these variables are potentially correlated with donations
from the donor side but possibly do not affect the teachers’ decisions, so we exploit these time-
varying school characteristics and district-fiscal information as instruments for the indirect network
externalities.

Last, we exploit two- and three-period lagged values of $(\xi_{ht}^A, \xi_{ht}^R)$ as instruments for identifying
$\rho_1$ and $\rho_2$, which are correlation parameters in $\nu_{ht}^A$ and $\nu_{ht}^R$. Regarding $Z_{ht,\Delta}^A$ and $Z_{ht,\Delta}^R$, we include
exactly the same sets of time-varying instruments, having one additional lagged period.
7 Results

7.1 Parameter Estimates

In this section, we present the results of structural estimation of the dynamic demand model. The computational complexity of the demand model makes it difficult to use the full data available for estimation. To estimate the model on a subset of the data, first we randomly select 1,000 public schools, which form 2% of the total number of schools (having 10 years of observations). These randomly selected schools come from all fifty states. This yields 10,000 school-year observations that are used in the model estimation.

We allow for two types of teachers who differ in their sensitivity of indirect network externalities and costs of adoption and repeated use decisions (i.e., $\kappa_A^l, \kappa_R^l, \lambda_A^l, \lambda_R^l$). We fix the discount factor, $\beta$, equal to 0.8, which has the lowest value of the GMM objective function. Table 8 and Table 9 present the estimates of demand model parameter and teacher expectation process, respectively.

We first discuss about the demand parameters in Table 8. All the estimates show the correct signs which are consistent with the reduced-form analysis. First, we find that type-1 teachers make up about 42% of the population and type-2 teachers are about 58% of the population and that these numbers are computed by using the segment proportion parameter estimate and logit formula. As for the peer effects sensitivity, we find consistent results with the reduced-form analysis, implying that peer effects have a positive impact on adoption, whereas they have a negative impact on the repeated use decision. We also find negative sensitivity of school finance, meaning that teachers from rich schools are less likely to adopt and reuse the platform, and the positive sensitivity of school characteristics related to degree of poverty (e.g., % of non-white students and % of free-lunch students), meaning that teachers from poor schools are more likely to adopt (and repeat to use) the platform.

As for the cost of platform adoption and repeated use decisions, recall that we use the following functional forms for adoption and repeated use, respectively: 

$$g\left(E_p[\tau_A^{ht}] ; \lambda_A^1, \lambda_A^2 \right) = -\lambda_A^1 + \lambda_A^2 \cdot p_{\tau} \cdot T_A^{ht}$$

and

$$g\left(E_p[\tau_R^{ht}] ; \lambda_R^1, \lambda_R^2 \right) = -\lambda_R^1 + \lambda_R^2 \cdot p_{\tau} \cdot T_R^{ht}.$$ 

The estimates for both $\lambda_A^1$ and $\lambda_R^1$ are positive, explaining that the number of adopters (repeated users) decreases as the adoption (repeated use) cost increases. Additionally, type-1 teachers have a higher level of adoption cost but a lower level of repeated use cost compared with type-2 teachers. In contrast, type-2 teachers have a lower level of adoption cost but a higher level of repeated use cost compared to type-1 teachers. Given the fact that type-2 teachers have a larger proportion than type-1 teachers, growth and evolution of the platform is mainly driven by type-2 teachers who have lower adoption cost, so they are more likely to adopt (as a pioneer). However, those teachers have higher repeated use
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (S.E.)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Segment Proportion</strong></td>
<td></td>
</tr>
<tr>
<td>$\psi$</td>
<td>0.592 (0.055)</td>
</tr>
<tr>
<td>Type1 Proportion</td>
<td>42%</td>
</tr>
<tr>
<td>Type2 Proportion</td>
<td>58%</td>
</tr>
<tr>
<td><strong>Peer Effects</strong></td>
<td></td>
</tr>
<tr>
<td>$\alpha^A$</td>
<td>0.537 (0.080)</td>
</tr>
<tr>
<td>$\alpha^R$</td>
<td>-0.454 (0.025)</td>
</tr>
<tr>
<td><strong>Finance</strong></td>
<td></td>
</tr>
<tr>
<td>$\gamma^A$</td>
<td>-1.017 (0.077)</td>
</tr>
<tr>
<td>$\gamma^R$</td>
<td>-0.505 (0.033)</td>
</tr>
<tr>
<td><strong>School Characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>$\delta_1^A$: free-lunch</td>
<td>-0.988 (2.413)</td>
</tr>
<tr>
<td>$\delta_2^A$: non-white</td>
<td>0.959 (0.160)</td>
</tr>
<tr>
<td>$\delta_3^A$: title1</td>
<td>0.886 (0.072)</td>
</tr>
<tr>
<td>$\delta_1^R$: free-lunch</td>
<td>0.986 (0.092)</td>
</tr>
<tr>
<td>$\delta_2^R$: non-white</td>
<td>0.955 (0.067)</td>
</tr>
<tr>
<td>$\delta_3^R$: title1</td>
<td>0.888 (0.034)</td>
</tr>
<tr>
<td><strong>Indirect Network Externalities</strong></td>
<td></td>
</tr>
<tr>
<td>$\kappa^A[type1]$</td>
<td>0.794 (0.142)</td>
</tr>
<tr>
<td>$\kappa^A[type2]$</td>
<td>0.760 (0.125)</td>
</tr>
<tr>
<td>$\kappa^R[type1]$</td>
<td>0.542 (0.121)</td>
</tr>
<tr>
<td>$\kappa^R[type2]$</td>
<td>0.503 (0.104)</td>
</tr>
<tr>
<td><strong>Target &amp; Cost</strong></td>
<td></td>
</tr>
<tr>
<td>$\lambda_1^A[type1]:$ cost</td>
<td>0.600 (0.118)</td>
</tr>
<tr>
<td>$\lambda_1^A[type2]:$ cost</td>
<td>0.496 (0.108)</td>
</tr>
<tr>
<td>$\lambda_1^R$: target</td>
<td>0.599 (0.031)</td>
</tr>
<tr>
<td>$\lambda_1^R[type1]:$ cost</td>
<td>0.387 (0.077)</td>
</tr>
<tr>
<td>$\lambda_1^R[type2]:$ cost</td>
<td>0.481 (0.103)</td>
</tr>
<tr>
<td>$\lambda_2^R$: target</td>
<td>0.517 (0.048)</td>
</tr>
<tr>
<td><strong>error correlation</strong></td>
<td></td>
</tr>
<tr>
<td>$\rho_1$</td>
<td>0.504 (0.004)</td>
</tr>
<tr>
<td>$\rho_2$</td>
<td>0.500 (1.415)</td>
</tr>
<tr>
<td><strong>Number of Schools (observations)</strong></td>
<td>1,000 (10,000)</td>
</tr>
</tbody>
</table>

Note: A proportion of segments is calculated by using a logit formula.

Table 8: Demand Model Parameter Estimates
cost, so they are less likely to reuse the platform. This result is consistent with our data pattern that growth of the platform is driven by new adopted teachers over time, whereas adopted teachers tend not to repeat to use the platform much.  

Last, the parameter estimates of expected benefit sensitivity (i.e., $\lambda^A_2$, $\lambda^R_2$) are also positive, implying that as the amount of future benefit of adopting (reusing) the platform, teachers are more likely to adopt (reuse) the platform.

Finally, the estimates for teacher expectation processes are reported in Table 9.

### 7.2 Counter-factual Experiments

Using these parameter estimates from the demand model, we conduct policy experiments (1) to quantify peer effects and (2) to examine the marginal effects of education budget cuts on teachers’ adoption and repeated-use decisions.

#### 7.2.1 Quantifying peer effects on teachers’ adoption and repeated-use decisions

Specifically, we first quantify the economic significance of peer effects. For example, how does the absence or presence of peer effects influence the diffusion process? This analysis simply computes the predicted share of adopting teachers and repeated-use teachers, respectively, at each school and for each year with shutting down peer effects (i.e., the number of adopters [repeated users] is equal to zero). Additionally, because our approach allows us to recover two latent classes of teachers, we investigate how heterogeneity in adoption and repeated-use cost generates different adoption and repeated-use decisions by teacher types depending on peer effects.

Figure 12 presents the results. The left figure shows the percentage point difference of the predicted share of adoption between the baseline and the absence of peer effects (i.e., zero previous adopters). First, overall, if we shut down peer effects, the predicted share of adoption decreases by 0.29 percent over time (i.e., ten years), and this effect is worse during the recession period. Second, peer effects have a stronger impact on type-1 teachers because they have a higher level of adoption cost than type-2 teachers do (e.g., type-1 decreased by 0.48 percent and type-2 decreased by 0.25 percent in 2014). As a result, type-1 teachers are more likely to rely on peer behavior that gives positive informational value. Thus, if we shut down peer effects, they might have no information resources and be less likely to adopt the platform. On the contrary, type-2 teachers have a lower level of adoption cost, so they are less likely to be influenced by peers’ behavior.

Second, more interestingly, if we shut down peer effects, the predicted share of repeated use increases by 5.94 percent over time, and this effect is amplified during the recession period. Because

---

31 In fact, this is consistent with a managerial question raised by the platform that repeated use rate is too low.
<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{ht+1}^A$</td>
<td>0.999***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00110)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N_{ht+1}^P$</td>
<td></td>
<td>0.864***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00189)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$IN_{ht}$</td>
<td>-0.0345***</td>
<td>-0.0711***</td>
<td>-0.0123</td>
<td>-0.373***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00265)</td>
<td>(0.00620)</td>
<td>(0.0116)</td>
<td>(0.0187)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$IN_{ht-1}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.782***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.00109)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C(lunch)_{ht}$</td>
<td>-0.0386***</td>
<td>0.199***</td>
<td>-0.443***</td>
<td></td>
<td>-0.0886***</td>
<td>0.0542</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00705)</td>
<td>(0.0161)</td>
<td>(0.00663)</td>
<td></td>
<td>(0.0307)</td>
<td>(0.0495)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C(lunch)_{ht-1}$</td>
<td></td>
<td></td>
<td></td>
<td>0.759***</td>
<td>-0.116***</td>
<td>-0.803***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.00188)</td>
<td>(0.00169)</td>
<td>(0.00846)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C(Race)_{ht}$</td>
<td>0.0979***</td>
<td>0.464***</td>
<td>0.286***</td>
<td></td>
<td>0.574***</td>
<td>0.648***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00580)</td>
<td>(0.0143)</td>
<td>(0.00546)</td>
<td></td>
<td>(0.0253)</td>
<td>(0.0407)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C(Race)_{ht-1}$</td>
<td></td>
<td></td>
<td></td>
<td>0.0553***</td>
<td>1.03***</td>
<td>0.183***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.00163)</td>
<td>(0.00147)</td>
<td>(0.00735)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C(Title1)_{ht}$</td>
<td>0.130***</td>
<td>0.317***</td>
<td>-0.107***</td>
<td></td>
<td>0.0380***</td>
<td>0.863***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00160)</td>
<td>(0.00365)</td>
<td>(0.00135)</td>
<td></td>
<td>(0.00628)</td>
<td>(0.0107)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C(Title1)_{ht-1}$</td>
<td></td>
<td>-0.0283***</td>
<td>-0.0248***</td>
<td>0.786***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000374)</td>
<td>(0.000337)</td>
<td>(0.00168)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$F_{dt}$</td>
<td>0.159***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00100)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_{ht}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.504***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.00255)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.0482***</td>
<td>0.0333*</td>
<td>2.508***</td>
<td>0.118***</td>
<td>0.0821***</td>
<td>0.566***</td>
<td>2.200***</td>
<td>0.844***</td>
</tr>
<tr>
<td></td>
<td>(0.00804)</td>
<td>(0.0186)</td>
<td>(0.00334)</td>
<td>(0.000511)</td>
<td>(0.000460)</td>
<td>(0.00230)</td>
<td>(0.0350)</td>
<td>(0.0565)</td>
</tr>
<tr>
<td>S.D Residual</td>
<td>0.331</td>
<td>0.495</td>
<td>0.317</td>
<td>0.090</td>
<td>0.081</td>
<td>0.405</td>
<td>1.443</td>
<td>2.333</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Teacher Expectation Process
peer effects have a negative impact on the repeated-use decision, absence of peers means that competition becomes weaker and teachers are more likely to repeat use of the platform. Overall, shutting down peer effects has a stronger impact on repeated use than on the platform adoption decision. Moreover, similar to the adoption decision, the effect of the absence of peer effects differs by teacher type. Because type-2 teachers have a higher level of repeated-use cost, if we shut down peer effects, type-2 teachers are more likely to repeat use of the platform compared to type-1 teachers.

7.2.2 Quantifying marginal effects of education budget cuts (incomplete)

We quantify not only the temporary effect but also the long-term effect that accounts for peer influence as a multiplier effect. We consider “N”% (from 1% to 10%)\textsuperscript{32} of education budget cuts and “M”% (from 1% to 10%) of peer effects change (could be either increased or decreased). The analysis is simply to compute the predicted numbers of adopted teachers and reused teachers, respectively, at each school and year with decreasing school funding “N”% and increasing (or decreasing) number of previous adopters (repeated users) “M”%. By combining different levels of

\textsuperscript{32}Because in the past ten years, on average, the education budget has been cut by approximately 10% across all states, we choose this range (i.e., from 1% to 10%).
change from both budget and peer effects, we would be able to quantify the marginal effects of education budget cuts on teachers’ adoption and repeated-use decisions that account for the peer effects.

This counterfactual result provides important implications for both online crowdfunding platforms and governments. First, the implications could help the government understand how teachers (or schools) behave to compensate for lack of government funding. The government, of course, does not decide an optimal level of funding based on schools’ own capabilities to make up funding\textsuperscript{33}, but it is worth understanding how teachers (or schools) react to drastic budget cuts. Moreover, we compute marginal effects of budget cuts by state, district, and school, so the government can observe a geographical variation of marginal effects of budget cuts. Second, online crowdfunding platforms should consider leveraging peer influence to not only trigger adoption but also support subsequent repeated use, at least for new technology products such as the one studied here. Further, marketing policies to leverage contagion should be designed and targeted differently between new and experienced teachers because the impact of peer effects is different based on usage experience.

8 Conclusion and Future Research

In this paper, we investigate the impact of education budget cuts and peer effects on the adoption and repeated use of online crowdfunding platforms. We examine a causal effect of education budget policy changes on the use of the online crowdfunding platform and demonstrate the presence and nature of peer effects in this diffusion process, which is a common-pool resource. Moreover, we look into heterogeneous peer effects by exploiting exogenous variations of education budget cuts (from both cross-sectional and time variations). Finally, we quantify (1) the economic significance of peer effects and (2) the marginal effects of policy changes and their geographical variations (in progress) by building and estimating a dynamic demand model of public school teachers’ adoption and repeated-use decisions that account for the peer influence as a multiplier effect.

To investigate these questions, we used a crowdfunding website’s data on approximately 400,000 teachers from 90,000 public schools (in all fifty states) for twelve years (from 2003 to 2014) in combination with Common Core Data to get fiscal and demographic information on public schools. Based on the data, we build a dynamic demand model of public school teachers’ decisions regarding platform adoption and usage. Using estimates provided by the demand model, we conduct a policy experiment to examine the marginal effects of education budget cuts and its

\textsuperscript{33}As we discussed in the above section, the government has its own functions to efficiently distribute funding.
However, this paper has several limitations. First, we do not observe public school funding at the school level. The finest unit of observation from the CCD data is at the district level. Thus, we assume that a distribution of public school funding across schools in the school district is homogeneous. In addition, we do not observe the proportion of outside funding (i.e., additional funding or self-funding other than the government subsidies) at the school level. If we have fiscal information for both government subsidies and outside funding resources at the school level, we can draw conclusions on the direct effect of budget cuts on the teachers’ behavior to compensate for lack of funding.

Second, this paper does not model the government-side decisions on school funding and the donor-side decisions on donation behavior (i.e., amount of donation). We could consider developing the government- and donor-side models for future research; implications from such an equilibrium model will generate interesting counterfactual experiments. For example, we may consider how education budget cuts would change donors’ behavior. Are donors more likely to contribute to the projects posted by teachers from poor schools to improve inequality? We would also be interested in looking into the government’s behavior to see how budget allocation would be changed based on teachers’ behavior to compensate for budget changes. To investigate the effect of this policy, we need to build a model on the government and donor sides; these analyses will be for future research.
Appendix

A1. Growth of the Online Crowdfunding Platform
A2. Teacher Individual-level Data (Peer Effects)

![Average Share of Adoption Chart]

A3. Parallel Time Trend Assumption Test

First, regarding the recoverability assumption, the difficulty in estimating the overall effects of the education budget cuts on public school teachers’ adoption and usage behaviors regarding the online crowdfunding platform is to find the appropriate counterfactual. We cannot simply compare the outcome variables of the states that had drastic budget cuts before and after the policy change because this may confound the pre and post differences with other unobservable changes in the market, such as demand shocks that may coincide with the policy changes. Thus, we need to find appropriate states comparable to the state where drastic budget cuts happened that are subject to the same state forces but are not directly affected by the policy change (i.e., budget cuts).

As we noted, after the recession, 31 states (out of fifty states) reduced their education budget over six years, whereas the other 19 states sustained the same level (or even increased) their budgets during this period. By exploiting this exogenous variation of education budget, we use these 19 states that maintained a similar budget to obtain the counterfactual against which to measure the treatment effects. We show that these states can serve as a control group, which provides a quasi-experiment that allows us to employ a difference-in-differences approach. This approach accounts for the fact that the states where budget cuts did or did not happen are potentially different in various confounding characteristics. Specifically, we compare the difference in outcome
variables-platform adoption and usage—before and after the recession between states where drastic budget cuts happened or did not.

Second, based on that, we test whether the parallel trend assumption holds between those two groups of states: drastic budget cuts versus not. We run the following regression as suggested in Angrist and Pischke (2009) by adding state-specific time trends to equation (4):

\[
Y_{ht} = \beta_0 + \beta_1 \cdot t \times 1 \{ \text{Budget-cuts States}_s \} \times 1 \{ \text{Recession}_t \} + \beta_2 \cdot 1 \{ \text{Budget-cuts States}_s \} \times 1 \{ \text{Recession}_t \} \\
+ \beta_3 \text{School-characteristics}_{ht} + \beta_4 \text{Finance}_{dt} + \beta_5 \text{Indirect-network}_{ht} + \mu_t + \zeta_h + \epsilon_{ht}
\]

As can be seen, we simply add state-specific time trends, which use a multiplication between the time trend, \( t \), and the interaction term (i.e., \( 1 \{ \text{Budget-cuts States}_s \} \times 1 \{ \text{Recession}_t \} \)). This allows treatment and control states to follow different trends in a limited but potentially revealing way. As a rule, DD estimation with state-specific trends is likely to be more robust and convincing when the pretreatment data establish a clear trend that can be extrapolated into the posttreatment period. If the parallel trend assumption holds, the \( \beta_1 \) is insignificant, and Table 10 represents the results of parallel trend assumption test. As can be seen, a coefficient of the state-specific time trends (i.e., \( \beta_1 \)) is insignificant at the 95% confidence level, suggesting that we can reasonably assume that the parallel trend assumption is satisfied.

A5. Correlation Between Finance and Scores

Mean of English Scores (Grade3)
<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Model1 DV: Adoption</th>
<th>(2) Model2 DV: Repeated Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t \times 1 { \text{Budget-cuts States}_s } \times$</td>
<td>0.000150</td>
<td>0.00218</td>
</tr>
<tr>
<td>$1 { \text{Recession}_t }$</td>
<td>(0.000114)</td>
<td>(0.00151)</td>
</tr>
<tr>
<td>$1 { \text{Budget-cuts States}_s } \times$</td>
<td>0.00149**</td>
<td>0.0317**</td>
</tr>
<tr>
<td>$1 { \text{Recession}_t }$</td>
<td>(0.000593)</td>
<td>(0.0132)</td>
</tr>
<tr>
<td>% of non-white students</td>
<td>0.00110</td>
<td>-0.0318</td>
</tr>
<tr>
<td></td>
<td>(0.00218)</td>
<td>(0.0311)</td>
</tr>
<tr>
<td>% of free-lunch students</td>
<td>0.00157</td>
<td>0.0135</td>
</tr>
<tr>
<td></td>
<td>(0.00109)</td>
<td>(0.0109)</td>
</tr>
<tr>
<td>Per-pupil Spending</td>
<td>-1.03e-07***</td>
<td>-9.28e-07</td>
</tr>
<tr>
<td></td>
<td>(2.85e-08)</td>
<td>(1.33e-06)</td>
</tr>
<tr>
<td>Indirect Network Externalities</td>
<td>2.25e-05***</td>
<td>4.27e-05***</td>
</tr>
<tr>
<td></td>
<td>(1.37e-06)</td>
<td>(4.20e-07)</td>
</tr>
<tr>
<td>Time-trend</td>
<td>0.00192***</td>
<td>0.0211***</td>
</tr>
<tr>
<td></td>
<td>(9.04e-05)</td>
<td>(0.00304)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.000286</td>
<td>0.225***</td>
</tr>
<tr>
<td></td>
<td>(0.000858)</td>
<td>(0.0189)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>School</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>799,460</td>
<td>209,750</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.598</td>
<td>0.640</td>
</tr>
</tbody>
</table>

School-district-level clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Results of Parallel Trend Assumption Test
Mean of English Scores (Grade 8)

Mean of Math Scores (Grade 3)
Mean of Math Scores (Grade8)

References


Michael Leachman, Nick Albares, Kathleen Masterson, and Marlana Wallace. Most states have cut school funding, and some continue cutting. Center on Budget and Policy Priorities, 4, 2016.


Ethan R Mollick and Venkat Kuppuswamy. After the campaign: Outcomes of crowdfunding. 2014.


