Teachers Teaching Teachers: The Role of Networks on Financial Decisions*

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This paper studies the role of peers in the transmission of information pertinent to household financial decisions. Specifically, we examine the effect of peers on the mortgage refinancing decision of Texas public school teachers by identifying networks based on common off-periods in teachers' schedules. Exploiting this within-campus variation, used to separate out campus-level unobservable shocks, we find that refinancing activity of a teacher's peers increases her likelihood of refinancing by 26%. Peers also affect a teacher's choice of lender. Our results have important policy implications; educating homeowners on the benefits of refinancing could potentially translate into substantial savings for households.

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I. Introduction

Economist have long studied the role that information acquisition plays in financial decision making.[1] We study how an individual's network contributes to this information gathering process. While peer effects have been explored at length as they relate to the decisions of the firm (Leary and Roberts (2014)) and financially affluent individuals such as CEOs (Shue (2013)), mutual fund managers (Cohen, Frazzini, and Malloy (2008), Pool, Stoffman, and Yonker (2015)), and sell-side analysts (Cohen, Frazzini, and Malloy (2010)), less is known about the role that networks play in the shaping of a household's financial decisions. We help fill this void by studying the impact of an individual's network in the context of his mortgage refinancing decision.

In 2010, home value comprised 43.1% of gross assets for individuals in the U.S., representing the largest portion of household wealth, compared to 28.5% in equities and pension accounts combined (Wolff (2012)). In most cases, homes are largely financed by debt. Embedded in this debt is the option, among others, to restructure by refinancing. This option to refinance can be particularly important for those borrowers who financed their homes in periods of high interest rates. For example, following the commonly used "rule of thumb" and refinancing after a 2% drop in lending rates could potentially reduce a borrower's monthly payment by more than 15%. Thus, an individual's refinancing choice serves as a nice testbed with which to better understand the role an individual's network plays in the making of important financial decisions.

Unfortunately, studying how household financial decisions are affected by peer networks and the information they generate is challenging for multiple reasons. First, it is difficult to identify links between individuals. For instance, online social networks suffer from participation bias, both restricting the population sample for which we are able to observe financial decisions and providing an incomplete picture of an individual's peer group. Second, individuals tend to self-select into peer groups. This is also a necessary feature in any empirical

1. For example, see Grossman and Stiglitz (1980), Ippolito (1989), and Ellison and Fudenberg (1995).

design studying the role of peer networks.[2] However, the identification of peer effects does require the selection of peers and their subsequent actions to be uncorrelated. Third, individuals in the same peer group may be subject to common unobservable shocks. Any influence of these shocks on the outcome variable would lead to biased estimates of the peer group's effect.

We use a novel micro dataset of employment records for Texas public school teachers to address these difficulties. First, the nature of the employment records allows us to clearly identify links between individuals. Furthermore, in contrast to data from social networks requiring voluntary participation, the comprehensive nature of our employment records are absent participation bias. Second, while teachers have a choice over which school district to apply to, they have little or no effect over which campus they are assigned to. This quasi-randomization of campus assignment mitigates the concern of endogenously formed networks while maintaining the self-selection of individual's into peer groups based on occupation. Third, we exploit variation in peer groups both across and within campuses to account for common unobservable shocks to peer groups, such as employment effects and campus-level loan supply exposure. We combine these employment records with county deed records to obtain the refinancing transactions of teachers in our sample.

We start by examining smaller campuses (less than 50 teachers) where there is likely to be more interaction amongst coworkers and thus a better representation of one's peer group. We find that a teacher is 9.9% more likely to refinance following the recent refinancing of a peer. While consistent with the effect of peers, this finding could also be the result of a common employment risk affecting the refinancing decisions of entire peer groups. Fortunately, employment risk is due to financial distress at the district level, which is made up of many campuses or peer groups. Inconsistent with employment effects, this result holds after including district-year fixed effects. This result also holds after controlling for other

2. For instance, while observing their behavior after randomly placing strangers in a room informs us regarding the effect of strangers, it does not yield significant insight into the role played by an individual's self-selected peers on her decision making.

determinants of refinancing, employment and demographic characteristics of teachers. Additionally, we find that the sensitivity of the refinancing decision increases with the amount of estimated savings associated to the transaction.

Although the campus-level analysis is largely consistent with peer effects playing an important role in the refinancing decisions of teachers, two main concerns remain. First, it is possible that there is potential variation in campus-level loan supply exposure, resulting in a clustering of mortgage refinances at the campus level. Second, even though teachers within a small campus share a physical space, this does not ensure that all teachers within the same campus interact on a daily basis. To address these concerns, we use teacher class assignments to construct a more refined measure of a teacher's peer group. More specifically, we identify each teacher's off-periods (i.e., when the teacher is not in the class room), and consider two teachers to be in the same peer group if they have at least 40 minutes of off-period overlap per day. This alternative definition of peer groups is both more accurate, increasing the likelihood of information sharing within the peer group, and also allows us to exploit within campus variation, strengthening our tests.

We find a stronger effect of peer groups on the refinancing decisions of teachers after redefining a teacher's peer group using off-periods. A teacher is 29% more likely to refinance conditional on sharing an off-period with a teacher who recently refinanced. In addition, this effect remains equal to 26% after controlling for possible campus-level effects due to variation in loan supply exposure with campus-year fixed effects. We also provide evidence that teachers are not choosing their schedules and therefore controlling their off-periods, further validating the previous results.

We next turn to a teacher's choice of lender. It is unlikely that information transferred from a teacher's peers, if any, is restricted to the prevailing rate while other pertinent information such as the lender offering such terms is not disclosed. To investigate if individuals refinancing their loan are more likely to share the same lender as their peer, we undertake a non-parametric approach. More specifically, we generate a set of pseudo peer-groups which are geographically similar to the true peer groups but fall under the null hypothesis of no information sharing within the peer group to serve as a benchmark. We find the probability of a teacher and their peer sharing a common lender is 8.16%, or 12.9 standard deviations larger than the expected overlap when considering the pseudo peer groups, strongly suggesting that a teacher's choice of lender is also influenced by his or her peer group.

Overall, our results strongly support peer effects playing an important role in households' refinancing decisions. Furthermore, because the sharing of refinancing information captured by our tests come from quasi-exogenously formed peer networks, our results have important implications for policymakers; Educating homeowners and disseminating interest rate information (and the benefits of refinancing) could potentially translate into important savings for households.

This paper relates to the literature on household finance choices. Hong, Kubik, and Stein (2004) and Guiso, Sapienza, and Zingales (2008) study household stock ownership. Von Gaudecker (2015) find that portfolio under-diversification is concentrated among households with below median financial literacy. Related to the effect of peers on household finance choices Beshears, Choi, Laibson, Madrian, and Milkman (2015) find an oppositional effect where individual's decrease savings when given information about the savings of their peers. We add to this literature by contributing to the understanding of how households incorporate information regarding the benefits of exercising their financial option to refinance mortgages.

Finally, this paper also relates to a broader literature that studies peer effects, beyond its effects on financial decisions. Recent work has shed light on the role of peer effects in fraud among financial advisors (Dimmock, Graham, and Gerken (2015)) and CEOs (Khanna, Kim, and Lu (2015)). Furthermore, Brogaard, Engelberg, and Parsons (2014) find an increased ability of journal editors in screening colleagues' papers. Finally, Eppel and Romano (1998) study the increase in positive externalities a high-ability student receives from her peers as the result of tuition vouchers. Sacerdote (2001) finds a continuation of this peer effect in a post-secondary setting, where a college student's class performance and participation in social activities is influenced by her randomly assigned freshman roommate.

The rest of the paper is organized as follows. The next section describes the data sources, the procedure we use to match the TEA records with county deed records, and the sample selection process. Section III provides institutional background on refinancing and shows the first set of results using small campuses to identify peer groups. Section IV further studies the effects of networks on the decision of refinancing of teachers using overlapping off-periods to identify peer groups, and Section V concludes.

II. Data and Sample Selection

II.A. Data Description

We collect data from multiple sources regarding teacher-level employment records, home mortgage actions, and housing characteristics. We briefly describe each data source.

II.A.1. Teacher Employment Records

To begin, we obtain payroll records for all public school employees in Texas from the Texas Education Agency (TEA). The data covers the period from 1999 to 2011, and represents 1,305 unique school districts. Each district is made up of an average of 7.98 campuses. While all employees are included in the payroll records, we restrict the sample to include only teachers. The result is a sample of over 3.6 million teacher-year observations across 585,000 teachers. Each employment record observation consists of the teacher's name, demographics, date of birth, education level, tenure, salary, and teaching assignments.

II.A.2. County Deed Records

We obtain property characteristics and residential transaction information from DataQuick's Assessor and History files. DataQuick compiles and cleans county deed records and it is one of the main real estate data providers in the U.S. The assessor file contains property addresses and characteristics. The History file contains detailed information about slightly over 11 million property transactions in the state of Texas between 2002 and 2011, involving around 4.6 million properties from the Assessor file. Examples of variables available in the History file include the transaction date, the transaction purpose (purchase or refinance), the loan amounts, the interest rate type (fixed or variable), and the names of the buyer and the lender.

II.A.3. Registered Voter Rolls

Central to our study is the matching of teachers with their corresponding refinancing transactions. To aid in the matching process, we obtain the full electoral roll of registered voters from the Texas Secretary of State. Each record contains the voter's name, date of birth, mailing address, and physical address.

II.A.4. Additional Data Sources

Since DataQuick does not provide interest rates and transaction price coverage is low in Texas, we use two additional datasets. For interest rates, we use the monthly 30-year fixed rates from Freddie Mac's Primary Mortgage Market Survey (PMMS).[3] Additionally, as a proxy for individual house prices we use zip code-level indices from Zillow.[4]

II.B. Matching Description

As mentioned above, to evaluate the role of peer effects on the refinancing decision of teachers in our sample, we must first map our teacher employment records to county deed records. Below, we describe each step of the matching procedure.

3. Freddie Mac surveys lenders on a weekly basis and records interest rates on first-lien prime conventional purchase mortgages. Currently, about 125 lenders are included in the survey. Additional information about this survey can be found at http://www.freddiemac.com/pmms/abtpmms.htm.

4. Zillow's indices are based on median home values. A more detailed description of their methodology can be found at http://www.zillow.com/research/zhvi-methodology-6032.

II.B.1. Teacher to Voter

While both the TEA payroll records and county deed records provide names, matching teacher records to mortgage transactions using legal names is problematic for multiple reasons. One particular concern is the matching of teachers who possess common names. While the distance between the teacher's campus and each deed holder's physical address can help alleviate this concern, it does not fully address the issue. For instance, our sample contains four occurrences of "Michael Cunningham" listed on active mortgage records in Denton County alone. In addition, the use of names alone would not be able to link the teachers in our sample to mortgage records in cases in which only the teacher's spouse was listed on the deed. For these reasons, we turn to the electoral roll of registered voters, which serves as a linchpin in our matching process. Included in our teacher employment records, along with legal name, is the individual's date of birth. Thus, we can use both name and date of birth to identify the voting record of every teacher in our sample who is a registered voter. We are able to match 76.2% of the payroll records to the voter roll.

II.B.2. Voter to County Deeds

We then use the resulting voting records, which contain both a physical and mailing address for the individual, to establish a link between our teacher records and county deed records. To do this, we require an exact match between the address number prefix, zip code, and individual's last name, and require that the Levenshtein ratio between the address name listed on the county and voting records exceeds 0.9. Figure I provides an illustration of the matching process.

[INSERT FIGURE I HERE]

II.C. Final Sample

After matching registered teacher voters with the county deed records we obtain slightly over 1.2 million teacher-year observations over the 1999 to 2011 period. The transactions associated with these teachers include purchases, refinances, subdivisions, and other less common types of transactions. We keep purchases and refinances. We use purchase transaction records to identify the time and the terms of the loan when a teacher buys a house. For a teacher to remain in the sample, we need to observe when the teacher bought the house, that is, the teacher needs to show a purchase transaction in the county deed records between 2002 and 2011.[5]

As our main focus is on rate refinances, we drop teacher-property observations where the teacher bought (or refinanced) the property using an adjustable-rate mortgage (ARM). We also drop teacher-property observations where a refinance appears to be a poor financial decision or appears to be a cash-out refinance. More specifically, based on the PMMS 30-year fixed rates at the time of the last and the current transactions, we estimate a measure of "savings" for each refinance. Then, if the savings of a refinance are lower than $10,000, we drop all the transactions associated with that teacher-property. Additionally, we drop all the transactions associated with the teacher-property if the loan amount of a refinance by the teacher is larger than 1.05 times the remaining principal balance of the existing loan.[6]

Finally, to increase the likelihood of teachers sharing information with each other, we restrict the sample to teachers from small campuses. Specifically, we keep teachers from campuses where the average number of teachers that work on the campus for more than 80% of their working hours is between 5 and 50.[7] The final sample consists of 62,246 teacher-year observations. Table I describes the final sample, along with the samples corresponding

5. Consequently, teachers that do not show any purchases and teacher-year observations prior to the purchase of the property are dropped from the sample.

6. As we do with the savings, we estimate the monthly unpaid principal balance of each mortgage in our sample based on the PMMS 30-year fixed rates and assuming a 30 year loan.

7. Additionally, for the accuracy of our measures, we also require campuses to have at least 70% of their teachers registered as voters, on average.

to each of the main steps of the matching procedure. Overall, all samples of teacher-years show similar salaries, tenure, demographics, and education level, providing reassurance of the representativeness of the final sample.

[INSERT TABLE I HERE]

III. Peer Effects on the Refinancing Decision

III.A. Institutional Details of Refinancing

Mortgage loans can be used to purchase a new property or to refinance an existing loan (on a previously purchased property). This paper focuses on mortgage loans used for refinancing. Loans for refinancing are classified into two main groups, depending on the borrower's objective. In a *rate or term* refinance, the interest rate and/or the term of the loan are modified, usually with the goal of lowering the mortgage payment. In contrast, in a *cash-out* refinance, the new mortgage amount exceeds the existing mortgage amount, since the objective of this type of refinance loan is to extract equity from the house. Typically, rate refinances are motivated by interest rate decreases while cash-out refinances are motivated by house price increases. Most of our analysis centers on rate refinances.

Households purchase their homes at different points in the business cycle. Therefore, refinancing the interest rate of an existing mortgage can result in significant savings for those borrowers that financed their purchases in a period of high interest rates. A key determinant for the amounts of savings following a rate refinance is the spread between the interest rate of the existing loan and the current (or new) interest rate. If this spread is large enough to lower the mortgage payment so that the present value of savings exceeds the costs of refinancing, then refinancing is recommended. The costs of refinancing, or *closing costs*, include application fees, appraisal fees, credit report fees, legal fees, home-inspection fees, and origination fees, among others. The most relevant fee is the origination fee, which typically equals around 1% of the loan amount. This is why the widely known "rule of thumb" for refinancing recommended by the industry suggests refinancing after interest rates have declined by 200 basis points.

However, the previously described saving that results from interest rate differentials is not the only main relevant factor for a rate refinance. Even if a borrower wants to refinance, he might not be able to obtain the loan if he is underwater (i.e., house prices have declined enough since the purchase to leave the borrower without equity on the house). Additionally, rate refinances depend heavily on the expectations of future interest rates. Even if interest rates differentials justify refinancing today, it might be better for the borrower to wait and refinance later if interest rates are expected to continue to decline in the near future.

III.B. Measuring Peer Effects

Studying peer effects is challenging for multiple reasons. First, it is difficult to identify links between individuals borne from a common environment. Second, individuals tend to self-select into peer groups. Third, individuals in the same peer group are subject to common shocks. Our empirical setting is useful to address these challenges in identifying peer effects. By focusing in campuses with less than 50 teachers, we increase the likelihood of teachers sharing information about their refinancing decisions. Additionally, the Texas public school setting is advantageous because teachers apply for jobs at the district, but have little or no effect on which campus they are assigned to, which mitigates concerns of individuals self-selecting into peer groups (i.e., teacher networks are less likely to be formed endogenously). Furthermore, in contrast to other settings where participation is voluntary, employment records include all the teachers in the system, which eliminates the concern of biased samples. Finally, the richness of our micro-level data allows exploiting variation across and within campuses to account for common shocks to the peer group.

III.C. Peer Effects Matter

We start using small campuses as a measure of peer group. Under the assumptions that teachers in small campuses share information about their refinancing decisions and that peer effects matter, then a teacher should refinance with a higher probability after a refinance occurs in his or her peer group, than when no one in the peer group has recently refinanced. Furthermore, the differences between these probabilities should be small when the savings net of closing costs are low and increase with the benefits of refinancing.

Figure II plots the relation between the probability of a teacher refinancing their existing mortgage and their estimated net savings.[8] Consistent with the intuition above, we separate teachers into two groups. The first group (black line with hollow markers) consists of teacher-month observations in which no individual in the teacher's peer group performed a mortgage refinance in the trailing three-month period. The second group (red & blue line with solid markers) consists of the remaining teacher-month observations, in which at least one individual in the teacher's peer group refinanced within the last three months. As we are interested in individuals for whom refinancing is a feasible option, we do not consider teachers who we estimate to be underwater (i.e., have negative equity on the house).[9] The figure confirms the positive relation between the probability of refinancing and net savings. As hypothesized, both groups of teachers show similar low levels of probability of refinancing when net savings are negative. However, for positive net savings, the probability of refinancing conditional on a peer refinancing is greater than the probability for the peer non-refinancing group for all net saving bins, and the difference increases with the amount of net savings. For example, for estimated net savings of $5,000, the likelihood of an individual refinancing increases 0.135% (from 0.559% to 0.694%) when the number of peers who recently refinanced a mortgage increases from zero to one or more. For estimated net savings of $15,000, the previous difference in the refinancing probabilities of both groups increases

8. Savings are estimated as described in Section II.C. To get the estimated net savings, closing costs of $5,000 are considered.

9. For this, we estimate house price fluctuations based on Zillow's zip code-level indices.

to 0.480% (1.727%−1.247%), or 38.5% in relative terms (1.727%/1.247%), an economically significant amount. Overall, Figure II suggests that peer effects are a significant determinant of the probability of refinancing of Texas teachers.

[INSERT FIGURE II HERE]

We now turn to a more formal framework which allows us to better evaluate the economic and statistical significance of peer effects while controlling for other determinants of refinancing activity in addition to savings. We estimate OLS regressions where the dependent variable is a 0/1 indicator for refinances and the main variable of interest is *Peer Refinances*, which captures the number of peers having undertaken a mortgage refinance in the previous three-month period, scaled by the size of the peer group. The first regression in Panel A of Table II, which controls for other determinants of refinancing such as the estimated savings, a 0/1 indicator for whether the teacher is underwater, and the underwater amount (in percent), confirms the results in Figure II. The coefficient of 6.172 (t-stat=5.82), indicates that a one standard deviation increase in the percent of an individual's peer group with recent refinancing activity is associated with a 6.2 bp increase in the individual's monthly probability of refinancing. To address the possible concern that refinancing activity is being driven by variation in local loan supply exposure or economic conditions, the second regression in Panel A of Table II includes Metropolitan Statistical Area (MSA)-Year fixed effects. Results are similar to the previous specification, with a coefficient on *Peer Refinances* of 5.479. To give this some additional economic perspective, the unconditional probability of a teacher refinancing their mortgage in a given month is 55.4 bp in the same sample. Therefore, a one standard deviation increase in *Peer Refinances* increases the probability of refinancing by 9.9% of its unconditional value.

However, there are other factors that may influence an individual's decision to refinance their mortgage beyond local economic conditions. For instance, the positive correlation between the refinancing activity of a teacher and her peer group could be the result of exposure of both sets of individuals to common employment risk shocks. Fortunately, the risk of unemployment is the result of economic hardship at the school district level. Thus, the third specification in Panel A of Table II includes school district-year fixed effects. The coefficient on *Peer Refinances* decreases slightly to 2.785 (t-stat=2.88). Finally, the last specification in the panel also includes controls for teacher characteristics such as gender, ethnicity, highest academic degree obtained, and salary. The results of the third specification remain virtually unchanged (coefficient of 2.792).

While the previous specifications include all teacher-month observations, as shown by Figure II, it is unlikely for an individual to refinance an existing mortgage when net savings are negative. Thus, Panel B of Table II repeats the previous analysis after restricting the sample to teacher-month observations in which the estimated net savings upon refinancing are positive. Compared to the full sample results, the effect of peer refinancing is stronger for the first two specifications while remains essentially the same for specifications three and four.

[INSERT TABLE II HERE]

Finally, as a complement to the results of this section, Internet Appendix Table IA.I shows that the effects of peer refinancing are even stronger (for all specifications) when *Peer Refinances* takes into account refinances in the previous two-month period, instead of the previous three-month period. Overall, the regression analysis shows that peer effects have an economically significant effect on the probability of refinancing of Texas teachers, that is, peer effects matter.

III.D. Falsification Test

We conduct a falsification test to further validate the results in the previous section. If peer effects indeed play a role in the refinancing decisions of our teachers, then if we repeat the analysis in Table II using a distinct sample of similar non-teachers (who are not part of the peer groups in our sample), the variable *Peer Refinances* should not significantly load.

We take advantage of the extensive coverage of the county deed records. For each teacher-property in the sample, we find a homeowner who is not a teacher, with a similar property (in terms of loan and physical characteristics). More specifically, within each zip code, we match properties based on the quarter in which the property was acquired and the loan amount (rounded to the nearest $2,000). To minimize the likelihood of the teacher knowing his or her match, we require properties to be in a different zip plus 4 code.[10] We also require the homeowner in the control group to continue to own the house after his or her match sold the house or dropped from the teacher employment records. Absent a match in the same zip code, we extend the search to the rest of the county, restricting zip codes of both properties to be within a 10 mile radius. Finally, in the case of multiple matches, we select the final match based on minimizing the difference between the square footage of the houses, the size of the lots, and the year that the houses was built, in that order of priority. We are able to match 69% of the 12,843 eligible teacher-properties in our small campuses.[11]

Using the matched sample of non-teacher homeowners and their corresponding teacher-properties, we repeat the estimations in Columns 2 and 3 of Panels A and B of Table II and present the results in Table III.[12] As in Table II, all the coefficients on *Peer Refinances* continue to be economically important and statistically significant in the subsample of teachers (with coefficients ranging from 3.403 to 6.056). However, this is not the case when estimating the regressions using the sample of non-teacher homeowners; the peer effect variable is indistinguishable from zero in all specifications both in the full sample and when restricting the non-teacher-month observations to have positive net savings. The results of this falsification test strongly support the result in the previous subsection; peer effects matter.

10. If the teacher and his or her match are close neighbors there is a higher chance of them sharing refinancing information, contaminating the results of the falsification test.

11. We allow properties in the control group to be matched to more than one teacher-property. However 99.5% of the matches are unique. The maximum number of times a property in the control group is matched is three (with a frequency of only 0.07%). Additionally, Table IA.II shows that the average characteristics of the teacher-properties are quite similar to the ones of the matched non-teachers.

12. Note that this requires estimating the savings, the underwater indicator, and the underwater amount for the matched sample of non-teachers.

[INSERT TABLE III HERE]

IV. Off-Periods

The previous section presents results consistent with an individual's refinancing decision being influenced by the refinancing activity of his or her peer group. While the use of within-district variation helps address endogeneity concerns related to common unobservable employment shocks influencing both a teacher and their peer group's decision to refinance, the results are also consistent with other plausible explanations. Of particular concern is the potential variation in campus-level loan supply exposure, resulting in the clustering of mortgage refinances at the campus level. For instance, the construction of a new billboard near a campus advertising a lender's superior mortgage terms would provide an alternative information channel which would be mistakenly attributed to a teacher's peers in our setting. Therefore, to disentangle the possibility of campus-level variation in loan supply exposure from the role of an individual's peers, we exploit a source of within-campus variation when constructing the peer groups, *common off-periods.*

IV.A. Description of Off-Periods

While the teachers within a school campus share a common set of buildings, this does not ensure that all teacher-pairs within the campus interact on a daily basis. In contrast, it is much more likely for an individual to acquire and incorporate information from a peer with whom they have frequent contact. While two teachers may be employed in the same campus, their amount of interaction is largely dictated by the teacher's class schedule. More specifically, a given school day is typically divided into multiple class periods. While the teachers in our sample are assigned a class during the majority of the class periods, each teacher is also allotted one or more periods which are designated as "*off-periods*". These non-teaching periods are used to prepare lectures, grade assignments, use office resources such as the school's copier, and to visit the teacher's lounge. More importantly, *off-periods* do not typically occur at a uniform time across all teachers for a given campus. Therefore, the extent to which two teachers interact on a daily basis, and thus share information, is significantly influenced by the amount of overlap between the teacher's *off-periods*.[13]

Fortunately, our employment records include detailed information on each teacher's class assignments, which includes the class's beginning and ending times. From this information we are able to recover the off-periods for each teacher in our sample. Using this data on teacher off-periods, we then construct a more refined measure of a teacher's peer group. For each pair-wise combination of teachers within a campus, we begin by identifying all overlapping off-period segments and compute the number of minutes of overlap for each segment. We exclude any segments which overlap by less than 10 minutes, as it is unlikely that teachers are able to interact in a meaningful way in such a brief amount of time before returning to their class assignments. We define a teacher's peer group as any teacher with an average of 40 minutes per school day or more of commonality in off-periods.[14] Finally, there exists some campuses with a uniform campus-wide off-period. Thus, we exclude any campus-year in which greater than 90% of teachers have at least 40 minutes of off-period overlap per day.

Figure III illustrates the class assignment schedule for three teachers and our classification of each teacher's peer group. The colored blocks denote a teacher's off-periods, while hatched regions indicate an overlap in off-periods with another teacher. The figure indicates that both the *Bob-Kim* and *Kim-Ava* pairs share 45 minutes of common off-periods per day while there is only 15 minutes of common off-periods for the *Bob-Ava* pair. This figure illustrates the asymmetric nature of each teacher's peer group. For instance, while *Bob's* peer group

13. We find anecdotal support for this claim based on multiple conversations with public school teachers who acknowledge they interact primarily with other teachers while in the teacher's lounge and teacher work room during their off-period.

14. In Texas, school districts have discretion over the format of the class schedule. While some districts have a standardized set of class periods across all days, other districts utilize an alternating, or "block", schedule. It is possible for two teachers to share an off-period block during some days of the week and have no overlap on other days. Thus, for each teacher-pair we compute the average number of overlapping minutes per school day.

consists of only *Kim*, *Kim's* peer group is made up of both *Bob* and *Ava*. We now turn to the importance of peer effects on a teacher's refinancing decision using this refined measure of one's peers.

[INSERT FIGURE III HERE]

IV.B. Off-Periods Matter

We begin by repeating the analysis performed in Figure II in light of our new measure of a teacher's peer group. Figure IV plots the probability of refinancing and expected net savings for the two mutually exclusive groups.[15] The probability of refinancing is relatively similar between the two groups, conditional on realizing net savings less than $5,000, similar to the results from Figure II. In contrast, the likelihood of an individual refinancing when their estimated net savings is $5,000 increases from 0.268% to 1.148% when the number of peers who recently refinanced a mortgage increases from zero to one or more. This increase, which represents over a four-fold increase in the monthly probability of refinancing, is significantly larger than the increase found in Figure II. In fact, for all bins with positive net savings, the probability of refinancing conditional on a peer refinancing is significantly greater than the probability for the peer non-refinancing group.

[INSERT FIGURE IV HERE]

As before, we now turn to a regression framework. Table IV presents the results of OLS regressions analogous to Figure IV. Recall that the peer group for each observation contains all other teachers whom have at least 40 minutes of overlap in off-periods per school day. Thus, the primary variable of interest, *Peer Refinances*, equals the number of teachers with

15. Similar to Figure II, the first group (black line with hollow markers) consists of teacher-month observations in which no individual in the teacher's peer group performed a mortgage refinance in the trailing three-month period. The second group (red & blue line with solid markers) consists of all teacher-month observations in which at least one teacher sharing a common off-period experienced a mortgage refinance over the past three-month period. We exclude any teacher-month observations in which we estimate the mortgage to be underwater.

overlapping off-periods having undertaken a mortgage refinance in the previous three-month period, scaled by the size of the peer group.[16] Similar to the Table II, we standardize *Peer Refinances* for ease of interpretation and report effects in basis points.

[INSERT TABLE IV HERE]

The first specification includes MSA-year fixed effects to control for the effect of local loan supply exposure or economic conditions. The coefficient of 8.465 (t-stat=3.13) indicates that a one standard deviation increase in the percent of an individual's peer group with recent refinancing activity is associated with a 8.47 bp increase in the individual's monthly probability of refinancing. The unconditional probability of a teacher refinancing their mortgage in a given month is 25.7 bp in the same sample. Therefore, a one standard deviation increase in *Peer Refinances* increases the probability of refinancing by 33% of its unconditional value.

The second specification includes school district-year fixed effects to control for the confounding effect of common employment risk shocks. With this change, the coefficient of *Peer Refinances* decreases slightly to 7.428. In contrast, an increase of \$10,000 in the net savings to an individual of refinancing is associated with a 23.4 bp increase in the likelihood of refinancing. Therefore, a one standard deviation increase in *Peer Refinances* has an equivalent effect as roughly a \$3,200 increase in the net savings realized upon refinancing.[17]

Thus far, these results are consistent with those of Table II while being larger in terms of economic magnitude. However, the previous specifications suffer from the same shortcoming at the analysis based on teachers of small campuses. Ultimately, the possibility remains that the measured effect of *Peer Refinances* is being driven by campus-level loan supply exposure. Fortunately, the within-campus variation in our definition of *Peer Refinances* based on off-periods allows us to separate out campus-level effects from those of peers. For this reason, the third specification includes campus-year fixed effects. Following the inclusion of campus level controls, a one standard deviation change in *Peer Refinances* is associated with a 25.6%

16. We obtain quantitatively similar results when scaling by the average peer group size across all teachers in a given campus-year.

17. $\frac{7.428}{23.390} \cdot \$10,000 = \$3,176$

increase in the monthly probability of refinancing relative to its unconditional probability. The effect remains virtually unchanged in the final specification with the inclusion of controls for employment and individual characteristics.

Panel B of Table IV repeats the previous analysis when considering only teacher-month observations in which the estimated net savings upon refinancing are positive. As with small campuses, the effect of *Peer Refinances* is stronger across all specifications following this restriction. In the final specification, a one standard deviation increase in *Peer Refinances* is associated with a 34.8%increase in the monthly probability of refinancing relative to its unconditional value.[18]

IV.C. Where it Matters: Interaction; The Importance of Net Savings

While Table IV presents additional evidence consistent with a teacher's refinancing decision being influenced by the actions of her peer group, the focus of the reduced-form specifications is on the average effect. However, Figure IV indicates that the effect is stronger precisely where theory predicts, for individuals who would receive a greater benefit from refinancing. Thus, we now formally re-examine this relation in a regression framework.

[INSERT TABLE V HERE]

Table V presents OLS coefficients for reduced-form specifications similar to those estimated in Table IV where *Peer Refinances* has been scaled by its standard deviation. However, in addition to the previous explanatory variables, we also include an interaction between *Peer Refinances* and *Savings*. Therefore, if the effect of peer group refinancing activity is concentrated among individuals with greater benefits of refinancing, we would expect a positive and significant coefficient on the interaction term.

18. The unconditional probability of refinancing is 35.47 bp in this sample.

Similar to the previous table, the first specification of Panel A includes MSA-year fixed effects to control for local economic conditions. First, note that the coefficient of *Savings* indicates that a \$10,000 increase in the estimated savings upon refinancing increases the probability of refinancing by 17.7 basis points. Thus, the coefficient of 19.733 (t-stat=4.63) on the interaction term indicates that a one standard deviation increase in *Peer Refinances* increases the effect of *Savings* by 19.7 bp, or 111% of its previous value. The effect remains largely unchanged when including school district-year fixed effects (Column 2) and campus-year fixed effects (Column 3).

However, while the previous specifications confirm the results of Table IV, the possibility remains that there is *within-year* variation in campus-level loan supply exposure which campus-month fixed effects are not able to address. Therefore, Column 5 includes campus-month fixed effects to control for the possibility of within-year targeting of specific campuses by lenders. Therefore, all of our variation comes from monthly differences between an individual's peer group, defined as the set of teachers who share a common off-period, and all other teachers within the same campus. The coefficient of 15.263 (t-stat=2.67) indicates that the sensitivity of a teacher's refinancing probability to realized savings upon refinancing increases by 77.7% with a one standard deviation increase in *Peer Refinances*. The results are virtually unchanged when including controls for teacher characteristics in the final specification. Panel B of Table V estimates the previous model specifications when considering only teacher-month observations who would realize positive net savings upon refinancing. Similar to the results of Table V, we observe a stronger effect of *Peer Refinances* on the sensitivity of refinancing likelihood to potential savings in this subsample.

IV.D. Do Peers Share the Same Lender?

The previous findings are consistent with an individual's peer group influencing his or her actions. However, if this effect is the result of information transmission within the peer network then the information passed between agents need not be confined to the prevailing lending rate in the market and thus the potential savings associated with refinancing.

The primary determinant in an individual's refinancing decision is the available lending rate at which they can secure a new loan. While the time-series of mortgage rates are certainly correlated across lenders, there likely exists a large amount of variation in lending rates across lenders.[19] Thus, the effort required to solicit rates from multiple lenders may provide an additional friction decreasing the amount of refinancing activity. However, this friction may be reduced if the information gained from a teacher's peers includes the local lender currently offering the most beneficial terms. To examine this possibility, we now turn to the commonality of lender choice within peer groups.

Specifically, if the information passed from a teacher upon refinancing to a peer who also refinanced contained the lender currently offering a superior rate, we would expect the likelihood of both teachers using the same lender to be greater than by random chance. Therefore, for each observation included in Tables IV and V in which we observe a refinance, we first select all teachers who share a common off period and who also performed a mortgage refinance over the trailing three month period. Using this peer group, we then compute the percentage of refinancing peers who use the same lender as our original teacher, or *lender overlap*. We find that the average of *lender overlap*, which we refer to as *common lender %*, across our sample is 8.16%.[20] However, it is possible that the refinancing activity of a given lender is either temporally or geographically concentrated. Such concentration would result in value of *common lender %* greater than the probability of two randomly selected refinances sharing a common lender. Thus, we need an appropriate counter-factual to benchmark our results against in order to evaluate its economic significance. To do this, we will generate pseudo peer-groups under the null hypothesis that there is no information sharing between individuals, and compute *common lender %* under this null. To address the concern of lender concentration across time or geographic region, for each observation we define the candidate

19. Scharfstein and Sunderam (2013) show that the sensitivity of local lending rates to MBS yields is related to the concentration of mortgage lenders in the area.

20. Note that this is conditional on having at least one peer who refinances over the trailing three month period.

pool of potential peers as all teacher refinances over the trailing three month period within the same MSA, but outside the true peer group. We then randomly select a peer group from this candidate pool of equal size to the peer group in the non-randomized sample. We repeat this randomized sampling procedure for 10,000 iterations to approximate the distribution of *common lender %* under the null of no information sharing within the peer group.

Panel A of Figure V reports the histogram of the results from the pseudo peer-group simulations. The figure indicates that under the null of no information dissemination within peer groups, the expected value of *common lender %* is 3.05%. In addition, the maximum value across the 10,000 iterations performed is 4.76%, or 8.6 standard deviations less than the value of 8.16% we find when computing *common lender %* using the true peer groups.

[INSERT FIGURE V HERE]

The previous panel suggests that in addition to the refinancing decision, a teacher's choice of lender is also influenced by his or her peer group. However, the possibility remains that the abnormally large percentage of common lenders within peer groups is being driven by geographically concentrated lender activity within an MSA. Alternatively, such a result could be explained by strategic partnerships between lenders and individual school districts. Ideally, these concerns would be addressed by further restricting the candidate pool from which pseudo peer-group are drawn to include only teachers from the same school district or even the same campus. Unfortunately, such constraints are too restrictive and result in an insufficient number of candidates for some observations when also requiring a candidate to have performed a mortgage refinance in the trailing three month period. Thus, we repeat our analysis after relaxing the latter constraint.

Specifically, for each observation in our sample in which we observe a refinance, we define *lender overlap* as the percentage of teachers who share a common off-period whose existing lender matches that of the teacher performing the refinance. Additionally, when constructing the pseudo peer-group we consider only teachers from the same campus but do not share a common off-period. Thus, our focus is now on the percentage of common lenders amongst the stock of all mortgages rather than in the flow of new refinances.

Panel B of Figure V reports the histogram of *common lender %* under the pseudo peer-groups. The figure indicates that the expected value of *lender overlap* when drawing peers from all teachers who do not share a common off period is 1.71%, compared to 2.57% when using the true peer groups. Additionally, in only 0.24% of the iterations does the value of *common lender %* in the randomized groups exceed the value when considering teachers with a common off period.

IV.E. Self-Selection in Peer Groups?

The results presented in Tables IV and V confirm the previous section's empirical finding that the probability of refinancing for a teacher increases with the refinancing activity of her peer group. Additionally, Figure V presents additional empirical evidence of the role of peers in that a teacher's choice of lender, conditional on refinancing, is influenced by her peer group's lender choices. Furthermore, by exploiting overlap in teacher off-periods we are able to disentangle the role of peers from other confounding factors, such as campus-level variation in supply effects.

Ultimately, the identification of peer effects in this empirical setting depends on the exogenous formation of a teacher's peer group. Specifically, this requires that the assignment of a teacher's schedule is uncorrelated with other factors which affect the probability of refinancing. Alternatively, a plausible scenario violating this assumption would be the self-selection of teachers into peer groups based on an individual's discretion of their class schedule. However, conversations with school officials are inconsistent with this view, providing anecdotal evidence that teacher assignments are determined by a scheduling algorithm to optimize the menu of classes available to students, and not under the influence of the teacher. However, the possibility remains that optimizing class assignments results in peer groups which share a set of common characteristics.

Thus, to address this concern we test the predictive power of a teacher's peer group in forecasting observable characteristics. Panel A of Table VI presents the results for our sample when regressing a teacher's characteristic on the average of her peer group, *Peer Group Average*. Alternatively, the possibility exists that there is clustering in teacher characteristics due to geographic or institutional effects. Most notably, teacher pay is likely correlated with a school district's tax base, resulting in district-level variation in teacher salaries. Furthermore, self-selection of teachers into student age groups could result in variation in teacher gender across campuses within a district, such as between elementary school and high school campuses. Thus, to control for this possibility we also include the average of all teachers within the campus, but outside the teacher's peer group, *Campus Average*. Standard errors are clustered at the campus level.

[INSERT TABLE VI HERE]

The first column examines the ability of a teacher's peers in predicting her age. While the coefficient of 0.416 (t-stat=9.41) on *Campus Average* indicates that there is clustering in teacher ages across the campuses in our sample, the coefficient of *Peer Group Average* is statistically insignificant. The second specification turns to an examination of teacher salaries. In contrast to age, *Peer Group Average* is a statistically significant predictor of a teacher's salary, suggesting that there is a clustering of teacher pay within off-period groups. However, the value of the coefficient is 0.061. Thus, a \$10,000 increase in the average salary of a teacher's peers is associated with a \$*610* increase in the teacher's pay, bringing into question the economic significance of the effect. The third column indicates no statistically significant ability of a teacher's peers to predict the likelihood of the teacher holding a graduate degree. The fourth specification examines the predictive power of peers to forecast gender where gender takes on a value of one when the teacher if female, yielding a statistically significant coefficient of 0.101 (t-state=4.60). However, note that a one standard deviation increase in *Peer Group Average* within a campus is 0.174, which is associated with an 1.76% increase in the likelihood of a teacher being female. Finally, we find largely insignificant results when examining a teacher's ethnicity in columns 5-8. Note that while we include all teachers when computing *Peer Group Average* and *Campus Average*, Panel A only considers the sample of teacher-year observations from Table IV as the dependent variable. Panel B of Table VI repeats the previous analysis when expanding the sample to include all teachers we are able to classify into off-period groups. The results remain largely unchanged from those of Panel A, with a decrease in the coefficient of *Peer Group Average* when examining teacher pay and the probability of a teacher being female.

V. Conclusion

Using a comprehensive data set of employment records of Texas teachers to identify peer groups, we find that one standard deviation increase in the amount of recent refinances by a teacher's peers increases her likelihood of refinancing by 26%. This result accounts for other determinants of refinancing, teacher characteristics, and even unobservable campus-level shocks. Additionally, we find that peer effects are stronger precisely when the benefits of refinancing are larger.

Consistent with information being transmitted within the peer network, we find that a teacher's choice of lender upon refinancing is also influenced by her peer group.

Overall, our results strongly support peer effects being an important determinant of households' refinancing decisions. Moreover, because the sharing of refinancing information captured by our tests comes from quasi-exogenously formed peer networks, our results have important policy implications; educating homeowners on the benefits of refinancing and making interest rate information widely available could potentially translate into substantial savings for households.

References

Beshears, John, James J. Choi, David Laibson, Brigitte C. Madrian, and Katherine L. Milkman, 2015, The effect of providing peer information on retirement savings decisions, *The Journal of Finance* 70, 1161–1202.

Brogaard, Jonathan, Joseph Engelberg, and Christopher Parsons, 2014, Network position and productivity: Causal evidence from editor rotations, *Journal of Financial Economics* 111, 251–270.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, pp. 951–979.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2010, Sell-side school ties, *The Journal of Finance* 65, 1409–1437.

Dimmock, Stephen, Nathaniel Graham, and William C. Gerken, 2015, Is fraud contagious? career networks and fraud by financial advisors, Working paper.

Ellison, Glenn, and Drew Fudenberg, 1995, Word-of-mouth communication and social learning, *Quarterly Journal of Economics* 93–125.

Eppel, Dennis, and Richard E. Romano, 1998, Competition between private and public schools, vouchers, and peer-group effects, *American Economic Review* 88, 33–62.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 393–408.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2008, Trusting the stock market, *The Journal of Finance* 63, 2557–2600.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social interaction and stock-market participation, *The Journal of Finance* 59, 137–163.

Ippolito, Richard A., 1989, Efficiency with costly information: A study of mutual fund performance, 1965-1984, *Quarterly Journal of Economics* 1–23.

Khanna, Vikramaditya, Han E. Kim, and Yao Lu, 2015, Ceo connectedness and corporate fraud, *The Journal of Finance* 70, 1203–1252.

Leary, Mark T, and Michael R Roberts, 2014, Do peer firms affect corporate financial policy?, *The Journal of Finance* 69, 139–178.

Pool, Veronika, Noah Stoffman, and Scott Yonker, 2015, The people in your neighborhood: Social interactions and mutual fund portfolios, *The Journal of Finance,* forthcoming.

Sacerdote, Bruce, 2001, Peer effects with random assignment: Results for dartmouth roommates, *Quarterly Journal of Economics* 116, 681–784.

Scharfstein, David S., and Adi Sunderam, 2013, Concentration in mortgage lending, refinancing activity and mortgage rates.

Shue, Kelly, 2013, Executive networks and firm policies: evidence from the random assignment of mba peers, *Review of Financial Studies* 26, 1401–1442.

Von Gaudecker, Hans-Martin, 2015, How does household portfolio diversification vary with financial literacy and financial advice?, *The Journal of Finance* 70, 489–508.

Wolff, Edward N., 2012, The asset price meltdown and the wealth of the middle class, Working paper.

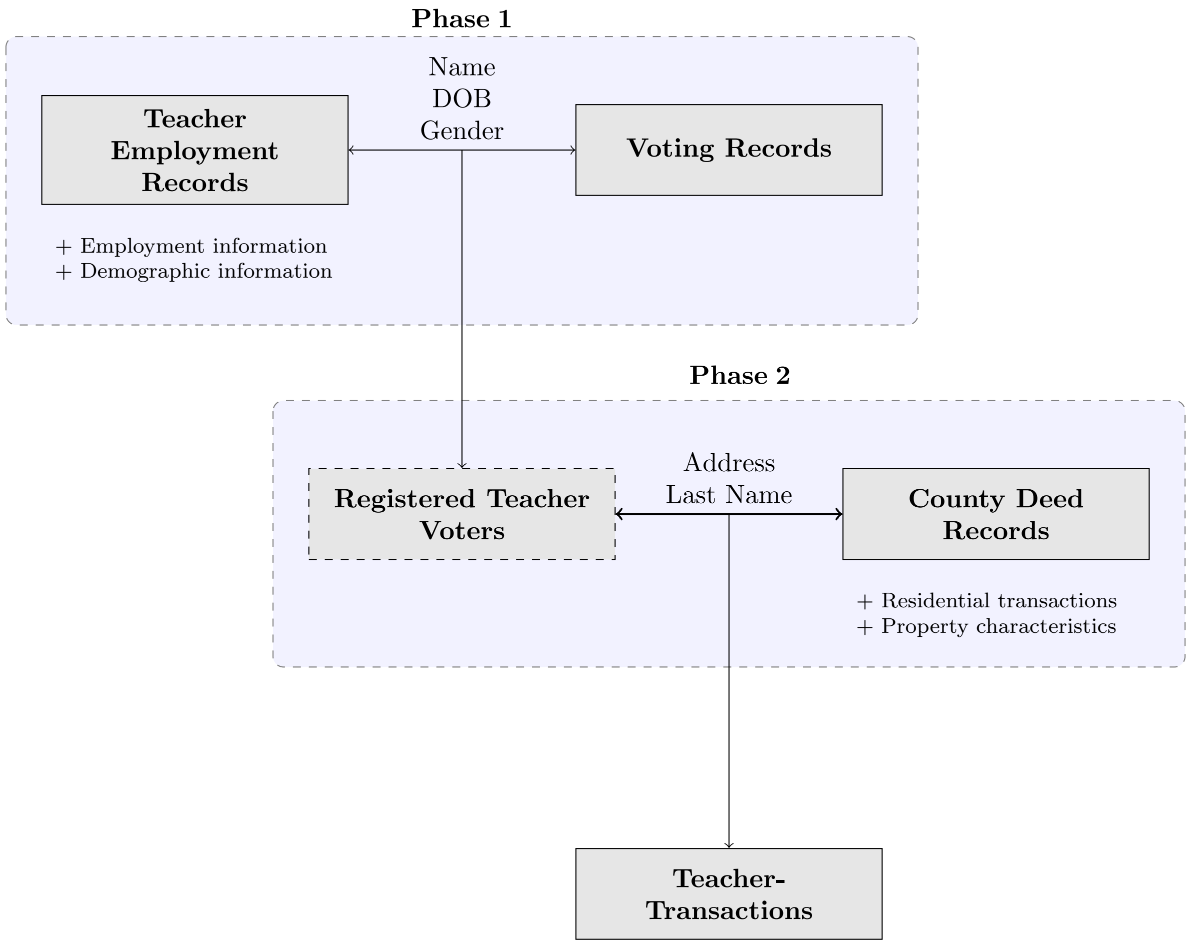


Figure I
Data Matching Procedure

This figure illustrates the process used to map teacher employment records to county deed records. First, the TEA payroll records are matched with electoral records of registered voters based on names, date of birth, and gender to obtain teachers' addresses (Phase 1). Then, we use these addresses and last names to match the resulting teacher-voter records with county deed records (Phase 2). We require an exact match between the address number prefix, zip code, and individual's last name, and require that the Levenshtein ratio between the address name listed on the county and voting records exceeds 0.9.

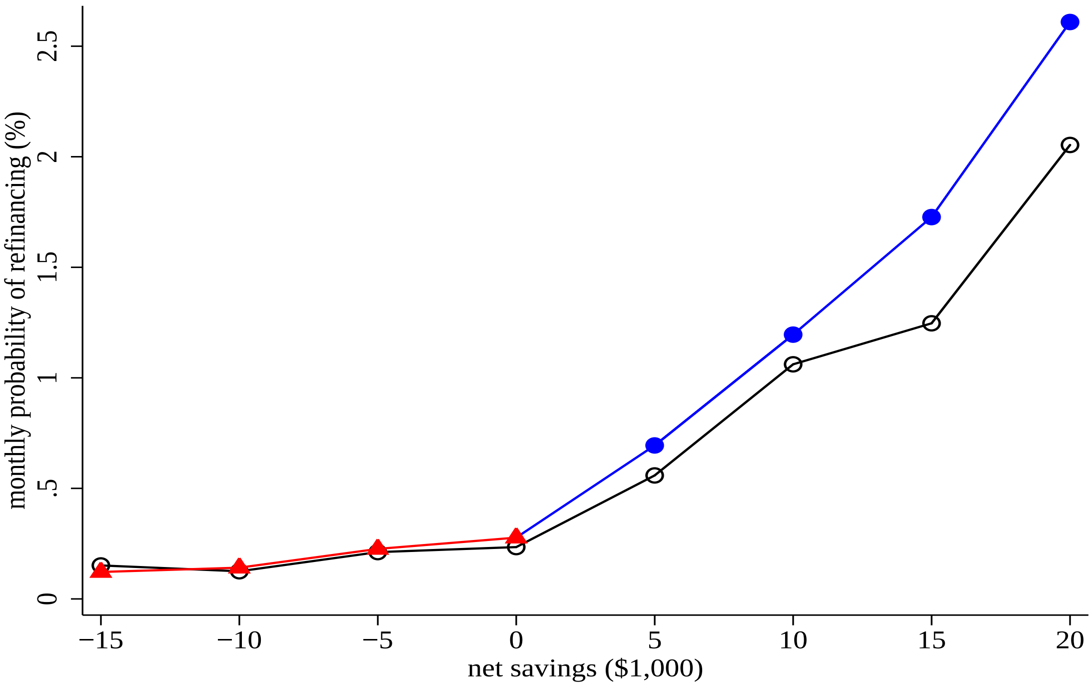


FIGURE II
Net Savings and Refinancing Probability

This figure shows the relation between the probability of a teacher refinancing their existing mortgage and their estimated net savings. Teachers are separated into two groups. The first group (black line with hollow markers) consists of teacher-month observations in which no individual in the teacher's peer group performed a mortgage refinance in the trailing three-month period. The second group (red & blue line with solid markers) consists of the remaining teacher-month observations, in which at least one individual in the teacher's peer group refinanced within the last three months. Teachers who we estimate to be underwater (i.e., have negative equity on the house) are not included.

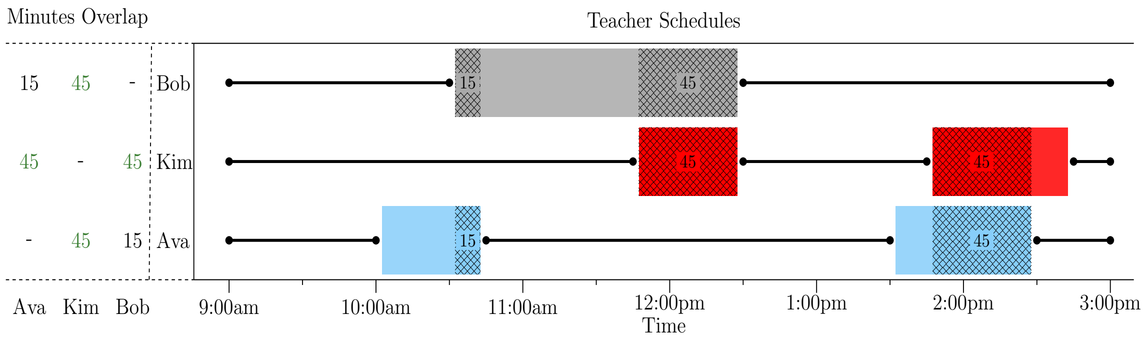


FIGURE III
Off-Periods Classification

This figure illustrates an example of the class assignment schedule for three teachers and our classification of each teacher's peer group using overlapping off-periods. The colored blocks denote a teacher's off-periods, while the hatched regions indicate an overlap in off-periods with another teacher. Both the *Bob-Kim* and *Kim-Ava* pairs share 45 minutes of common off-periods per day while there is only 15 minutes of common off-periods for the *Bob-Ava* pair. This figure illustrates the asymmetric nature of each teacher's peer group; while *Bob's* peer group consists of only *Kim*, *Kim's* peer group is made up of both *Bob* and *Ava*.

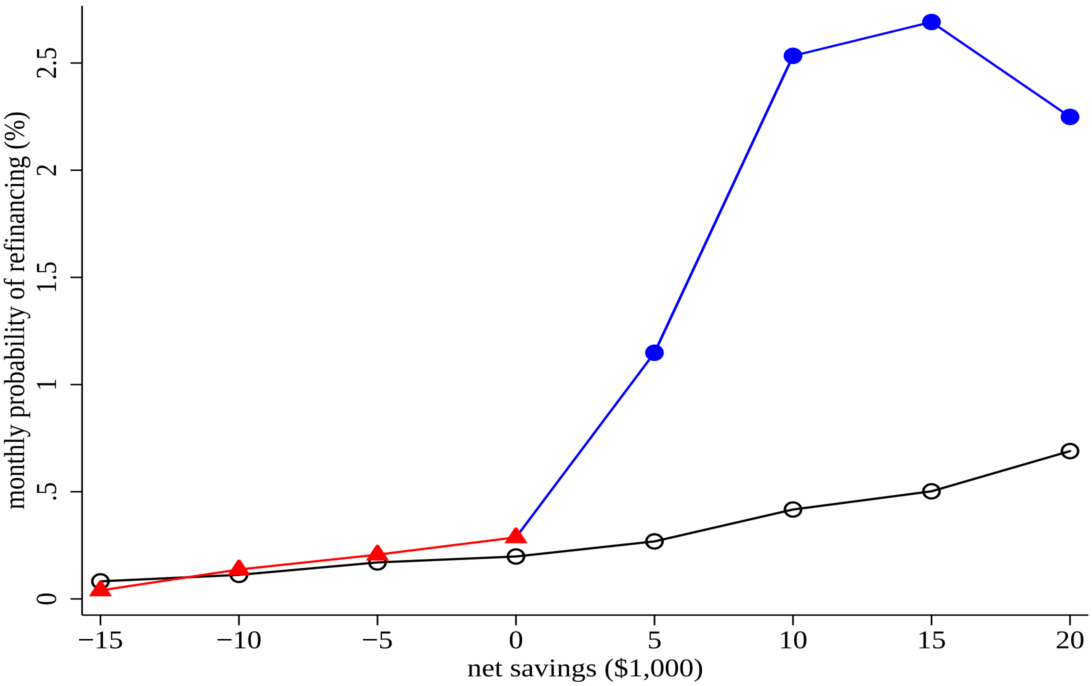


Figure IV
Net Savings and Refinancing Probability using Overlapping Off-Periods

This figure shows the relation between the probability of an individual refinancing their mortgage and their estimated net savings upon refinancing, when using overlapping off-periods to identify peer groups. Teachers are separated into two groups. The first group (black line with hollow markers) consists of teacher-month observations in which no individual in the teacher's peer group performed a mortgage refinance in the trailing three-month period. The second group (red & blue line with solid markers) consists of the remaining teacher-month observations, in which at least one individual in the teacher's peer group refinanced within the last three months. Teachers who we estimate to be underwater (i.e., have negative equity on the house) are not included.

Panel A

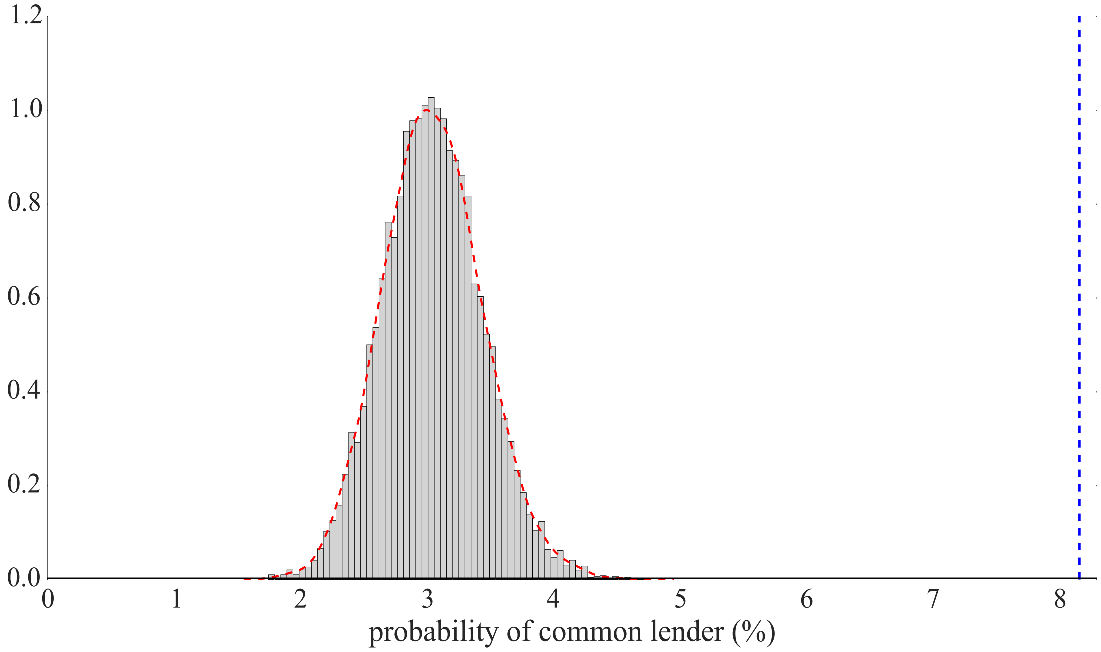
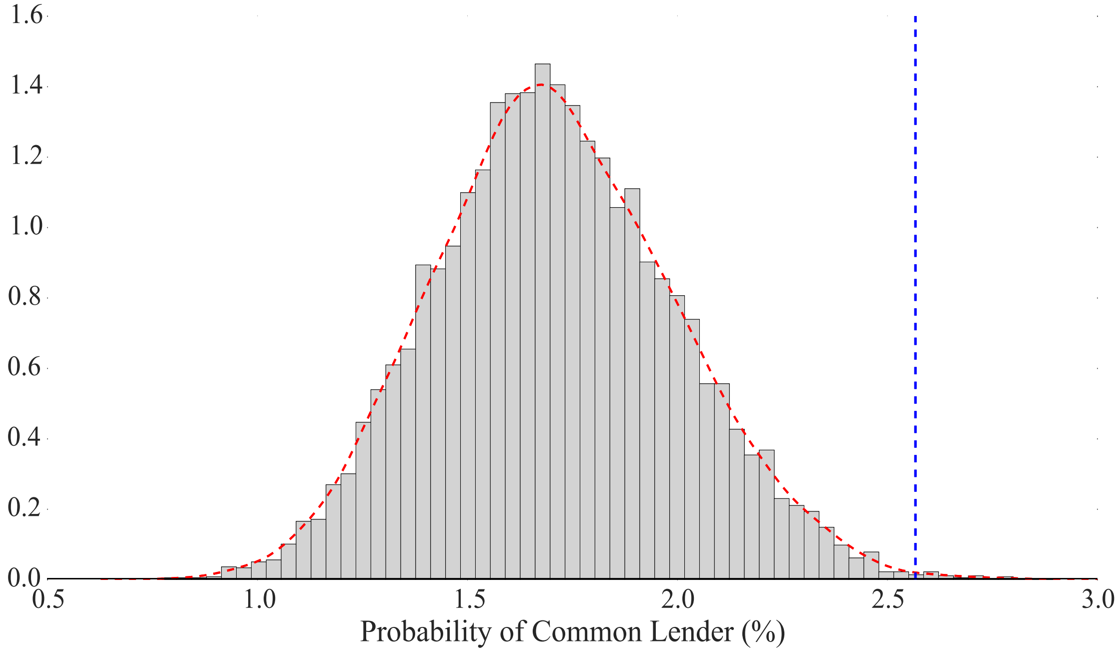


FIGURE V
Simulation

This figure illustrates the probability of a teacher and her peer sharing a common lender relative to pseudo peer groups. Panel A reports the probability of a common lender between a teacher refinancing and her peer, conditional the peer also refinancing in the prior three month period (dashed blue line). The figure also reports the distribution of probabilities for pseudo peer groups. Pseudo peer groups are formed by constructing a pool of candidate peers by selecting all individuals refinancing within the prior three month period who are within a teacher's MSA, but not in her peer group, and randomly selecting candidates from the pool to match the true size of the teacher's peer group. Panel B reports the probability of a common lender between a teacher refinancing and the current lender of her peer. Pseudo peer groups are formed by drawing candidates from the pool of all other individuals within a teacher's campus but outside of her peer group.

Panel B



1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Probability of Common Lender (%)

TABLE I
Summary Statistics

	All Teachers		Registered Voters		Teacher-Transactions		Final Sample	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Employment:								
Pay	43998.67	(9558.94)	44339.12	(9678.51)	45330.83	(9730.22)	47849.60	(7126.32)
Tenure	7.65	(8.05)	8.23	(8.20)	7.70	(7.79)	7.27	(6.82)
Ethnicity:								
Caucasian	0.694	(0.461)	0.705	(0.456)	0.700	(0.458)	0.713	(0.452)
African Amercian	0.090	(0.287)	0.089	(0.285)	0.100	(0.300)	0.068	(0.252)
Asian	0.010	(0.100)	0.007	(0.084)	0.009	(0.094)	0.008	(0.092)
Hispanic	0.199	(0.400)	0.193	(0.395)	0.185	(0.388)	0.198	(0.399)
Other	0.006	(0.079)	0.006	(0.075)	0.006	(0.079)	0.012	(0.107)
Other Characteristics:								
Bachelor's Degree	0.764	(0.425)	0.757	(0.429)	0.742	(0.438)	0.775	(0.418)
Advanced Degree	0.227	(0.419)	0.234	(0.423)	0.250	(0.433)	0.223	(0.416)
Age	42.49	(11.19)	43.31	(10.97)	42.72	(10.88)	41.87	(10.22)
Female	0.772	(0.420)	0.771	(0.420)	0.771	(0.420)	0.864	(0.342)
N	3,672,937		2,798,802		1,258,810		62,246	

This table describes the different samples corresponding to each of the main steps of the matching procedure and the sample selection process. More specifically, the table provides the mean and standard deviation of multiple employment and demographic variables of: 1) all teachers in the TEA payroll records, 2) teachers who are registered voters, 3) teachers that were matched to county deed transaction records, and 4) teachers in the final sample. The units of observation are teacher-years.

TABLE II
Peer Effects on the Decision of Refinancing

	Panel A: Full Sample			
	(1)	(2)	(3)	(4)
Peer Refinances	6.172***	5.479***	2.785***	2.792***
	(5.82)	(5.59)	(2.88)	(2.89)
Savings ($, ×10,000)	55.777***	58.464***	59.617***	59.657***
	(14.99)	(15.13)	(15.17)	(15.18)
1(Underwater)	-14.694***	-16.823***	-18.866***	-19.001***
	(-3.97)	(-4.43)	(-5.13)	(-5.13)
Percent Underwater	-101.409*	-100.000*	-33.537	-35.121
	(-1.83)	(-1.73)	(-0.85)	(-0.90)
Teacher Characteristics	N	N	N	Y
MSA-Year FE	N	Y	N	N
District-Year FE	N	N	Y	Y
N	670,954	670,954	670,954	670,954
R^2	0.007	0.007	0.011	0.011

	Panel B: Positive Net Savings			
	(1)	(2)	(3)	(4)
Peer Refinances	7.740***	6.402***	2.809**	2.820**
	(5.38)	(5.13)	(2.26)	(2.27)
Savings ($, ×10,000)	72.255***	72.695***	74.220***	74.318***
	(15.97)	(15.13)	(15.49)	(15.61)
1(Underwater)	-13.978***	-16.975***	-20.027***	-20.118***
	(-3.19)	(-3.96)	(-4.71)	(-4.66)
Percent Underwater	-108.883*	-105.088*	-34.850	-37.893
	(-1.86)	(-1.72)	(-0.83)	(-0.93)
Teacher Characteristics	N	N	N	Y
MSA-Year FE	N	Y	N	N
District-Year FE	N	N	Y	Y
N	469,796	469,796	469,796	469,796
R^2	0.007	0.007	0.012	0.012

This table shows OLS regressions where the dependent variable is a 0/1 indicator for refinances and the main variable of interest is *Peer Refinances*, a variable that captures the number of peers having undertaken a mortgage refinance in the previous three-month period, scaled by the size of the peer group (the campus). Reported are the effects of a one standard deviation change in *Peer Refinances*. The regressions also include controls for other determinants of refinancing such as the estimated savings, a 0/1 indicator for whether the teacher is underwater, and the underwater amount (in percent). Depending on the specification, Metropolitan Statistical Area (MSA)-year fixed effects, district-year fixed effects, or teacher characteristics such as gender, ethnicity, highest academic degree obtained, and salary are also included. Panel A uses the full sample, while Panel B uses teacher-month observations in which the estimated net savings upon refinancing are positive. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered by MSA-year. ***p<0.01, **p<0.05, *p<0.1.

TABLE III

Falsification Test

	Panel A: Full Sample			
	FALSE	TRUE	FALSE	TRUE
	(1)	(2)	(3)	(4)
Peer Refinances	1.521	5.765***	1.141	3.740***
	(1.52)	(4.30)	(1.24)	(2.72)
Savings ($, ×10,000)	29.439***	56.431***	30.043***	58.027***
	(12.80)	(14.10)	(12.94)	(14.29)
1(Underwater)	-8.951***	-13.684***	-8.360***	-14.597***
	(-3.86)	(-3.11)	(-3.39)	(-3.39)
Percent Underwater	-11.091	-175.908**	-0.790	-121.815**
	(-0.37)	(-2.62)	(-0.02)	(-2.36)
MSA-Year FE	Y	Y	N	N
District-Year FE	N	N	Y	Y
N	433,360	433,360	433,360	433,360
R^2	0.003	0.007	0.008	0.012

	Panel B: Positive Net Savings			
	FALSE	TRUE	FALSE	TRUE
	(1)	(2)	(3)	(4)
Peer Refinances	1.509	6.056***	1.046	3.403**
	(1.19)	(3.56)	(0.89)	(2.00)
Savings ($, ×10,000)	35.748***	71.643***	36.047***	73.441***
	(13.09)	(14.81)	(12.61)	(15.49)
1(Underwater)	-10.897***	-13.830***	-10.333***	-16.184***
	(-2.92)	(-2.66)	(-2.86)	(-3.15)
Percent Underwater	12.395	-193.727***	27.216	-132.083**
	(0.43)	(-2.67)	(0.78)	(-2.31)
MSA-Year FE	N	Y	N	N
District-Year FE	N	N	Y	Y
N	281,237	281,237	281,237	281,237
R^2	0.003	0.007	0.010	0.014

This table shows the results of the same estimations shown in Columns 2 and 3 of of Table II using sumbsamples of teachers and non-teacher homeowners. Reported are the effects of a one standard deviation change in *Peer Refinances*. For each teacher-property in the sample, we find a similar property from a homeowner who is not a Texas teacher both in terms of loan and physical characteristics. More specifically, within each zip code, we match properties based on the quarter in which the property was acquired and the loan amount (rounded to the nearest $2,000). We require properties to be in a different zip plus 4 code and the homeowner in the control group to continue to own the house after its match sold the house or dropped from the teacher employment records. Absent a match in the same zip code, we extend the search to the rest of the county, but requiring zip codes of both properties to be within a 10 mile radius. Finally, in the case of multiple matches we select the final match based on minimizing the differences among the square footage of the houses, the size of the lots, and the year that the houses was built, in that priority. The columns labeled as "FALSE" use the non-teacher homeowners, while the columns labeled as "TRUE" use the teacher for whom we found a match. Panel A uses the full sample, while Panel B uses teacher-month observations in which the estimated net savings upon refinancing are positive. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered by MSA-year. ***p<0.01, **p<0.05, *p<0.1.

TABLE IV
PEER EFFECTS ON THE DECISION OF REFINANCING – OFF PERIODS

Panel A: Full Sample

	(1)	(2)	(3)	(4)
Peer Refinances	8.465***	7.428***	6.587***	6.573***
	(3.13)	(2.90)	(2.69)	(2.68)
Savings ($, ×10,000)	23.104***	23.390***	26.160***	26.225***
	(4.78)	(4.92)	(4.98)	(4.97)
1(Underwater)	-16.251***	-17.597***	-16.952***	-16.827***
	(-3.22)	(-3.41)	(-3.10)	(-3.10)
Percent Underwater	25.153	47.023	39.576	32.888
	(0.54)	(0.97)	(0.88)	(0.72)
Teacher Characteristics	N	N	N	Y
MSA-Year FE	Y	N	N	N
District-Year FE	N	Y	N	N
Campus-Year FE	N	N	Y	Y
N	226,721	226,721	226,721	226,721
R^2	0.003	0.017	0.047	0.047

Panel B: Positive Net Savings

	(1)	(2)	(3)	(4)
Peer Refinances	15.394***	14.112***	12.364***	12.346***
	(4.04)	(3.68)	(3.02)	(3.01)
Savings ($, ×10,000)	31.326***	32.336***	35.656***	35.692***
	(3.93)	(4.00)	(3.90)	(3.89)
1(Underwater)	-13.377**	-15.291**	-13.149*	-13.153*
	(-2.14)	(-2.33)	(-1.96)	(-1.97)
Percent Underwater	16.069	44.026	18.784	7.426
	(0.32)	(0.77)	(0.32)	(0.12)
Teacher Characteristics	N	N	N	Y
MSA-Year FE	Y	N	N	N
District-Year FE	N	Y	N	N
Campus-Year FE	N	N	Y	Y
N	130,237	130,237	130,237	130,237
R^2	0.004	0.024	0.065	0.065

This table shows OLS regressions where the dependent variable is a 0/1 indicator for refinances and the main variable of interest is *Peer Refinances*, a variable that captures the number of peers having undertaken a mortgage refinance in the previous three-month period, scaled by the size of the peer group. Reported are the effects of a one standard deviation change in *Peer Refinances*. The main difference with Table II is the definition of peer groups, which are defined as any teachers with at least 40 minutes of overlap in off-period per day. Panel A uses the full sample, while Panel B uses teacher-month observations in which the estimated net savings upon refinancing are positive. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered by MSA-year. ***p<0.01, **p<0.05, *p<0.1.

TABLE V
Peer Effects and Savings

Panel A: Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Peer Refinances	2.618*	1.914	0.994	0.978	-2.249	-2.301
	(1.75)	(1.23)	(0.52)	(0.60)	(-0.63)	(-0.64)
Savings×Peer Refinances	19.733***	19.067***	18.694***	16.976***	15.263***	15.247***
	(4.63)	(4.40)	(3.74)	(3.70)	(2.67)	(2.67)
Savings ($, ×10,000)	17.774***	18.276***	21.043***	20.420***	19.652***	19.781***
	(4.37)	(4.56)	(4.78)	(3.43)	(3.62)	(3.63)
1(Underwater)	-15.335***	-16.558***	-15.901***	-17.507***	-16.486**	-16.297**
	(-3.12)	(-3.32)	(-3.04)	(-3.06)	(-2.51)	(-2.48)
Percent Underwater	21.430	40.108	35.129	6.039	12.987	5.573
	(0.46)	(0.85)	(0.81)	(0.11)	(0.23)	(0.10)
Teacher Characteristics	N	N	N	N	N	Y
MSA-Year FE	Y	N	N	N	N	N
District-Year FE	N	Y	N	N	N	N
Campus-Year FE	N	N	Y	N	N	N
District-Month FE	N	N	N	Y	N	N
Campus-Month FE	N	N	N	N	Y	Y
N	226,721	226,721	226,721	226,721	226,721	226,721
R^2	0.004	0.018	0.047	0.085	0.272	0.272

Panel B: Positive Net Savings

	(1)	(2)	(3)	(4)	(5)	(6)
Peer Refinances	-4.764	-5.456	-8.058	-7.105	-17.253*	-17.189*
	(-1.11)	(-1.22)	(-1.39)	(-1.55)	(-1.72)	(-1.71)
Savings×Peer Refinances	25.469***	24.541***	24.699***	22.483***	22.502**	22.422**
	(3.56)	(3.35)	(2.90)	(3.09)	(2.26)	(2.25)
Savings ($, ×10,000)	23.472***	24.867***	28.053***	23.387***	21.146***	21.216***
	(3.58)	(3.73)	(3.82)	(2.95)	(3.12)	(3.12)
1(Underwater)	-13.220**	-14.968**	-12.776*	-14.934*	-10.880	-10.956
	(-2.17)	(-2.34)	(-1.96)	(-1.87)	(-1.09)	(-1.09)
Percent Underwater	18.907	41.853	17.965	7.440	-3.994	-16.634
	(0.37)	(0.75)	(0.31)	(0.11)	(-0.04)	(-0.16)
Teacher Characteristics	N	N	N	N	N	Y
MSA-Year FE	Y	N	N	N	N	N
District-Year FE	N	Y	N	N	N	N
Campus-Year FE	N	N	Y	N	N	N
District-Month FE	N	N	N	Y	N	N
Campus-Month FE	N	N	N	N	Y	Y
N	130,237	130,237	130,237	130,237	130,237	130,237
R^2	0.005	0.025	0.065	0.115	0.334	0.334

This table shows OLS regressions where the dependent variable is a 0/1 indicator for refinances and the main variable of interest is the interaction of *Peer Refinances*, defined in Table IV, and *Savings*. *Peer Refinances* has been scaled by its standard deviation. Peer groups are defined as any teachers with at least 40 minutes of overlap in off-periods per day. Panel A uses the full sample, while Panel B uses teacher-month observations in which the estimated net savings upon refinancing are positive. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered by MSA-year. ***p<0.01, **p<0.05, *p<0.1.

TABLE VI

TEACHER CHARACTERISTICS AND GROUP CHARACTERISTICS

Panel A: Final Sample

	Employment Characteristics			Demographics				
	Age	Pay	Grad Degree	Female	White	Black	Asian	Hispanic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Group Average	0.025	0.061***	-0.015	0.101***	0.050**	0.030	0.026	0.036
	(1.15)	(2.88)	(-0.71)	(4.60)	(2.05)	(0.96)	(0.66)	(1.17)
Campus Average	0.416***	0.784***	0.448***	0.508***	0.815***	0.775***	0.086	0.912***
	(9.41)	(27.59)	(9.56)	(13.48)	(26.30)	(18.00)	(1.24)	(24.14)
N	18,730	18,730	18,730	18,730	18,730	18,730	18,730	18,730
R^2	0.022	0.211	0.016	0.041	0.254	0.259	0.001	0.284

Panel B: All Teachers

	Employment Characteristics			Demographics				
	Age	Pay	Grad Degree	Female	White	Black	Asian	Hispanic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Group Average	0.030***	0.042***	0.006	0.075***	0.026**	0.009	-0.001	0.011
	(3.31)	(3.95)	(0.66)	(8.10)	(2.36)	(0.63)	(-0.11)	(0.87)
Campus Average	0.424***	0.830***	0.407***	0.469***	0.863***	0.891***	0.139***	0.878***
	(26.35)	(86.22)	(20.64)	(30.65)	(71.43)	(56.50)	(4.19)	(57.23)
N	187,369	187,369	187,369	187,369	187,369	187,369	187,369	187,369
R^2	0.024	0.254	0.017	0.038	0.287	0.286	0.001	0.303

This table shows OLS regressions of a teacher's characteristic on the average of her peer group (*Peer Group Average*) and the average of all teachers within the campus but outside the teacher's peer group (*Campus Average*). Panel A use the teachers in the main sample and Panel B uses all teachers in the TEA records. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered by campus. ***p<0.01, **p<0.05, *p<0.1.

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Internet Appendix

Table IA.I
ROBUSTNESS FOR TABLE II

Panel A: Full Sample

	(1)	(2)	(3)	(4)
Peer Refinances	5.804***	5.134***	2.824**	2.828**
	(4.70)	(4.45)	(2.31)	(2.31)
Savings ($, ×10,000)	55.843***	58.471***	59.609***	59.648***
	(14.93)	(15.08)	(15.14)	(15.15)
1(Underwater)	-14.688***	-16.833***	-18.872***	-19.006***
	(-3.95)	(-4.43)	(-5.13)	(-5.13)
Percent Underwater	-102.257*	-100.777*	-33.394	-34.962
	(-1.83)	(-1.73)	(-0.84)	(-0.90)
Teacher Characteristics	N	N	N	Y
MSA-Year FE	N	Y	N	N
District-Year FE	N	N	Y	Y
N	670,954	670,954	670,954	670,954
R^2	0.007	0.007	0.011	0.011

Panel B: Positive Net Savings

	(1)	(2)	(3)	(4)
Peer Refinances	7.240***	6.040***	2.920*	2.926*
	(4.38)	(4.01)	(1.82)	(1.83)
Savings ($, ×10,000)	72.340***	72.727***	74.216***	74.314***
	(15.87)	(15.07)	(15.45)	(15.57)
1(Underwater)	-14.019***	-16.997***	-20.037***	-20.127***
	(-3.19)	(-3.96)	(-4.71)	(-4.66)
Percent Underwater	-109.793*	-105.958*	-34.706	-37.735
	(-1.86)	(-1.72)	(-0.82)	(-0.92)
Teacher Characteristics	N	N	N	Y
MSA-Year FE	N	Y	N	N
District-Year FE	N	N	Y	Y
N	469,796	469,796	469,796	469,796
R^2	0.007	0.007	0.012	0.012

This table shows the same estimations as in Table II, with the only difference being that the variable *Peer Refinances* takes into account refinances in the previous two-month period, instead of the previous three months.

Table IA.II
TEACHER-MATCHED SAMPLE COMPARISON

	Teacher	Match	Difference	t-statistic
Loan Amount ($)	139,614.7	139,599.8	14.9	2.80
House Size (sq ft)	2,052.6	2,024.8	27.9	1.50
Lot Size (sq ft)	12,105.9	56,639.7	-44,533.9	-1.02
Year Built	1,988.3	1,986.8	1.5	8.16

This table compares the average characteristics of the two subsamples of teachers and non-teacher homeowners used in the regression analysis shown in Table III (the falsification test).