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Salary Incentives and Teacher Quality:
The Effect of a District-Level Salary Increase on Teacher Recruitment

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There is a consensus in both research and practice that teachers matter (Chetty, et al., 2010; Rivkin, Hanushek, & Kain, 2005; Sanders & Rivers, 1996), and there are strong indicators that low-performing, low-income, and/or minority students are more likely to have lower-quality teachers (Carroll, Reichardt, Guarino, & Mejia, 2000; Humphrey, Koppich, & Hough, 2005; Lankford, Loeb, & Wyckoff, 2002; Peske & Haycock, 2006; Woodworth, et al., 2009). This problem can be traced back to teacher recruitment; districts that serve these students – particularly urban school districts – have a harder time recruiting teachers than their suburban counterparts (Lankford, et al., 2002).

In an effort to improve teacher recruitment, educational leaders often consider changes to teacher compensation. Given that teacher compensation comprises the majority of K-12 education expenditure (Loeb, Grissom, & Strunk, 2006), it is not surprising that the reform agenda has focused here. Despite the recent focus on teacher performance pay (see, for example, Podgursky & Springer, 2006), many districts also use other market-based strategies for improving teacher quality. An increasingly popular intervention for school districts is raising teacher salaries, often in targeted areas, with the intention of recruiting more qualified teachers (Murphy & DeArmond, 2003; Prince, 2003; Strunk & Zeehandelaar, 2011).

Despite a growing body of literature that discusses the prevalence and theoretical promise of these economic incentive policies (Imazeki, 2008; Koppich, 2008; Loeb & Miller, 2006; Odden & Kelly, 2008; Podgursky, 2008; Prince, 2003), little empirical research has explored their effectiveness in recruiting high-quality teachers to high-need schools and districts. Furthermore, there is particularly scant research investigating whether salary increases make urban school districts more attractive relative to neighboring districts.

To investigate how a compensation increase can affect teacher recruitment in an urban school district, I study the effect of a differential salary increase on teacher recruitment in the San Francisco Unified School District (SFUSD). The Quality Teacher and Education Act of 2008 (QTEA) introduced an overall salary increase ($500-$6,300, varying by placement on the salary schedule) and a $1,000 bonus for teaching in a hard-to-fill subject.

This paper employs a unique and robust data system from SFUSD. In addition to 9 years of administrative data linking teachers, students, and schools, I have survey responses from teachers and applicants to SFUSD from the time period 2004-05 through 2010-11, including those who applied and did not take a position (either were not offered or declined) and those who applied and were hired. On these surveys, I asked a number of questions about teachers' preferences and career choices, including what districts they applied to in addition to SFUSD.

With these unique data, I am able to study both how the applicant pool changed as a result of QTEA and how these changes may have impacted the cohorts of new-hires after QTEA. I use these data, as well as evidence from surveys and interviews of teachers and principals to answer the following questions:

- Changes to the applicant pool
  - To what extent did QTEA affect the size of the applicant pool? Was there a differential effect of QTEA in hard-to-fill subject areas?
  - To what extent did QTEA affect the quality of the applicant pool? Was there a differential effect of QTEA in hard-to-fill subject areas?
- Changes to the cohorts of new-hires
  - Did SFUSD hire more teachers in areas targeted by QTEA?
  - Did QTEA improve the quality of new-hires in SFUSD?

QTEA implementation corresponded with an economic downturn, which could affect teacher recruitment even in the absence of the policy. In order to identify the effect of the policy on teacher recruitment in SFUSD, the empirical approach needs to separate the effect of QTEA from other secular trends. To this end, for each question, I exploit natural variation in the distribution of teacher salary increases. The uneven distribution of teacher salary increases across applicants at different levels of experience and education allows me to compare teachers before and after QTEA who were similarly affected by the economy but differently affected by the policy.

In what follows, first I review the relevant literature and provide a framework for studying the effect of QTEA on teacher recruitment in SFUSD and then describe the context in SFUSD and the specific provisions of QTEA. I then detail the data sources employed. After exploring principal reports of the effect of QTEA on teacher recruitment, I provide the methods and results for each question estimating the extent to which QTEA affected teacher recruitment. Finally, I discuss the findings and their implications.

Literature Review

At the core of this investigation is the question of whether salary matters to teachers and whether changes in salary can be effective in recruiting more or better teachers. Indeed, the existing research indicates that compensation has the potential to improve the teacher workforce. A basic way to look at this question is to ask teachers about their preferences. Studies taking this approach conclude that salary is important to teachers when they are considering potential jobs, but that other non-monetary factors are equally or more important (Milanowski, et al., 2009; Painter, Haladyna, & Hurwitz, 2007; Winter & Melloy, 2005). While this descriptive research is useful for understanding teacher attitudes and beliefs, such studies suffer from problems of response bias; teacher reports do not necessarily correspond with behavior, and responses are highly sensitive to question phrasing and framing (Hippler & Schwarz, 1987).

Thus, a better approach is to study how teacher outcomes change as a result of compensation increases. Typically, studies look at the effect of salary on teacher recruitment, teacher retention or general teacher quality (Guarino, Santibanez, & Daley, 2006). Overall, this research provides some evidence that the teacher workforce can be improved by compensation increases, but there is very little research exploring whether compensation can be used to affect the recruitment, retention, or quality of teachers specifically in hard-to-staff schools or districts. In teacher retention, there is some evidence to suggest that teacher compensation can improve teacher retention system-wide. For example, Reed, Rueben and Barbour (2006) show that an overall salary increase of $4,400 instituted in California in the 1990s reduced the probability that a new elementary school teacher would exit teaching by 17%. There are few studies investigating the effect of compensation on improving teacher retention in targeted schools or districts, but most produce null findings. For example, Steele, Murnane and Willett (2010) find that a California state incentive policy (which provided $5,000 per year for four years to academically talented new teachers teaching in the state's lowest performing schools) had no significant effect on the retention patterns of new teachers after four years. Similarly, there was no significant improvement in teacher retention as a result of the Massachusetts Signing Bonus Program, which offered a $20,000 bonus to alternate route new teachers as an incentive to teach in the state for four years (Fowler, 2003). One notable exception is a study by Clotfelter, Glennie, Ladd and Vigdor (2008), which shows that a state incentive policy in North Carolina was successful at reducing turnover rates by an average of 17% in targeted schools and subjects.

Similarly, there is some evidence to suggest that overall teacher quality can improve through increases in compensation. For example, Loeb and Page (2000) investigate whether student outcomes improved over a 30 year period in states that increased their teaching wages relative to the wages of college-educated women in other occupations. They find that a 10% salary increase produced a 3-4% decrease in high school dropout rates. However, Hanushek, Kain and Rivkin (1999) show that differences in salary across districts do not have a significant effect on student performance.

Finally, there is some evidence that teacher compensation can have an effect on teacher recruitment overall, but there is very little evidence on whether compensation can improve teacher recruitment in the hardest-to-staff schools or districts. A substantial body of research shows that teacher salaries can encourage more individuals to enter teaching and increase the size of the national teacher workforce (see, for example, Dolton & Makepeace, 1993; Manski, 1987; Murnane, Singer, & Willett, 1989). However, there are very few studies investigating whether salary can have an effect on the sorting behavior of teachers already in the profession. In one study, Figlio (2002) used the Schools and Staffing Survey and administrative data to study increases in teacher compensation and found that districts that raised salaries relative to other teacher salaries in their county increased the probability of hiring new teachers (both first-time and experienced transfer teachers) from more selective undergraduate institutions and with college majors in their teaching field. In another study, Steele, Murnane and Willett (2010) find that a California state incentive policy (which provided $5,000 per year for four years to academically talented new teachers teaching in the state's lowest performing schools) increased the likelihood of targeted teachers working in hard-to-staff schools by 28%.

Across the areas of teacher retention, teacher quality, and teacher recruitment, the existing research investigating teacher response to salary interventions suffers from two major flaws. First, the existing research provides few empirical investigations of the effect of salary interventions at the district or school level; most existing research investigates the effect of state-level or nationwide salary increases (see, for example, Clotfelter, et al., 2008; Fowler, 2003; Loeb & Page, 2000; Manski, 1987; Reed, et al., 2006; Steele, et al., 2010). These studies do not allow for an understanding of how changes in salary can affect the distribution of teachers across districts. Furthermore, they do not tell us how compensation increases might affect an urban school district's relative competitiveness within the local labor market. Figlio's (2002) study and Hanushek, et al.'s (1999) study are exceptions, as they specifically look at the effect of a district's relative salary increases on teacher outcomes. However, these studies suffer from the second of this body of literature's major flaws: they only look at teachers' ultimate placement, not at the whole application process.

Studies that only observe teacher placement are highly problematic, since a teacher labor market involves both applicants looking for positions and districts/schools looking for applicants. Where teachers ultimately accept positions is a complex interplay of both this demand and supply side. On the demand side, employers theoretically make job offers based on their valuing of employee characteristics and skills. On the supply side, applicants theoretically decide which jobs to pursue and which offers to accept based on their preferences for a variety of district and school characteristics. How these elements interact determines the final distribution of new teachers across schools and districts.[1] Despite this complexity, most empirical work investigating the effect of salaries on teacher recruitment looks only at one step in this process: teachers' ultimate placement. In such studies it is difficult to distinguish whether findings (or a lack thereof) are related to supply or demand in the teacher labor market.

In understanding the effect of a salary increase on the attractiveness of a particular school district, it would be best to observe the preferences of applicants *for school districts* and to see if these preferences changed as a result of a relative salary increase. With my unique dataset, I am able to do just that; I observe all of the districts applicants applied to and construct with this

[1] For a more detailed treatment of the functioning of a teacher labor market, see, for example, Boyd, Lankford, Loeb, and Wyckoff (2003); Carroll, et al. (2000); or Guarino, et al. (2006)

information applicants' preferences for school districts. Thus, I am able to isolate the supply side and determine how a salary increase within a school district changed the district's attractiveness, and thus the teacher applicant pool. I can then couple this analysis with the traditional approach – observing whether the quality of new-hires increased as a result of a compensation increase – to analyze more completely the recruitment process. I detail my conceptual approach below.

Conceptual Framework

The goal of introducing a salary increase as through QTEA is to increase the district's appeal in the local labor market. In this paper, I investigate whether there is an increase in the quantity and/or quality of applicants in the targeted areas as a result of QTEA, and, if so, whether this increase leads to an increase in the quality of new-hires. To test various hypotheses for how QTEA's salary increases could affect the teacher applicant pool, I employ a framework which is depicted in Figure 1. In brief, the introduction of QTEA could have increased the district's appeal within the local labor market. This increased appeal could lead to an increase in the quantity and/or quantity of applicants, thus leading to an increase in the quality of new-hires.

[Insert Figure 1 here.]

Increase in quantity of applicants

Higher salaries introduced through QTEA may attract more applicants to the district simply because the higher salary makes teaching in San Francisco more appealing. In this scenario, the applicant pool to SFUSD would be larger than before because teachers with every kind of qualification and characteristic would be attracted to the higher salary. As discussed above, there is research to suggest that higher salaries can increase the size of the applicant pool (Dolton & Makepeace, 1993; Manski, 1987; Murnane, et al., 1989), however there is little research exploring whether a differential salary increase can increase the size of the applicant pool in an urban school district.

It is important to note that while teachers might be motivated by the higher salaries, they also care about other factors when looking for a job. Previous research has documented the numerous factors that come into play when teachers are choosing positions. In addition to salary, teachers value geographic location (Boyd, Lankford, Loeb, & Wyckoff, 2005) and the demographic characteristics and achievement of the students they would be teaching (Hanushek, Kain, & Rivkin, 2004; Scafidi, Sjoquist, & Stinebrickner, 2007). Teachers are also drawn to on-the-job characteristics such as class size, school facilities, and the availability of technology and support staff (Buckley, Schneider, & Shang, 2004; Ingersoll, 2003; Kirby, Berends, & Naftel, 1999). Finally, the level of support from administrators and fellow teachers seems to be important (Boyd, Grossman, et al., 2011; Ingersoll, 2001; Johnson & Birkeland, 2003; Loeb, Darling-Hammond, & Luczak, 2005).

Each applicant values these things in different proportions. If QTEA is able to motivate more teachers to apply, it will be because the increase in salary is enough for (at least some) teachers to trade off more salary for what may be perceived as less advantageous working conditions. Teachers who previously did not consider SFUSD but may have been on the margin (on any number of dimensions) will now apply because the increased salary is enough to matter more than their other preferences.

Increase in quality of applicants

There is reason to believe that the increase in salary would make SFUSD differentially attractive to high quality workers (Weiss, 1980). Consider the case where teacher quality is uni-dimensional and known. Higher quality teachers are able to obtain jobs in districts paying higher salaries. Before SFUSD raised salaries, the teachers who did not apply were those teachers who knew their quality was high enough to obtain higher paying jobs. Once SFUSD raises its salary, some teachers who were "too good" for SFUSD initially, now are willing to apply to teach there. Of course, quality is not one dimensional and, more importantly, quality is not widely known. However, elements of this hypothesized process may still be relevant. Some teachers who were drawn to higher paying districts initially may now be willing to teach in SFUSD.

This theory may be particularly applicable when considering teacher labor markets since teachers are typically not paid for productivity within a school district; instead they are paid on a single schedule that rewards only the observable characteristics of years of experience and education (Koppich & Rigby, 2009). Even though they are not directly compensated for it, the theory presented above provides reason to believe that teachers who know their true productivity (their ability to affect student achievement) are drawn to higher salaries. In an environment where compensation is set by school district salary schedules, this would mean that higher-quality teachers would be drawn to higher-paying school districts, where they would be compensated appropriately for their productivity (i.e., their ability to improve the achievement of their students). Thus, because there are substantial salary differences across districts even within the same labor market (Boyd, et al., 2003), we would expect higher-quality teachers to be drawn to higher paying districts, resulting in productivity differences across districts. If this holds true, teachers that previously were only applying to higher-paying districts (presumably because they themselves are higher quality) may consider applying to SFUSD after QTEA as part of their job search. In this case, we would expect an increase in the average salary of the other districts teachers applied to after QTEA.

There is a practical as well as a theoretical reason to test whether applicants were drawn from higher-salary districts. In my interviews with SFUSD district staff and stakeholders about the passage of the policy, they were hopeful that QTEA might attract teachers that previously only applied to higher paying school districts (Hough & Loeb, 2009). The ability to differentially attract higher quality teachers was clearly the motivation of district leaders in the formulation of QTEA. Thus, in the analyses presented in this paper, the average salaries of other districts applied to will serve as a proxy for applicant quality.

Increase in quality of new-hires

If either of the two hypotheses presented above for how QTEA might affect the teacher applicant pool hold true, the available number of high quality teachers within the applicant pool should increase. How this affects the quality of new-hires depends on the district's hiring abilities. The right side of Figure 1 illustrates this effect.

Under the first scenario (that the quantity of applicants increases), the school district can now hire better teachers simply because there are more high-quality candidates in the recruitment pool (even though the ratio of low-quality to high-quality candidates does not change). The outcome of hiring more high-quality teachers, however, depends on the school districts' ability to hire good teachers given the information that they receive in the application process. Some research has suggested that schools and districts are not always skilled in this regard, showing that candidates from selective universities are less likely to be hired as teachers after applying (Ballou, 1996) or that the teachers who obtain teaching positions have lower levels of academic ability than those who do not obtain positions (Murnane, Singer, Willett, Kemple, & Olsen, 1991). However, recent research has shown that when given the opportunity, schools often select higher quality teachers as measured by teachers' gains to student achievement (Boyd, Lankford, Loeb, Ronfeldt, & Wyckoff, 2011).

Under the second scenario (that the quality of applicants increases), the school district can now choose better candidates, because the overall quality of the applicant pool increased. This is true even if the district chooses randomly, since the number of high-quality applicants has increased as well as the ratio of high-quality to low-quality teachers (Weiss, 1980).

There has been one study employing a similar framework in a simulation looking at the effect of salary increases on the quality of the entire teacher workforce. Ballou and Podgursky (1995) found that a 20% across-the-board teacher salary increase (assuming that districts did not select on academic ability) was associated with a slight increase in the share of high-ability teachers (those in the top 15% in SAT scores) in the workforce, from 5.1% to 5.4%. They show that new-hires do indeed respond to increases in salary, but that in the long term, there would be no positive effect on the quality of the workforce because of perverse feedback mechanisms. Since salaries are increased across-the-board, older teachers stay longer, which leaves fewer openings, and when there are fewer openings, the most capable workers select other jobs.

My paper builds on this work as it is an empirical investigation of a real intervention (rather than a simulation). In addition, I investigate the short-term effect of a salary increase within a single school district rather than the long-term, systemic effect of a salary increase on the entire teaching workforce. If I am able to find an effect in the short-term quantity or quality of applicants, or the ultimate quality of new-hires, it is important to consider the long-term lessons presented by Ballou and Podgursky. To sustain a long term, systemic increase in teacher quality, SFUSD would need to attempt to prevent the perverse feedbacks by creating systems for removing low-ability teachers to make room for higher-ability new teachers.

Background: The Quality Teacher and Education Act in SFUSD

San Francisco serves as a good case study for testing whether an urban school district can improve teacher recruitment through compensation increases. First, SFUSD is a large urban school district – the largest district in San Francisco Bay Area. SFUSD is the 60th largest school district in the country and the 5th largest school district in California.[2] San Francisco is in the 6th largest Combined Statistical Area (CSA) in the country (2nd in California after Los Angeles),[3] and SFUSD is the largest school district within this CSA. Like many large urban school districts, SFUSD sees itself in competition for teachers with local suburban districts, which may be perceived as "easier" places to work.

Indeed, on measurable characteristics, SFUSD does seem to have more challenging working conditions than other local school districts. As shown in Table 1, of the 186 public school districts in the CSA of San Jose-San Francisco-Oakland, SFUSD is in the top quartile of the percent of students who are English Learners and who are eligible for Free or Reduced Price Lunch (76th and 83rd percentile, respectively), meaning that SFUSD has more students eligible for Free or Reduced Price Lunch than 76% of other local school districts. In addition, 38.5% of SFUSD's schools are in the bottom decile of achievement among other schools in California (which is in the 83rd percentile compared to other local districts); 43.6% of students lack proficiency in English Language Arts (which puts SFUSD in the 69th percentile); and 39.2% lack proficiency in math (which puts SFUSD in the 53rd percentile). The effect of these demographic and performance metrics seems to have an effect on teacher quality in the district: 4.9% of SFUSD's teachers lack a full credential and 6.5% have fewer than two years of experience. These metrics place SFUSD in 75th and 79th percentile amongst other local districts, meaning that

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[2] http://nces.ed.gov/pubs2001/100_largest/table01.asp
[3] http://www.census.gov/popest/metro/tables/2009/CBSA-EST2009-02.xls

SFUSD has less experienced teachers than most other school districts in this CSA. This disparity between SFUSD and local districts in the qualifications of their teachers led many policy makers in SFUSD to make a change.

[Insert Table 1 here.]

The Quality Teacher and Education Act

The main impetus for the passage of QTEA was a concern among education stakeholders in San Francisco that teacher salaries were too low, and that in order to increase teacher quality, teachers had to be paid more. Many leaders in the district believed that in order to lure teachers to SFUSD, and retain them, the salary needed to be higher than in neighboring suburban districts, where the job is considered "easier." Mark Sanchez, who was Board of Education president when QTEA was passed, said, "Why would [a teacher] be teaching at a really difficult school and get paid really poorly and get treated by a system that didn't have structures in place to treat you well? … Why would you put up with that if you didn't need to? You could go somewhere else suburban to teach or go into another profession and do better … financially and probably emotionally" (Hough & Loeb, 2009, p. 6).

In June 2008, the voters of San Francisco approved QTEA, a parcel tax authorizing SFUSD to collect $198 per parcel of taxable property annually for 20 years. These revenues add up to over $500 per student per year[4] and since March 2009 have been used to fund changes in teacher compensation, support, and accountability and support for school improvement initiatives, such as technology and charter schools.[5] Teachers received an across-the-board salary

[4] Funding per student is an estimate based on parcel tax revenue projections ($28,529,226) and student enrollment at the time of passage (55,497).
[5] QTEA introduced an overall increase in teacher salaries, a number of strategic compensation incentives for teaching in subjects and schools that are hard-to-staff, enhancements to teacher support and accountability, and school-based rewards for increased student performance. For more detail on the passage of this policy and the specific provisions, see Hough (2009) and Hough and Loeb (2009).

increase that varied by placement on the salary schedule. For teachers with 3 and 10 years of service, respectively, 2009-10 increases were $7,030 and $2,028 (compared to 2007-08). This represents an increase of 15% and 3%, respectively. As a percentage increase, these salary increases were much larger than surrounding districts during the same time period. Table 2 shows, for example, that while SFUSD salaries were more than $6,370 lower than San Jose Unified's for Step 3 teachers before QTEA, they were $660 *higher* after QTEA. While SFUSD's Step 10 salaries also increased, the increase was substantially smaller and salaries remained below San Jose's. In addition, as a result of QTEA some teachers received targeted bonuses as well. Teachers in Special Education, Math, Science, and Bilingual Education earned an additional $1,000 for teaching in a hard-to-fill (HTF) subject[6], teachers working in one of 25 schools designated hard-to-staff received an additional $2,000, and teachers received retention bonuses of $2,500 after four years of service in SFUSD and $3,000 after eight years.[7]

[Insert Table 2 here.]

The only way for the district to significantly increase teacher salaries was for the money to come from a parcel tax. The lack of alternative options is a direct result of California's Proposition 13 in 1978, which set a 1% cap on property tax rates. As part of that legislation, the parcel tax emerged as one of few sources of discretionary tax revenue available to school districts; local governments are allowed to levy "special taxes" subject to the approval of two-thirds of the electorate. Because of this funding restriction, the parcel tax was widely seen as the only mechanism through which the district would eventually be able to raise teacher salaries. Although this mechanism of raising revenue may be specific to California, local school districts'

[6] Note that in 2010-11, this bonus was reduced by half and only awarded to teachers in Special Education.
[7] The hard-to-staff school bonus and the retention bonuses will not be considered in this paper, as they would have no effect on teacher recruitment.

interest in raising wages relative to other local school districts is one that is felt throughout the country.

QTEA implementation period. The research questions in this paper aim to understand whether QTEA's compensation changes affected teacher recruitment in SFUSD. For this reason, a careful definition of the QTEA implementation period is required. As shown in the timeline in Figure 2, QTEA was passed in June 2008, and the first salary payments were made to teachers in March 2009.

[Insert Figure 2 here.]

Figure 3 shows that the majority of teachers (66%) apply for jobs in March, April, May and June of the prior school year. Thus, it is safe to assume that teachers applying to teach in the 2007-08 school year or prior would not have been affected by QTEA, as they would have been applying in the spring of 2007, well before QTEA passed (in June of 2008). Similarly, it is safe to assume that those teachers applying to teach in 2009-10 or after would be affected (as they would have applied in or after the spring of 2009, which is when QTEA went into effect). While it is more difficult to ascertain whether the 2008-09 cohort should be included in the pre- or post-QTEA period, I argue that QTEA affected those teachers who applied to teach in the 2008-09 school year. QTEA was passed in June 2008, and there was substantial publicity about the policy in the months leading to its passage. Because 37% of applicants apply in or after June, it stands to reason that the salary provisions of QTEA would affect at least some teachers applying to teach in 2008-09. Furthermore, those that applied in the months leading to QTEA's passage could have been influenced by the anticipation of its passage. For these reasons, for studying the effect of QTEA on teacher recruitment, I assume that the 2008-09 school year is part of the implementation period.

[Insert Figure 3 here.]

This decision is reinforced by survey responses from applicants indicating that the top ways they learned about QTEA was through the local media (39%) or from living in SF and hearing about QTEA (33%) (see Figure 4). Nonetheless, in the analyses that follow, I include a specification to test whether there is a different effect in 2008-09 as compared to 2009-10 through 2010-11.

[Insert Figure 4 here.]

Defining "targeted" applicants. While the vast majority of applicants were affected by QTEA in some way, some stood to gain much more than others. In creating the new salary schedule, district officials frontloaded the salary increases, and after that determined step and column increases conditional on availability of funds. This resulted in an uneven distribution of teacher salary increases across teachers at different levels of experience and education. In SFUSD, as in most districts, teachers are placed on the salary schedule corresponding with their number of years of experience and their continuing education units.[8] At each level of experience, teachers are distinguished by having just a bachelor's degree, a bachelor's degree plus 30 additional units, or a bachelor's degree plus 60 additional units.[9] I determined the increase that an applicant would gain from QTEA as the difference between teacher salaries before and after QTEA (or more specifically, the difference between the 2009-10 and the 2008-09 salary before QTEA payments).[10] Figure 5 shows the distribution of the percentage increases across teachers with different levels of experience on the three different salary schedules. For teachers with just a

[8] When teachers enter into SFUSD they receive credit on the salary schedule for all of their years of experience. Per Section 11.8.7 in the 2007-10 Contract between San Francisco Unified School District and United Educators of San Francisco, new-hires receive year-for-year credit for verified outside teaching.

[9] Note that in SFUSD, there are actually 9 schedules: three B schedules are for credentialed teachers, three C schedules are for uncredentialed teachers, and three S schedules are for department heads. However, the vast majority of teachers enter on the schedule detailed above.

[10] Note that the variable indicating percent increase in salary as a result of QTEA was constructed this way for all teachers in all cohorts.

BA, salary increases as a result of QTEA never go above 6%. For teachers with a BA plus 30 units, salary increases hover around 10% for teachers with zero to five years of experience, and then drop quickly to 6% or less. And teachers with a BA plus 60 units experience the highest salary increase, with the amount again decreasing sharply after five years of prior experience. Figure 5 provides some visual evidence that there is a cutoff for applicants to be “targeted” by QTEA if their salary would have increased by 6% or more as a result of the policy, but this will be further discussed below.

[Insert Figure 5 here.]

Data

In order to study the effect of QTEA on the applicant pool and the cohorts of new-hires, I combine 6 years of SFUSD’s administrative data, publicly available data on local school districts, and surveys of teachers and teacher applicants to create an Applicant Database, which contains a sample of all applicants to SFUSD over a seven year period, and a Teacher Database, which contains all teachers linked with students and schools during the same time period. In addition, I use responses from principal surveys and interviews about their views on the effect of QTEA on teacher recruitment. These data sources allow for the triangulation of findings and shed light on the mechanisms behind effects.

Applicant Database

In order to investigate how the applicant pool may have changed in response to QTEA, I created a database representing all applicants to the district from the time period 2004-05 through 2010-11. To do so, I combined administrative data and responses from teacher and applicant surveys administered in 2008 and 2010. This combined dataset contains responses representing all applicants to SFUSD, including those who applied and did not take a position (either were not offered or declined) and those who applied and were hired. The surveys were administered in two separate years (2008 and 2010) and to two separate populations in each administration (applicant and teacher); thus, in order to conduct analysis on the full set of applicants, I merged three separate datasets – 2008 Applicant Survey, 2010 Applicant Survey, and 2010 Teacher Survey (which also includes administrative data). The data sources used and the construction of the Applicant Database are detailed below.

Surveys. In 2010, I surveyed all the teachers in SFUSD and a sample of recent applicants to the district. These surveys included questions about job search, roles, perceptions, attitudes and future plans as well as questions about QTEA implementation. An important feature of the 2010 SFUSD survey administration is that it builds from The New Teacher Project surveys (2009) on teacher hiring, assignment, and evaluation administered in San Francisco in June 2008 to leverage existing data and detect change in responses. Using these responses increases the sample size and the period of analysis in question. All surveys were web based[11] and were administered to participants using email addresses on file with SFUSD.

Despite the fact that TNTP administered a teacher survey in 2008, these data are not used in analysis. My analysis requires that I am able to determine how many years of experience teachers had at the time they applied to SFUSD (to determine the amount that QTEA would have increased their salaries) and the 2008 Teacher Survey did not solicit this information. In addition, survey responses in 2008 were anonymous, and it is beneficial to our analysis to be able to link teacher survey responses to SFUSD's administrative data. The population was surveyed in all

[11] The actual survey instruments for 2010 can be found online at http://suse.qualtrics.com/SE/?SID=SV_3KjOwbfuWNudn6c&Preview=Survey&BrandID=suse (Teacher); http://suse.qualtrics.com/SE/?SID=SV_enyG4W3uYRv5d9G&Preview=Survey&BrandID=suse (Applicant).

surveys except the 2010 Applicant Survey, in which I drew a random sample of applicants from the population.[12] Detail on survey samples and response rates can be found in Table 3.[13]

[Insert Table 3 here.]

Administrative data. Through combining a diverse array of data sources, including SFUSD administrative data and public data from the California Department of Education, I have constructed a longitudinal database which links teachers, students, and schools. I merge these data with the teacher and applicant surveys to include the following information for those applicants who were hired and became teachers: school placement, subject(s) taught, years of experience, education levels, and receipt of QTEA salary and bonuses in the first year of teaching.

Cohort identification. The Applicant Dataset contains the cohort of applicants who applied to teach for each school year, including those who applied and did not take a position (either were not offered or declined) and those who applied and were hired. For example, the 2009 Cohort includes both teachers whose first year in SFUSD was 2008-09 and applicants who most recently applied to teach in 2008-09 and were not hired. To create these cohorts, in the Applicant Surveys I used self-report of the year respondents most recently applied to teach in SFUSD and assigned them to that applicant cohort. For example, if an applicant reported that he most recently applied to teach in SFUSD for a position that would start in the 2006-07 school year, he was subsequently placed in the 2007 Cohort. For teachers who were hired, I used the administrative files to determine which year they first appeared in the district. Teachers were placed in the 2005 Cohort if they appeared in year 2004-05 but did not appear in years 2002-03

[12] After removing teachers who had been surveyed in 2008 (N=225), the population remaining was 5180. Based on power calculations, I initially sampled 1200 and sampled an additional 400 based on initial survey responses indicating that 28% of applicants in the dataset had not actually applied for teaching positions.
[13] Note that in the 2010 surveys I incentivized response with 50 $150 gift certificates for teachers and a one-in-ten chance of winning $99 for applicants.

and 2003-04, teachers were placed in the 2006 Cohort if they appeared in 2005-06 but not in 2002-03, 2003-04, or 2004-05, and so on.[14]

As shown in Table 4, of those applicants who were not hired, the 2005 Cohort through 2009 Cohort are surveyed in 2008, and Cohorts 2009 through 2011 are surveyed in 2010.[15] For all applicants who were subsequently hired, they are surveyed in the 2010 Teacher Survey, which means that some teachers who were surveyed in 2010 had as many as six years of experience in the district by the time they were surveyed. This is not ideal, since there is a relatively high attrition rate among early-career teachers (Boyd, Grossman, Lankford , Loeb, & Wyckoff, 2007; Ingersoll, 2003). Furthermore, the surveys probe on details of the application process, and the quality of responses may degrade over time as respondents are asked to recall past experiences (Hippler & Schwarz, 1987). However, the database has to be constructed in this way due to data problems in the 2008 Teacher Survey[16] and resource constraints preventing us from surveying teacher applicants every year. In order to test for any bias introduced by this cohort construction, I will include a specification in my analyses limiting the cohorts being analyzed to those more recently surveyed.

[Insert Table 4 here.]

Weighting. Because the surveys had different sampling procedures and response rates across the years, I use survey weights in analysis (Cochran, 1977; Kish, 1965). Table 5 details the surveys that were administered, with the number of teachers in the population, the number sampled, and the number that responded. Weighting for the applicant surveys is relatively

[14] Note that the majority of teacher reports line up with this cohort construction: 71.2% of 2010 Cohort teachers report that it was their first year in SFUSD, 78.4% of 2009 Cohort teachers report that it was their second year, and so on; overall, 70.9% of reports correspond.
[15] Note that because of the timing of the survey administrations, some 2008-09 applicants were surveyed in both years, although these are not the same applicants.
[16] The 2008 Teacher survey did not ask about years of experience prior to working in SFUSD, and it is not possible to link responses to administrative data.

straightforward; in 2008, the population (4,508) was sampled and 1440 responded, and in 2010, a random sample was taken (1,600/5,180) and 776 responded. Thus, each year the respondents must be weighted to represent the population; in 2008, the 1,440 respondents must be weighted to 4,508, and in 2010, the 776 respondents must be weighted to 5,180. With the teacher survey, however, the population that the survey is intended to represent is the cohort of new teachers in each year, so the weighting scheme is more complicated. I used the same method as discussed above for identifying the applicant cohort for hired teachers to determine the number of new teachers in each year. Not all of the new teachers in each cohort were surveyed in 2010, mostly due to the fact that some of them were no longer in teaching positions in SFUSD. For example, the 2005 Cohort had 415 new teachers in 2004-05, but only 151 were sampled in the 2010 survey, and 87 responded (for a 57.24% response rate of those actually surveyed). Thus, the 87 respondents must be weighted to represent the 415 teachers in the population.

[Insert Table 5 here.]

Due to this sampling and response structure, I use post-estimation weights to weight teachers up to the population that they are meant to represent. (In other words, each observation has a weight which is calculated as the inverse of the probability of having responded.) This approach decreases bias due to non-response and underrepresented groups in the population and results in smaller variance estimates.[17] Table 5 displays the weights that are used in analysis, as well as the population that respondents are meant to represent. In the 2008 Applicant Survey, the population of applicants was sampled, and 1,440 responded, so the weight is 3.13. In the 2010 Applicant Survey, 776 respondents represent the population of 5,180, so the weight is 6.68. For the 2010 Teacher Survey, because the proportion of teachers represented in each cohort decreases for earlier cohorts, the weight is highest for the 2005 Cohort (4.77) and lowest for the

[17] STATA 11 manual.

2010 Cohort (1.92). Table 4 presents the composition of the Applicant Database, showing the makeup of the Applicant Database in number as well as weighted proportion.[18]

This completed dataset represents all applicants to SFUSD for all applicant cohorts from 2004-05 through 2010-11 and contains information about applicants' years of experience and education levels (which allows me to approximate the salary impact of QTEA), the specific school districts they applied to in addition to SFUSD, and the subject(s) that they applied to teach in. Because I investigate here whether QTEA had an additional effect on applicants in hard-to-fill subjects, I use this information to determine whether applicants taught in hard-to-fill subjects. As shown in Table 6, 32% of the applicants were in a hard-to-staff subject across all years under study.

[Insert Table 6 here.]

Identifying "targeted" applicants. As discussed above, QTEA specified increases that varied for teachers based on their placement on the salary schedule. In SFUSD, teachers are placed on the salary schedule corresponding with their number of years of experience and their continuing education units. Thus, to determine whether each applicant was "targeted" by QTEA for salary increases, I used self-reported experience level (which is a categorical indicator) and self-reported level of education attained.[19] Applicants with only a Bachelors degree were placed on the schedule for those with no continuing credits, and applicants with a Masters degree or

[18] The sample presented in Table 4 is smaller than the number of respondents for all survey administrations. This is because respondents had to be removed if they had missing data in variables that identify cohorts, if they did not actually apply to SFUSD, or if they took the applicant survey but were hired (with the exception of the 2011 Cohort, where hired teachers taking the applicant survey were retained). In all cases, the respondents, not analytic sample, are used for weighting. This is particularly important in the applicant surveys. Due to data management problems in SFUSD, the population of applicants actually contains people who are ineligible for the surveys. A large number of respondents reported that they had not actually applied. In the 2010 survey, 190 teachers (25% of respondents) reported they had never applied for a teaching position in SFUSD and 54 (7%) reported that they had been hired; in 2008, 125 (8.7%) responded that they had not actually applied and 952 (31%) reported that they had been hired.

[19] For applicants that were ultimately hired (and took the 2010 Teacher survey), we did not ask the question about education levels because we already had this information in the administrative files; the data from the administrative files are used here.

higher were given the average increase that teachers on the two higher schedules (Bachelor's degree plus 60 or 90 units) would receive as a result of QTEA at each level of experience. Note that in 2008, the survey asked teachers to identify their years of prior experience categorically (none, 1, 2, 3, 4, 5, 6-10, 11-15, 16-20, 20+), so these categories are used in analysis. Table 7 shows the range of salary increases at each level of experience and education (as specified on the salary schedule). For example, for applicants with a bachelor's degree and 11-15 years of experience, the average percentage increase on the salary schedules is 1.2%; the range on the salary schedule at this number of years of experience is 0.2% to 2.3%. I determined that applicants were in the "targeted" group if the salary increase at their placement on the salary schedule was 6% or higher, as the salary increases applicants would have received as a result of QTEA approximates a bimodal distribution with a clear cutoff at this point (as shown in Figure 6).[20] (The "targeted" column in Table 7 indicates whether applicants at the various levels of education and experience are in this targeted group.) Finally, the "N" column indicates the number of applicants in each category after the variables are constructed. (Because it is of primary interest in this study whether or not an applicant was targeted by the policy, only applicants for whom we were able to create this variable are included in analysis. This analytic sample is detailed in Table 4.) (Please see Appendix A for further descriptive information about teacher applicants.)

[Insert Table 7 here.]

[Insert Figure 6 here.]

[20] Note that I tried many variants on the construction of this variable, including using a continuous variable to indicate whether an applicant was targeted (the continuous variable representing the percentage increase in salary they gained as a result of QTEA), determining whether an applicant was in the targeted group using just experience (rather than experience and education), and using real salary to determine increases (for the applicants who were ultimately hired). All of these variations have the same outcome when used in analysis, so I retained only the binary indication to identify "targeted" applicants.

Teacher Database

To study how cohorts of new-hires changed after QTEA, I constructed a Teacher Dataset by combining information from longitudinal student records, staff files, and school records in order to create a database that contains all teachers in the district and includes their salary information and "value-added scores," or an estimation of the amount that an individual teacher contributes to student achievement. Again, I limit this database to teachers in the years 2004-05 through 2010-11. Below I discuss the identification of new teachers, how I determined which teachers were targeted for QTEA salary increases, and the creation of teachers' value-added scores.

Cohort identification. Again, I am primarily concerned here with the characteristics of teachers in the cohorts hired in 2004-05 through 2010-11. To create these cohorts, I used the administrative files to determine which year teachers first appeared in the district. As with the Applicant Database, Teachers were placed in the 2005 Cohort if they appeared in year 2004-05 but did not appear in years 2002-03 and 2003-04, teachers were placed in the 2006 Cohort if they appeared in 2005-06 but not in 2002-03, 2003-04, or 2004-05, and so on.[21] The number of new teachers in each year can be found in Table 8. Across all time periods, there were 2,462 total new-hires.

[Insert Table 8 here.]

Identifying teachers "targeted" by QTEA. In SFUSD, teachers are placed on the salary schedule corresponding with their number of years of experience and their continuing education units. In the Teacher Database, I have actual salary information that identifies where teachers fall on the salary schedule. Thus, to determine the amount that each applicant would gain as a result

[21] Note that the majority of teacher reports line up with this cohort construction: 71.2% of 2010 Cohort teachers report that it was their first year in SFUSD, 78.4% of 2009 Cohort teachers report that it was their second year, and so on; overall, 70.9% of reports correspond.

of QTEA, I used their placement on the salary schedule when they were new to the district to determine what the benefit gained would be for new teachers as a result of QTEA (or, in other words, whether they were in the targeted group at the time that they were first hired to teach in SFUSD). Here I identify teachers as targeted if they would have gained 6% or more in their first year of teaching as a result of QTEA. Table 8 displays the number and percentage of teachers in the targeted group in each year; across all years, there were 2,462 total new-hires, 2,456 of them had salary information, and 1,199 (49%) were in the "targeted" group.

Identifying teacher effectiveness. A goal in this paper is to develop a measure of teacher quality to employ in studying whether teacher quality improved for new-hires as a result of QTEA. While some researchers use teacher characteristics such as years of experience, education, or certification as a proxy for teacher quality (Goe, 2007), these measures explain very little of the total variation in teacher quality as measured by gains in student test scores (Goldhaber, 2008). For this reason, I have chosen to measure teacher quality using teacher "value-added" scores. The benefit of using such scores is that they provide a direct measure of teachers' contributions to student achievement. However, such measures also have their drawbacks; research has shown that value-added measures can be instable for individual teachers from year-to-year (Atteberry, 2011; 2007; McCaffrey, Sass, Lockwood, & Mihaly, 2009), and such scores can only be estimated for teachers in grades and courses that are tested annually, often making them available for only a subset of teachers. Nonetheless, these scores have been used in a growing body of research that shows they are related to other measures of teaching quality (Grossman, et al., 2010; Hough, et al., Forthcoming; Tyler, Taylor, Kane, & Wooten, 2010), and that the students of teachers with high value-added scores succeed in other ways later in life (Chetty, et al., 2010).

A goal in this paper is to evaluate the quality (as measured by value-added scores) of new-hires *in their first year of teaching*. Thus, in this paper, I use a relatively standard teacher-by-year fixed effects model that includes lagged student test scores (in both subjects) from the prior year, a set of time-invariant student demographic characteristics, and grade and teacher-by-year fixed effects (see, for example, McCaffrey, Koretz, Lockwood, & Hamilton, 2003; McCaffrey, Lockwood, Koretz, Louis, & Hamilton, 2004). This model is formalized for math outcomes below:

(1) $$MathAch_{igjst} = \alpha MathAch_{igjst-1} + \gamma ElaAch_{igjst-1} + X_{igjst}\beta + W_s\varphi + \theta_g + \delta_{jt} + e_{igjst}$$

Student i, in grade g, in teacher j's classroom in school s in year t, has a math achievement score ($MathAch_{igjst}$, standardized within grade, subject, and year) which is a linear function of prior achievement in both subjects the previous year; a vector of student demographic characteristics (X_{igjst}) including race, gender, English language status, parental education status, special education status, enrollment in the Gifted and Talented Program, eligibility for free/reduced price lunch program (which serves as a proxy for socioeconomic status); a vector of time-invariant school-level means of the student-level covariates (W_s); the grade level (θ_g); and the teacher to which the student is exposed in the given year (δ_{jt}). The key parameter of interest is δ_{jt}, which captures the average achievement of teacher j's students in year t, conditional on prior skill and student characteristics, relative to the average teacher in the same subject and grade.

The student-level covariates are intended to capture the background factors of students that account for variability in student test scores. In essence, each student's test score is adjusted for the fact that, on average, students of certain prior achievement, race/ethnicities, genders, language statuses, etc., perform, on average, at different levels. The goal in employing student level covariates is to eliminate the bias due to non-random sorting of students into teachers' classrooms.

Some researchers advocate for using a student fixed effect in analysis, as such an approach compares only teachers who have taught the same students across years, thus controlling for all observed and unobserved, time-invariant student factors, perhaps strengthening protections against bias. Student fixed effects are not employed here, however, since recent research has shown that student fixed effects estimates can be more biased than similar models using student covariates (Kane & Staiger, 2008). Another approach that could be used here is a model with school-level fixed effects to control for time-invariant school-level factors that might influence the outcome of interest. However, the inclusion of school fixed effects fundamentally changes the meaning of δ_{jt}, which then becomes a comparison of adjusted student outcomes among teachers in the same school. As a result, valid comparisons can only be made within the same school, while nothing can be learned about the relative performance of teachers in two different schools. In this analysis, I am interested in comparing teachers across, rather than within, schools, since new teachers are distributed across schools over time. Thus, in lieu of school fixed effects, a vector of school-level characteristics (W_s) is included, to compare student outcomes in schools that are similar on these dimensions. Finally, classroom covariates are not included in the model, since year-specific classroom variables are completely collinear with a teacher-by-year fixed effect for teachers in self-contained classrooms (McCaffrey, et al., 2003).

The value-added scores for this study were generated from a database that follows students longitudinally as they encounter teachers from kindergarten through graduation (or their entry/exit to the SFUSD district).[22] The sample is restricted to teachers who taught math or English language arts (ELA) in grades three through eight since 2000-01 – when California began to administer the current statewide standardized test, called the California Standards Test (CST). High school teachers are excluded from the study because it is more difficult to clearly attribute test scores to the correct teacher when students have the opportunity to take multiple math or ELA courses each year. In addition, math course-taking can vary dramatically from year to year in high school (e.g., geometry, algebra, statistics, calculus, etc.), and it becomes difficult to meaningfully interpret differences in year-specific standardized test scores from one year to the next.[23]

The final dataset employed here includes teacher-years in which the teacher is linked to students with complete covariate information, including current-year test score, prior-year test scores, race, gender, English language status, and free-reduced price lunch program eligibility. Table 9 provides the total number of teachers in each year, the number of new-hires, and the numbers in each group with teacher-by-year value-added scores.[24] Teachers are identified as such if they were compensated on the teacher salary schedule in a given year. It is important to note that not all teachers on the teacher salary schedule are directly linked with students. Some d their construction and validity have been detailed by Atteberry ‼ ADDIN EN.CITE

[22] The value-added scores were created as part of a larger project studying teacher quality in SFUSD, and their construction and validity have been detailed by Atteberry (2011). The scores were

[23] For instance, if a student has a lower-than-expected test score in ninth grade and then a higher-than-expected test score in the following year, this could be due to the fact that she experienced a particularly effective tenth grade teacher. But it could also simply be due to the fact that the student is better at geometry than she is at Algebra II.

[24] In analyses of this kind, it is a common practice to exclude teachers with low numbers of students included in the construction of the value-added score. However, doing so in this analysis disproportionately drops first-year teachers. This is likely due to teacher assignment, in which new teachers may be assigned to work with students who are new to the district and thus do not have prior year test information. In any case, since new teachers are the focus of these analyses, I want to retain as many of them as possible. In each analysis presented in this paper, I tested if the results would be different if I excluded teachers with fewer than 4 students. (This is the point at which standard errors become higher.) In every case, the exclusion of these teachers did not drastically modify the point estimates, although the standard errors were affected (due to the reduced number of observations). Thus, I have retained all teachers in these analysis, regardless of the number of students that were used in the generation of their value-added scores.

important in my overall analyses, in which I am interested in all new-hires, not just those linked with students. Of those, approximately 20% of teachers have either a value-added score in math or ELA in each year. Overall, there are 3,978 teacher-by-year value-added scores in ELA in the time period 2004-05 to 2009-10. The average score is -0.101 with a standard deviation of 0.258. There are 3,791 teacher-by-year value-added scores in Mathematics in the time period 2004-05 to 2009-10; the average score is 0.217 with a standard deviation of 0.306.

[Insert Table 9 here.]

It is important to note that the percentage of new teachers with value-added scores is lower in 2009-10 (only 10% of new teachers have value-added scores in this year, compared to 20% for all teachers). While this is a concern, since new teachers in 2009-10 are precisely the group of interest in this analysis, the reduced percentage is a reflection of real teaching assignments of new teachers in that school year. In 2009-10, 44% of the new-hires were in elementary school (compared with 34% in the other years). Of these teachers, 65% were in grades K-2, which cannot be used to create value-added scores (compared with 50% in the other years). This dramatically reduced the number of teachers for whom scores could be generated, but is a result of the real assignment of teachers, not an artifact of the value-added model. Please see Appendix A for further descriptive information about new-hires.

In analyses using these value-added scores, less than a quarter of the teachers in the district can be included in the analysis. While this is a standard outcome in the creation of value-added scores, it has clear implications for evaluating the effect of a policy (such as QTEA) that intends to improve teacher quality. Even when assuming that the estimates are unbiased and reliable, value-added scores can only be calculated for less than one quarter of teachers. Despite this limitation, value-added scores are the only available way to measure teacher quality within

SFUSD. While these results are not comprehensive in understanding QTEA's effect on teacher quality, they shed light on whether QTEA was effective in improving the quality of new-hires in grades 3-8 in English Language Arts and Mathematics.

Principal surveys and interviews

In this paper, I also use survey evidence of principals in SFUSD (surveyed in spring 2010). These surveys built off of the The New Teacher Project surveys (2009) of principals on teacher hiring, assignment, and evaluation administered in San Francisco in June 2008. These surveys included questions about teacher recruitment, retention, and quality, as well as specific questions about QTEA implementation. These surveys were also web based[25] and were administered to participants using email addresses on file with SFUSD. Detail on survey samples and response rates can be found in Table 10.[26]

[Insert Table 10 here.]

I also use evidence from school case studies conducted during the 2009-10 school year (QTEA's first full implementation year) in 11 schools. Throughout the school year, I interviewed principals up to four times to understand their personnel practices over the course of the year and to determine how QTEA affected their ability to recruit and retain highly-effective teachers. (See Appendix B for the protocols used.) The goal of the case studies was to delve deeper into QTEA implementation in a subset of schools and to better understand the effect of additional QTEA resources in some of the 25 schools designated hard-to-staff. To select the schools, I developed an index of school characteristics which included turnover rates, student demographics, and student achievement scores. After matching schools on these characteristics, I sampled the

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[25] The actual survey instrument can be found online at https://suse.qualtrics.com/SE/?SID=SV_6r2xdGWMprjs8Pa&Preview=Survey&BrandID=suse (Principal).

[26] Note that in the 2010 surveys I incentivized response with 50 $150 gift certificates for teachers and a one-in-ten chance of winning $99 for applicants.

schools randomly for inclusion, stratifying by school level. The final school case study sample included eight hard-to-staff schools and three schools that are very similar to hard-to-staff schools in terms of turnover rates, student demographics, and achievement scores, but that did not receive the additional resources for hard-to-staff schools through QTEA.[27] Table 11 shows how case study schools (and hard-to-staff schools) are distributed across grade levels, and Table 12 shows how the student demographics in the case study schools compare to the demographics district-wide.

[Insert Table 11 here.]

[Insert Table 12 here.]

Principal Reports on how QTEA Affected Teacher Recruitment

As a first line of questioning, I investigated principal reports about how the quantity and quality of applicants changed from the time period before QTEA to the time period after. On the 2010 survey, principals were asked if QTEA aided their teacher recruitment efforts. While the majority of principals in non-hard-to-staff schools reported no effect (54%), 44% of principals in hard-to-staff schools reported that QTEA salary and bonuses helped them recruit teachers (see Figure 7). In addition to the fact that teachers in these schools received a $2,000 bonus, these schools also historically have more positions to fill every year and have a harder time recruiting teachers.

[Insert Figure 7 here.]

In 2010, principals were also asked whether QTEA's salary and bonuses helped recruitment in hard-to-fill subjects. Again, while the majority of principals in non-hard-to-staff

[27] Originally, 15 schools were sampled for inclusion, but 4 declined to participate. Coincidentally, these schools had been matched to one another, so all 4 were dropped and not re-sampled.

schools reported no effect (55%), 47% of principals in hard-to-staff schools reported that bonuses helped in recruiting teachers in hard-to-fill subjects (see Figure 8).

[Insert Figure 8 here.]

In both 2008 and 2010, principals were asked whether there were enough candidates in "high need areas" in the applicant pool. In 2010, 42% of principals said yes, compared to only 28% in 2008.[28] These results indicate that principals perceived a change between 2008 and 2010 in the strength of the applicant pool. Principals were also asked questions to gauge how the quality of the applicant pool has changed since the implementation of QTEA. On the 2008 and 2010 surveys, principals were asked to rate their satisfaction with the quality of the pool of external applicants. More principals in 2010 reported that they were satisfied with the quality of the external applicant pool than in 2008. As shown in Figure 9, in 2008, 69% of principals reported that they were "satisfied" or "very satisfied" with the quality of external applicants, compared to 81% in 2010.

[Insert Figure 9 here.]

In interviews with principals, while most agreed that the quality of applicants was higher than in previous years, many attributed this improvement to general economic conditions rather than to QTEA. One principal said, "This year…there's just a lot of stronger teachers coming in to interview." Another principal succinctly stated, "I used to [have a hard time recruiting teachers in hard-to-fill areas], but last year because of the economy – and it is going to be the same this year – there are a lot of candidates out there." In any policy environment, many things change at once – in the first year of QTEA implementation, principals noticed an improvement in the quality of applicants, but they attributed it to the downturn in the economy. This is precisely why

[28] Source: 2008 TNTP Principal Survey (N=67), 2010 Stanford Principal Survey (N=81). Chi-square = 2.96, p = 0.09.

a causal approach is needed; a more careful analysis can sort out the effect of QTEA from other district interventions or secular trends (such as economic downturn).

Method

In this paper, I investigate how the applicant pool might have changed as a result of QTEA, and whether observed changes led to improvements in the cohorts of new teachers. I discuss the approach for each question in turn.

Changes to the applicant pool

In SFUSD, prospective teachers apply to the district central office and, after clearing a first round screening, are interviewed and ultimately hired by individual schools. Thus, to understand how the attractiveness *of the district* may have changed after QTEA, I can look at how the characteristics of applicants to the central office may have changed after QTEA. Because applicants apply to the central office initially (rather than specific schools), changes to the applicant pool would indicate changes in the district's overall attractiveness. Specifically, I investigate whether QTEA was effective in 1) attracting more applicants to SFUSD, and 2) attracting applicants from higher-paying school districts. However, I cannot simply compare applicants before and after implementation of the policy because of the economic downturn that occurred simultaneously. When QTEA was passed, unemployment in the San Francisco Bay Area was 5.6%, but was 9.6% by the following year and continued to climb.[29] This downturn in the economy has serious implications for studying QTEA. The scarcity of jobs, either in teaching or in other occupations, could have led to a change in the applicant pool even in the absence of QTEA. Control for secular trends is often warranted, but it is particularly important in this time frame. It is an important characteristic of the job search that applicants only apply to jobs in districts where there are available positions. In a down economy, often the most desirable school

[29] http://www.bls.gov/lau/#tables

districts (those with higher salaries) have fewer jobs, which could mean that applicants were applying more to lower paying districts after QTEA, not because of the policy, but because of broader economic conditions.

In isolating the causal effect of QTEA, the basic goal is to identify applicants who are similarly affected by economic changes but differently affected by QTEA. The natural variation in the distribution of teacher salary increases across teachers at different levels of experience and education provides this identification. Because the salary increase introduced as a result of QTEA varies across teachers at different placements on the salary schedule, the implementation of QTEA can be thought of as a natural experiment. That is, we can observe the way that applicants who are "targeted" for the increases responded in comparison to those who were "non-targeted" both before and after the implementation of QTEA. If we can assume that the variation in salary increases would not affect changes in applicant behavior by any route other than through the salary increase itself, any changes we see in retention can be attributed to QTEA's salary increases.

However, QTEA's salary increases are a function of teaching experience, which could be related to how teachers are affected by the economy. Less experienced teachers are most affected by QTEA, but they also may be most affected by changes in the economy: new teachers may have problems securing their first positions, and teachers with very few years of experience are most often those targeted by layoffs. Thus, to isolate the QTEA effect, and to ensure that I compare teachers who would be similarly affected by the economy, I exclude first and second year teachers (applicants who have zero or one year of prior experience at the time of application) and applicants with more than 15 years of teaching experience, whose retirement decisions may be affected by the economy. As shown above in Figure 5, teachers in this range of prior experience are differently affected by QTEA's overall salary increases, however, they should be similarly affected by the economy. I also include a specification in which I limit the population even further, comparing teachers with 3-10 years of experience, which provides an even more rigorous test of QTEA's effectiveness. If I observe more or better applicants specifically in those targeted steps on the salary scale, then we can attribute that change to QTEA. The specific approach for each question is detailed below.

Change in the proportion of targeted applicants. Here I seek to understand whether more teachers applied to teach in SFUSD as a result of QTEA. To answer this question, I use the Applicant Database to analyze if the proportion of targeted applicants increased after QTEA.[30] An increase in the proportion of targeted applicants after QTEA would suggest that the salary increase was effective in recruiting teachers in the targeted areas. We can compare the percentage of applicants in each targeted area to cohorts before and after QTEA, even if the number of applicants in each time period is not comparable across cohorts.[31] As discussed above, I limit the analysis to applicants with 2-15 years of prior experience, as teachers in this experience range differ drastically in the extent to which they are targeted by QTEA, yet would respond very similarly to economic changes. This brings the number of observations for this

[30] The ideal method for answering this question would be to use the district's administrative data to analyze if more people overall applied to the district, and if there were more applications specifically in targeted areas (in hard-to-fill subjects and in the salary steps that have large increases). However, I cannot use the administrative data in this way. The district switched to a new applicant system in the same year as QTEA was implemented. At this time, their data systems switched, and the way people applied (and were tracked) was different. Even if the files were accurate, the district did not keep track of subject area of applicants or their years of experience (which determined their level of salary and hence the percentage that they would gain as a result of QTEA salary increases) in the old system. Furthermore, we have evidence from the survey that around 20% of applicants in the new database actually did not apply to SFUSD for teaching jobs. (The first question on our survey was if people had actually applied, and this, combined with email responses to our request, revealed the data problem.)

[31] Attributing a change in proportion of targeted teachers to QTEA relies on the assumption that response patterns of applicants did not change before-to-after QTEA. If more targeted teachers responded to the survey in 2010 than 2008, this would be interpreted here as a QTEA effect; but I have no reason to believe that response patterns changed in this way. Furthermore, in looking at change in the average salary of other districts applied to, I do not rely on this assumption, so together, these questions form a triangulated approach to understanding how targeted applicants responded to QTEA.

analysis to 749, with 30% of the applicants in the targeted group over the entire time period. The basic model is as follows:

(2) $$Y_i = \beta_0 + \beta_1 QTEA + e_i$$

Where Y_i indicates whether an applicant was in the targeted group, β_0 is the proportion of targeted applicants before QTEA and β_1 is the difference in the proportion of targeted applicants after QTEA. Thus, a positive value of β_1 would indicate that there was a higher proportion of targeted applicants after the introduction of QTEA.

Change in the average salary of other districts applied to. Here I investigate whether higher-quality applicants applied to SFUSD after QTEA, or more specifically, if QTEA has been effective in attracting teachers who otherwise only would have applied to higher-paying school districts. An increase in the average salary of other districts applied to by the targeted group after QTEA would show that these applicants included SFUSD in their job search because they prefer districts with higher salaries and now consider SFUSD to be more competitive with higher-paying school districts. My basic approach is to compare the average salary of the other districts applicants applied to (in addition to SFUSD) for cohorts before and after QTEA.

Specifically, I use a difference-in-differences approach, taking the difference in the average salaries of other districts applied to for targeted applicants before and after QTEA, and comparing this to the difference in the average salaries of other districts applied to for non-targeted applicants before and after QTEA. In a difference-in-differences framework, if some external policy change (in this case QTEA) produces exogenous variation in treatment status, then this exogenous variation can be used to estimate the causal effects associated with this variation in treatment status. If QTEA had an effect, we would expect to see the average salary of other districts teachers applied to increase for those who were targeted compared to those who were not targeted. The basic difference-in-differences model is as follows:

(3) $$Y_i = \beta_0 + \beta_1 QTEA + \beta_2 TARGETED + \beta_3 QTEA * TARGETED + e_i$$

where the average salary of other districts applied to is a function of whether the teacher would have been targeted for the salary increase in the next year (*TARGETED*), whether the year in question is in the QTEA implementation period (*QTEA*), and the interaction of whether the teacher was targeted for salary increases in the time period after QTEA (*TARGETED*QTEA*). In Equation 3, β_3 is the difference-in-differences estimator, and my parameter of interest.[32] This approach is presented graphically in Figure 10. In this depiction of a hypothesized effect, those applicants that would have been targeted by QTEA before the policy apply to lower salary districts than those that are non-targeted (which seems possible since these applicants also have slightly fewer years of experience). If there is an effect, after the implementation of QTEA, the average salary of other districts applied to would increase for the "targeted" group but remains the same for the "non-targeted" group. The estimator β_3 represents the difference between the actual effect for the targeted group and the *hypothesized effect* without QTEA, which is estimated based on the trend for the non-targeted group.

[Insert Figure 10 here.]

The outcome in this analysis is the average salary of the other school districts that each applicant applied to. On the survey, applicants were given a list of local school districts that they could select, and there was also a write-in option. In this analysis, I include only local districts; this analytic decision is justified by research showing that teachers tend to look for positions in a small geographic area (Boyd, et al., 2005). Thus, I included districts in the Combined Statistical

[32] (Post-QTEA/TARGETED – Pre-QTEA/TARGETED) - (Post-QTEA/Non-TARGETED – Pre-QTEA/Non-TARGETED) = $[(\beta_0 + \beta_1 + \beta_2 + \beta_3) – (\beta_0 + \beta_2)] – [(\beta_0 + \beta_1) - \beta_0] = \beta_3$

Area (CSA) of San Jose-San Francisco-Oakland, in which there are six Metropolitan Statistical Areas (MSA), with a total of 186 school districts. (See Table 13 for the number of school districts in each MSA.)[33]

[Insert Table 13 here.]

The analytic sample for this question is the number of teachers who applied to SFUSD in addition to at least one other school district, which means that I exclude 710 teachers who only applied to SFUSD. After excluding teachers with fewer than two or more than 15 years of prior experience, the analytic sample for this analysis is 454 teachers (with 32% of the applicants in the targeted group over the entire time period). (See Table 14 for detail on the sample used to answer this question and the number of applicants in hard-to-fill subjects in each cohort.)

[Insert Table 14 here.]

Of teachers who applied to at least one school district, the average teacher applied to 4.92 other local school districts. As shown in Figure 11, the largest number of applicants (228) applied to only one other school district, although a substantial number of applicants applied to many.

[Insert Figure 11 here.]

Of the 186 school districts in the CSA, the majority (52%) were not applied to, although 19% were applied to by 1-2 people, 21% were applied to by 3-100 people, and 8% were applied to by over 100 people. To create a variable that captures the average salary of school districts applied to that is comparable over time, I took the mean of the salaries of each district applied to (for teachers at BA + 60, Step 10) in 2007-08 (regardless of the year applied), to enable

[33] Information on CSAs and MSAs is from the National Center for Education Statistics, Common Core of Data (CCD), Local Education Agency Universe Survey (2008-09).

comparisons across time.[34] Table 15 shows the mean salary of the other districts teachers applied to in each cohort. Overall, the average salary of the local school districts that teachers applied to in the CSA is $65,075, with a standard deviation of $5,392.

[Insert Table 15 here.]

In each investigation, I also include a specification where I test for varied effects for teachers in hard-to-fill (HTF) subjects. QTEA provided a $1,000 increase to those teachers in hard-to-fill subjects, and it is important to understand how these teachers responded to the policy. However, because there is no variation in the way the hard-to-fill subject bonus was assigned (since all teachers in hard-to-fill subjects received the bonus), it can not be analyzed in the same way as the overall salary increase. Those teachers who benefit from the hard-to-fill subject bonus are highly affected by downturns in the economy and thus it is difficult to separate their response to QTEA from their response to the economic changes that occurred at the same time. To understand differential effects for teachers in hard-to-fill subjects, modifications to the basic model are required for each question; these will be discussed below.

I also include a number of specification checks in each investigation. First, I test my definition of the implementation period by separating the year 2008-09 from the time period 2009-10 to 2010-11 (since 2008-09 was a partial implementation year). Next, to test the idea that there may be trends over time that could affect the proportion of applicants in targeted areas (such as availability of positions or generally increasing attractiveness of SFUSD), I include a cohort trend in the analysis. I also include a specification in which I reduce the sample even further, limiting it to applicants with 3-10 years of experience, which should provide further assurance that the applicants being compared would be similarly affected by the economy but differently affected by QTEA. Finally, I discussed above that responses on the surveys are likely

[34] These files were pulled from http://www.ed-data.k12.ca.us.

more valid if respondents are asked to provide information that is more recent; to ensure that response bias does not affect findings, I limit the cohorts under study to those after 2006.

Changes to cohorts of new-hires

In the first section, I investigate whether the size and quality of the applicant pool increased in SFUSD in response to QTEA. In this section, I investigate whether observed changes in the applicant pool resulted in improvements in the cohorts of new-hires after QTEA. As discussed in the conceptual framework, improvements in either the quantity or quality of applicants in the pool should result in an increase in the quality of new-hires after QTEA regardless of district policies and practices.[35] In Figure 12, I illustrate two scenarios for how the quality of new-hires could change as a result of QTEA. The top graphic represents what would happen if the size of the applicant pool increased proportionally across quality levels, and the bottom graphic represents what would happen if QTEA disproportionately attracted high-quality applicants. In each graphic, the blue line depicts the quality distribution of applicants before QTEA, and the pink line depicts how the pool of targeted applicants could have changed due to QTEA. In this stylized depiction of how changes to the applicant pool can lead to changes in the quality of new-hires, I assume that the district has a "quality cutoff," which is depicted by the dotted line in both diagrams. In this scenario, the district does not consider applicants below the quality cutoff and ultimately selects new-hires from the area to the right of the cutoff (after a more personalized hiring process). If QTEA is effective in improving teacher recruitment, we would expect to see more and/or better applicants, specifically in targeted areas. If the size of the pool increases proportionally (as shown in the top graphic), there would be more targeted applicants above the "quality cutoff" because there are more targeted applicants at all levels of

[35] While this is true on a basic level, it is also true that refinement in district hiring practices can enable the district to hone in on the best candidates, thus futher improving the quality of new-hires.

teacher quality. If the proportion of high-quality teachers in the pool increases as a result of QTEA (as shown in the bottom graphic), there would be *many* more targeted applicants above the quality cutoff, since high-quality applicants were differentially attracted by the policy. It is clear from these depictions that there would be more high-quality applicants above the "quality cutoff" in either scenario, and that these applicants are the "targeted" applicants, drawn by the higher salaries. This should mean that the district ultimately hires more of these targeted teachers, simply because there are more of them in the pool, and in either scenario, at least some of them are higher-quality applicants. Thus, we would expect to see more "targeted" new-hires after the introduction of QTEA, and we would expect them to be higher-quality teachers on average. I pose the following hypotheses, which will be tested here: 1) An increase in the *proportion* of new-hires in targeted areas would provide an indication that these targeted applicants are higher quality, since they were ultimately hired; 2) An increase in the *quality* of new-hires overall would provide evidence that QTEA had been effective in improving the size and/or quality of the applicant pool, since the overall quality of new-hires increased; and 3) An increase in quality of new-hires in targeted areas (relative to non-targeted new-hires) would provide a confirmation that the overall quality of new teachers is being driven by the higher-quality of the targeted group. In order to investigate these questions, I employ the Teacher Dataset; below I present the specific methods for each question.

[Insert Figure 12 here.]

Change in the proportion of new-hires in targeted areas. More new-hires in the targeted group suggests that there were more of them in the pool, and also provides an indication that they are higher quality candidates, since they were ultimately hired. I use the following equation to examine whether the proportion of targeted teachers who were hired increased after QTEA:

(4) $Y_i = \beta_0 + \beta_1(QTEA_i) + \varepsilon_i$

Where Y_i indicates if a teacher is in the targeted group, β_0 is the average proportion of targeted applicants before QTEA and β_1 is the difference in the proportion of new-hires in the targeted group after QTEA. Thus, a positive value of β_1 would indicate that there was a higher proportion of new-hires in the targeted group after the implementation of QTEA.

Unlike the models investigating how QTEA changed the applicant pool, here I do not restrict the sample by teacher experience; which applicants are hired is a very different process than which teachers apply. As a result of a downturn in the economy, we might expect more less experienced teachers to be in the applicant pool (as a result of layoffs or simply not getting a job), which could inflate my estimate of the "QTEA effect" if they are not excluded. However, more of these applicants in the pool does not mean that they would necessarily be hired, unless they were of higher quality.[36] Thus, a higher proportion of targeted teachers in the pool of new-hires would indicate a QTEA effect, even if the least experienced teachers are included, and would even suggest an even stronger QTEA effect; if the least experienced teachers are being hired, they might be of even higher quality. Nonetheless, I include a specification in which I limit to teachers with 2-15 years of prior experience to ensure that applicant experience does not explain a possible increase in targeted applicants. (The full sample of new teachers is 2,462; 6 of these are not included in analysis because their salary increase as a result of QTEA could not be

[36] New hires in the "targeted" group are still less expensive than non-targeted teachers, since they have fewer years of total experience. Thus, an alternate explanation for more new hires in the targeted group could be that the district hires these less expensive teachers in higher numbers as budgets decline. This scenario is highly unlikely in SFUSD, where hiring is done at the school site, and schools pay the average (not actual) teacher salary, giving them no incentive to hire less expensive teachers.

calculated from the administrative files, bringing the analytic sample to 2,456. The sample is reduced to 754 after restricting the sample to teachers with 2-15 years of prior experience.)

Change in the quality of new-hires. Here, I investigate whether the quality of new-hires (in their first year) is higher after QTEA than before. I cannot simply compare the value-added scores of new-hires before and after QTEA because scores are not easily compared across years. (Since the tests change every year, and the value-added models used to generate the scores include year fixed-effects, it is most accurate to compare scores within the same year.) Thus, I create a reference group that I use to analyze changes in the quality new-hires both before and after the implementation of QTEA. Here, I construct the reference group as the group of teachers that has VAM scores in the appropriate subjects (Math or ELA) for the entire time period of interest (six years: 2004-05 to 2009-10). (Note that I cannot use the cohort of teachers hired in 2010-11 since their students' test scores were not yet available for analysis.) By establishing this reference group, I am able to control for trends in tests across years, assuming that the teachers in the reference group are relatively stable over time in their contributions to student achievement. (If their scores vary year-to-year, this can be thought of as model-based variation in the value-added scores, so their scores provide a baseline within each year, controlling for differences in tests and scores across years.) To further ensure this stability, I exclude teachers from the reference group who had fewer than three years of experience at any time during the observation period. (For ELA, this reference group is the same 203 teachers in each year; for Math, this reference group is the same 210 teachers.) For each outcome (Math and ELA), I regress QTEA implementation time periods (before/after) on value-added scores against this reference group:

(5) $VA_i = \beta_1(New_i) + \beta_2(New*QTEA_i) + (Year_i)\beta_3 + \varepsilon_i$

Where β_1 is the average value-added of new teachers before QTEA (compared to the reference group), and β_2 is the average value-added of new teachers after QTEA (in addition to β_1). β_3 is a vector containing a fixed-effect for every year 2004-05 through 2009-10. The coefficient of interest here $\beta_{2,}$ which indicates whether the value-added scores of new teachers increased after the implementation of QTEA, relative to the reference group. As discussed above, for each outcome (Math and ELA), I use a non-restricted model as the baseline model. In two additional specifications, I 1) include the varied definition of QTEA implementation period; and 2) include indicators for whether new-hires had fewer than 2 years of prior experience or more than 15, which allows me to ensure that quality changes were not related to prior experience, even as these teachers are included in the model.

Change in the quality of new-hires in targeted areas. Finally, I conduct a test investigating whether increases in quality are driven by increases specifically in the quality of targeted teachers after QTEA. As discussed above, if quality increases of new-hires is driven by an increase in the quality of targeted applicants, we should expect to see the quality increase differentially for new-hires in the targeted group. To test this idea, I use a difference-in-differences approach, taking the difference in the value-added scores of targeted applicants before and after QTEA, and comparing this to the difference in the value-added scores of targeted applicants before and after QTEA. If quality increases of new-hires after QTEA are driven by new-hires in the targeted group, we would expect to see an increase in the value-added of targeted applicants after QTEA compared to those who were not targeted. The equation for this basic difference-in-differences model is as follows:

(6)

$$VA_i = \beta_1(New_i) + \beta_2(New*QTEA_i) + \beta_3(New*Targeted) + \beta_4(New*Targeted*QTEA) + (Year_i)\beta_5$$

Where again β_1 is the average value-added of new teachers before QTEA (compared to the reference group) and β_2 is the average value-added of new teachers after QTEA (in addition to β_1). In this model, β_3 would provide an average value-added for targeted, new-hires both before and after QTEA and the estimator β_4 represents the difference between the actual effect for the targeted group and the *hypothesized effect* without QTEA, which is estimated based on the trend for the non-targeted group. Finally, β_5 is a vector containing a fixed-effect for every year 2004-05 through 2009-10.

Results

To study the effect of QTEA on teacher recruitment, I investigate how both the teacher applicant pool and the cohorts of new hires could have improved after the policy was implemented. I posit that the quantity and quality of the applicant pool could improve as a result of the salary increase, and that (in either scenario) these improvements in the applicant pool could lead to an increase in the quality of new-hires. I now present the findings for each question.

Changes to the applicant pool

In order to understand the effect of QTEA on the applicant pool, I first look at changes in the proportion of targeted applicants; an increase in the proportion of targeted applicants would indicate that QTEA had been effective in increasing the size of the applicant pool. Second, I look at the changes in the average salary of other districts to which applicants apply; an increase in the average salary of the other school districts applied to for targeted applicants would indicate that the targeted applicants were drawn from higher-salary districts, which would indicate (by proxy) that the quality of the applicant pool increased as a result of QTEA.

Change in the proportion of targeted applicants. Using the model laid out in Equation 2, I find that a higher proportion of targeted applicants applied after QTEA went into effect, which indicates that QTEA was effective in drawing these targeted applicants. Table 16 presents the full results. In the basic model (Table 16, Model 1), which is limited to applicants with 2-15 years of prior experience, I show that the proportion of targeted applicants increased by 9.9 percentage points after QTEA. Before QTEA, 26.8% of applicants were in this targeted group, and after QTEA, 36.7% of applicants were in this targeted group.

[Insert Table 16 here.]

To test the robustness of these findings, I ran a number of variations on the basic model. First, I used a varied definition of the implementation period by using the years 2008-09 and 2009-10/2010-11 as two separate variables. As shown in Table 16, Model 2, while a larger proportion of targeted applicants applied in both 2008-09 and 2009-10/2010-11, the effect is only significant after the first year of implementation. Prior to QTEA, 26.8% of the applicants were in the targeted group, and in the period 2009-10/2010-11 this had increased to 37.4% (a change of 10.6 percentage points compared to the pre-implementation period).

To test the idea that there may be trends over time that could affect the proportion of applicants in targeted areas (such as availability of positions or generally increasing attractiveness of SFUSD), I included a cohort trend in the analysis. As shown in Table 16, Model 3, the point estimates are similar to those in Model 1, but the effect is no longer significant. This change when cohort trend is included could be a result of diminished statistical power rather than indication of a weak QTEA effect.

I also included a specification in which I reduced the sample even further, limiting it to applicants with 3-10 years of experience. As shown in Table 16, Model 4, when all applicants are included, 25.9% of applicants were in this targeted group before QTEA, and after QTEA, 34.8% of applicants were in this targeted group (a change of 8.9 percentage points). The effect here is still positive and significant, indicating that the effect is quite robust; the reduction of the sample to teachers with 3-10 years should provide additional assurance that teachers in this experience range would be similarly affected by the economy but differently affected by QTEA.

Finally, I discussed above that responses on the surveys are likely more valid if respondents are providing information that is more recent. To ensure that response bias is not affecting these findings, I limited the cohorts under study to those after 2006. As shown in Table 16, Model 5, the point estimates are similar to those in Model 1, but the effect is no longer significant. Again, this change when the sample is limited to applicants after 2006 could be a result of diminished statistical power rather than an indication of a weak QTEA effect.

Effect for applicants in hard-to-fill subjects. A basic approach for studying whether the hard-to-fill subject bonus had an effect is to employ Equation 2, using whether a teacher was in a hard-to-fill subject as the outcome. This approach would indicate whether there was an increased proportion of applicants in hard-to-fill subjects after QTEA. When I do this (as shown in Table 17), it appears as though there is no effect of QTEA in attracting such teachers to SFUSD; the non-statistically significant coefficient 0.007 indicates that the proportion of applicants in hard-to-staff subjects was the same before and after QTEA. However, in order to investigate the effect of QTEA on increasing the proportion of applicants in hard-to-fill subjects, a more sophisticated approach is needed. As discussed above, the hard-to-fill subject bonus is not exogenous in the same way that the salary increase is exogenous; those teachers who benefit from the hard-to-fill subject bonus are highly affected by downturns in the economy and thus it is difficult to separate their response to QTEA from their response to the economic changes that occurred at the same time.

[Insert Table 17 here.]

To get around this, I use a different method that allows me to compare the proportion of targeted applicants in hard-to-fill subjects to non-targeted applicants in hard-to-fill subjects before and after QTEA. Because these teachers are differently affected by the policy but similarly affected by the economy, this approach enables me observe whether applicants in hard-to-fill subjects who are also targeted by overall QTEA salary increases respond by applying in higher numbers after QTEA. In this way, I can obtain a causal estimate of how applicants in hard-to-fill subjects responded if they were targeted compared to the non-targeted group. To conduct this analysis, I created a categorical variable that is an interaction of whether the applicant is in the targeted group and/or teaches in a hard-to fill subject. See Table 18 for the number of applicants in each of the four categories and the weighted percent of the total.

[Insert Table 18 here.]

To compare the proportion of targeted applicants in hard-to-fill subjects to non-targeted applicants in hard-to-fill subjects, I use this categorical variable as the outcome in a multinomial logit regression model. A multinomial logit model is appropriate for analyzing categorical data; in such a model, the probability of each occurrence is estimated relative to a base outcome (Long, 1997). I use this model to predict the likelihood of being in the applicant pool after QTEA for each group compared to the reference group. In this model, the reference group (or base outcome) is those applicants who were targeted for the hard-to-fill subject bonus but not the overall salary increase; the three additional categories are compared to this reference group. The basic model is as follows:

(7) $$P_{ij}^{h} = \frac{\exp(\beta_0^h + \beta_1^h QTEA_j)}{\sum_{g=1}^{G} \exp(\beta_0^g + \beta_1^g QTEA_j)}$$

In this model, being "Non-HTF & Non-Targeted" (h=1), "HTF & Non-Targeted" (h=2), "Non-HTF & Targeted" (h=3), or "HTF & Targeted" (h=4) are a function of whether the year in question is in the QTEA implementation period. The primary comparison of interest is represented when "HTF & Targeted" (h=4) applicants are compared to the base case, "HTF & Non-targeted" (h=2), as this isolates the effect of QTEA's overall salary increase on targeted applicants in hard-to-fill subject areas. Again, I limit the sample to those teachers with 2-15 years of experience to compare teachers who are differently affected by the policy but similarly affected by the economy.

The results are presented in Table 19 as relative risk ratios (generally, the ratio of the probability of choosing one outcome category over the probability of choosing the reference category). As shown in Model 1, Table 19, the proportion of targeted applicants in hard-to-fill subjects (HTF & Targeted) increases after QTEA by a factor of 1.47 compared to the reference group (HTF & Non-targeted). (As a point of comparison, the proportion of applicants not in hard-to-fill subjects nor the targeted group (Non-HTF & Non-targeted) is not significantly different from the reference group after QTEA, and the proportion of targeted applicants not in hard-to-fill subjects (Non-HTF & Targeted) increases after QTEA by a factor of 1.55 compared to the reference group (HTF & Non-targeted).) The results presented here in Table 19 show that applicants in hard-to-fill subjects who are *also* targeted by QTEA overall salary increases respond by applying in higher proportions than those in hard-to-fill subjects who were not targeted by overall salary increases. Taken together with the results in Table 18, these results suggests that QTEA may not have been effective in recruiting more teachers in hard-to-fill subjects overall, but that applicants who were targeted by overall salary increases *and* the hard-to-fill subject bonus responded by applying in larger numbers.

[Insert Table 19 here.]

To test the robustness of these findings, I ran a number of variations on the basic model. (Full model results are presented in Table 19, but I only explain the effect for targeted applicants in hard-to-fill subjects (HTF & Targeted) compared to the reference group (HTF & Non-targeted).) First, I used a varied definition of the implementation period by separating the year 2008-09 from 2009-10/2010-11. As shown in Table 19, Model 2, a larger proportion of targeted applicants in hard-to-fill subjects (HTF & Targeted) applied in both 2009 and 2010/2011 compared to the reference group (HTF & Non-Targeted), but the effect is stronger in the first year of implementation. In 2008-09, the proportion of applicants in hard-to-fill subjects who are in the targeted group (HTF & Targeted) increases by a factor of 1.75 relative to the reference group. In 2010/2011, the proportion of applicants in hard-to-fill subjects who are in the targeted group (HTF & Targeted) increases by a factor of 1.39 relative to the reference group.

To test the idea that there may be trends over time that could affect the proportion of targeted applicants (such as availability of positions or generally increasing attractiveness of SFUSD), I included a cohort trend in the analysis. As shown in Table 19, Model 3, the QTEA effect remains strong. After QTEA, the proportion of applicants in hard-to-fill subjects who are in the targeted group (HTF & targeted) increases by a factor of 2.70 relative to the reference group (HTF & Non-targeted).

I also included a specification which I reduced the sample even further, limiting it to applicants with 3-10 years of experience. As shown in Table 19, Model 4, when the sample is restricted in this way, after QTEA, the proportion of applicants in hard-to-fill subjects who are in the targeted group (HTF & Targeted) increases by a factor of 1.55 relative to the reference group (HTF & Non-targeted).

Finally, I discussed above that responses on the surveys are likely more valid if respondents are providing information that is more recent. To ensure that response bias is not affecting these findings, I limited the cohorts under study to those after 2006. As shown in Table 19, Model 5, again, the effect remains positive and significant. After QTEA, the proportion of applicants in hard-to-fill subjects who are in the targeted group (HTF & Targeted) increases by a factor of 1.68 relative to the reference group (HTF & Non-Targeted).

Change in the average salary of other districts applied to. Using the model laid out in Equation 3, I find that applicants targeted by QTEA applied to higher salary districts after the introduction of the policy. As shown in the basic model (Table 20, Model 1), the overall trend is that applicants applied to lower salary districts after QTEA (the average salary of other districts applied to is $1,491.10 lower than before QTEA implementation); this is likely due to the downturn in the economy discussed above, in which higher paying districts were even less likely to be hiring than lower paying districts. Targeted applicants apply in general to lower salary districts (the average salary of other districts applied to is $1,005.29 lower for targeted teachers); this is likely because they have slightly fewer years of experience. The difference-in-differences estimator is positive and significant, indicating that targeted applicants applied to higher salary districts after QTEA: the average salary of other districts applied to is $2,254.75 higher for targeted teachers after QTEA. This effect is both statistically significant and substantively significant. As shown in Table 15, the standard deviation in the average salaries of the districts that applicants applied to is $5,392.01. Thus, in standard deviation units, the QTEA effect is 0.42

of a standard deviation. This indicates that after QTEA, targeted applicants applied to districts with substantively higher salaries than before.

[Insert Table 20 here.]

Figure 13 provides a graphical representation of this finding. For the non-targeted group, the average salary of other districts applied to *decreased* after QTEA, likely due to the downturn in the economy. The targeted group applied to lower salary districts than the non-targeted group before QTEA; probably because they have slightly fewer years of teaching experience. However, for the targeted group, the average salary of other districts applied to *increased* after QTEA. The true "QTEA effect" is the difference between the targeted group's actual average salary and the hypothesized outcome if QTEA had not been implemented. Thus, for targeted teachers, the average salaries of other districts applied to were $2,255 higher than they would have been in the absence of QTEA.

[Insert Figure 13 here.]

To test the robustness of this finding, I ran a number of variations on the basic model. First, I tested a varied definition of the implementation period by using the years 2009 and 2010/2011 as two separate variables. As shown in Table 20, Model 2, while there is a positive effect of QTEA in both 2009 and 2010/2011, the effect is larger after the first year of implementation. Compared to the pre-implementation period, in 2009, targeted teachers applied to districts with average salaries $1751.44 higher than they would have in the absence of QTEA, and in 2010/2011, targeted teachers applied to districts with average salaries $2391.62 higher. (Note that the effect in 2009 and 2010/2011 are statistically different from one another at p=0.04.) This indicates that the effect is larger once QTEA was in full implementation.

To test the idea that there may be trends over time that could affect the average salary of other districts applied to (such as availability of positions or generally increasing attractiveness of SFUSD), I included a cohort trend in the analysis (Table 20, Model 3). When this variable is included, the effect of QTEA remains positive and significant. After QTEA, targeted applicants applied to districts with average salaries $2217.61 higher than they would have in the absence of QTEA.

I also included a specification in which I reduced the sample even further, limiting it to applicants with 3-10 years of experience. As shown in Table 20, Model 4, the difference-in-differences estimator remains positive and significant. In this specification, after QTEA, targeted applicants applied to districts with average salaries $1,931.80 higher than they would have in the absence of QTEA. The effect here is still positive and significant, indicating that the effect is quite robust; the reduction of the sample to teachers with 3-10 years should provide additional assurance that teachers in this experience range would be similarly affected by the economy but differently affected by QTEA.

Finally, I discussed above that responses on the surveys are likely more valid if respondents are providing information that is more recent. To ensure that response bias is not affecting these findings, I limited the cohorts under study to those after 2006. As shown in Table 20, Model 5, again, the effect remains positive and significant. After QTEA, targeted applicants applied to districts with average salaries $1,943.51 higher than they would have in the absence of QTEA.

Effect for applicants in hard-to-fill subjects. As discussed above, QTEA also included bonuses for teachers in hard-to-fill subject areas, as one of the policy's goals was to attract such teachers to the district. Thus, I seek to understand whether QTEA was differentially effective in attracting high quality teachers in hard-to-fill subjects. To study whether teachers in hard-to-fill subjects were specifically drawn from higher-paying districts, I include each applicant's hard-to-fill subject status in the difference-in-differences approach presented in Equation 3. Specifically, I interact each teachers' hard-to-fill subject status with QTEA implementation variables and indicators of whether applicants were in the targeted group:

(8) $$Y_i = \beta_0 + \beta_1(QTEA_i) + \beta_2(TARGETED_i) + \beta_3(QTEA_i{*}TARGETED_i) + \beta_4(HTF_i) + \beta_5(HTF_i{*}QTEA_i) + \beta_6(HTF_i{*}TARGETED_i) + \beta_7(HTF_i{*}TARGETED_i{*}QTEA_i) + \varepsilon_i$$

where β_{HTF} indicates whether the applicant teaches in a hard-to-fill subject, $\beta_{HTF*QTEA}$ indicates whether the applicant teaches in a hard-to-fill subject after QTEA, $\beta_{HTF*Targeted}$ indicates whether the applicant both teaches in a hard-to-fill subject and is targeted by overall salary increases, and $\beta_{HTF*Targeted*QTEA}$ indicates whether the applicant both teaches in a hard-to-fill subject and is targeted by overall salary increases after QTEA. The causal effect of interest here is $\beta_{HTF*Targeted*QTEA}$, which is the differential effect for applicants in hard-to-fill subjects who were targeted by QTEA's overall salary increases. The coefficient $\beta_{HTF*QTEA}$ tells us if the average salary of other districts applied to increased for those in hard-to-fill subjects after QTEA. While this could indicate a QTEA effect, the hard-to-fill subject bonus is not exogenous in the same way that the overall salary increase is exogenous; those teachers who benefit from the hard-to-fill subject bonus are highly affected by downturns in the economy and thus it is difficult to separate their response to QTEA from their response to the economic changes that occurred at the same time. Thus, $\beta_{HTF*Targeted*QTEA}$ is the causal effect for applicants in hard-to-fill subjects, but, $\beta_{Targeted*QTEA}$ remains a causal estimate of the overall QTEA effect.

In the basic model (Table 21, Model 1), I find that QTEA did have a differential effect on teachers in hard-to-fill subjects who were also targeted by QTEA overall salary increases. Most importantly, the indicator for targeted applicants in hard-to-fill subjects after QTEA is positive and significant ($\beta_{HTF*Targeted*QTEA}$ = \$967.81, $p<0.10$), which provides an indication that there was a differential effect for teachers in hard-to-fill subjects who were also targeted by the overall salary increases. Walking through the rest of the table, we see that the targeted applicants generally apply to lower salary districts than the non-targeted group ($\beta_{TARGETED}$ = -\$792.80, $p<0.05$); as with the main model, this is likely because such applicants have slightly fewer years of experience. The indicators for applicants in hard-to-fill subjects (β_{HTF} = -\$428.98) and for targeted applicants in hard-to-fill subjects ($\beta_{HTF*TARGETED}$ = -\$716.75) are not significant, indicating that those in hard-to-fill subjects in general apply to districts with the same average salary as other applicants. As in the main model, the overall trend is that applicants applied to lower salary districts after QTEA (β_{QTEA} = -\$1,811.57, $p<0.10$), likely due to the downturn in the economy, but targeted that applicants applied to higher salary districts after QTEA ($\beta_{TARGETED*QTEA}$ = \$1,953.37, $p<0.01$). Finally, after QTEA, applicants in hard-to-fill subjects in general applied to higher salary districts ($\beta_{HTF*QTEA}$ = \$943.22, $p<0.10$), perhaps indicating that the hard-to-fill subject bonus was an attractive incentive even without the added benefit of the overall salary increase.

[Insert Table 21 here.]

While these observations are useful, full interpretation of the model requires additional calculation, as the difference-in-differences estimator in this case is not as straightforward as in the basic model specified in Equation 3 above for comparing targeted teachers to non-targeted teachers before and after QTEA. I am primarily interested in how applicants who were targeted for the overall salary increases and hard-to-fill subject bonuses (HTF & Targeted) compare to teachers in other groups. In this case, there are three separate reference groups: applicants who were targeted for the hard-to-fill subject bonus but not the overall salary increase (HTF & Non-targeted), applicants who were targeted for the overall salary increase but not the hard-to-fill subject bonus (Non-HTF & Targeted), and applicants who were not targeted for either (Non-HTF & Non-targeted). Because the estimate must be compared to three other reference groups, additional calculations are required to understand the marginal effect for applicants targeted for hard-to-fill subject bonuses and overall salary increases (HTF & Targeted).

Table 22 provides these calculations, which produce an estimate for the differential effect of being an applicant in a hard-to-fill subject who is also targeted for general salary increases (HTF & Targeted) above just being targeted for one or the other (or neither). After QTEA those applicants in hard-to-fill subjects who were also targeted by QTEA overall salary increases (HTF & Targeted) applied to districts with an average salary \$3,864.40 higher than those in the non-targeted group (Non-HTF & Non-Targeted), \$2,921.18 higher than those that were in hard-to-fill subjects but not targeted for overall salary increases (HTF & Non-targeted), and \$1,911.03 higher than those who were only targeted for general salary increases (Non-HTF & Targeted). This last calculation is particularly important; this result indicates that targeted applicants are drawn from higher salary districts after QTEA, and that this effect is even stronger for those in hard-to-fill subjects.

[Insert Table 22 here.]

To test the robustness of these findings, I ran a number of variations on the basic model. (In my discussion of these tests, I focus on the main effect, $\beta_{HTF*Targeted*QTEA,}$ since this coefficient should be significant if there is an effect; for full model interpretation, the calculations Table 22 would need to be employed.) First, I tested a varied definition of the implementation period by using the years 2009 and 2010/2011 as two separate variables. As shown in Table 21, Model 2, the effect of QTEA on applicants targeted for both the hard-to-fill subject bonus and the overall salary increase is only detectable in 2010/2011. The coefficient identifying targeted applicants in hard-to-fill subjects after QTEA ($\beta_{HTF*Targeted*QTEA}$) is $920.80 in 2010/2011. (Note, however, that the difference between QTEA-2009 and QTEA-2010/2011 is not statistically significant.)

To test the idea that there may be trends over time that could affect the average salary of other districts applied to (such as availability of positions or generally increasing attractiveness of SFUSD), I included a cohort trend in the analysis (Table 21, Model 3). When this variable is included, the effect of QTEA remains positive and significant for the targeted applicants in hard-to-fill subjects. The coefficient identifying targeted applicants in hard-to-fill subjects after QTEA ($\beta_{HTF*Targeted*QTEA}$) is $890.22 in this model.

I also included a specification in which I reduced the sample even further, limiting it to applicants with 3-10 years of experience. As shown in Table 21, Model 4, in this specification, the coefficient $\beta_{HTF*Targeted*QTEA}$ is now negative and significant (-$1051.82), suggesting that the "QTEA effect" found in the basic model may be overstated. However, after calculating the difference for targeted teachers in hard-to-fill subjects as compared to others (as in Table 22), I find that after QTEA those applicants in hard-to-fill subjects who were also targeted by QTEA overall salary increases (HTF & Targeted) applied to districts with an average salary $1,240.09 ($p<0.05$) higher than those that were in hard-to-fill subjects but not targeted for overall salary increases (HTF & Non-targeted). This result indicates that there was a QTEA effect for applicants in hard-to-fill subjects who also were targeted for overall salary increases compared to applicants in hard-to-fill subjects who were *not* targeted for overall salary increases. However, comparing to those who were only targeted for general salary increases (Non-HTF & Targeted), the salary is only $205.09 higher, and not significant. This result indicates that QTEA's overall salary increases may have been only as effective in recruiting high-quality applicants in hard-to-fill subjects as in non-hard-to-fill subjects.

Finally, I discussed above that responses on the surveys are likely more valid if respondents are asked to provide information that is more recent. As a check on this, I limited the cohorts under study to those after 2006. As shown in Table 21, Model 5, when this variable is included, the point estimate ($\beta_{HTF*Targeted*QTEA}$) remains positive, but is no longer significant. This change when the population is limited in this way could be a result of diminished statistical power rather than indication of a weak QTEA effect.

Changes to cohorts of new-hires

I have shown that both the size and quality of the applicant pool increased in SFUSD in response to QTEA. In the targeted areas, more applicants applied, and these applicants seem to have those who would have applied only to higher-paying school districts in the absence of QTEA (which serves as a proxy for teacher quality). As discussed in the conceptual framework, in either case, these improvements in the applicant pool should result in an increase in the quality of new-hires after QTEA. In order to understand the effect of QTEA on the cohorts of new-hires, I conduct three separate analyses. First, I look at changes in the proportion of new-hires in targeted areas; if the proportion of new-hires in the targeted group increases after QTEA, this would provide an indication that they are higher quality candidates, since they were ultimately hired. Second, I use teachers' value-added scores in their first year to test whether the quality of new-hires (as measured in this way) increased as a result of QTEA. Finally, I test whether the quality of new-hires increased specifically in targeted areas.

Change in the proportion of new-hires in targeted areas. As shown in the basic model (Table 23, Model 1), before QTEA, 48.8% of the new-hires were in the targeted group, and there is not a statistically significant difference after QTEA (although the coefficient indicates a change of 5 percentage points). However, Model 2 (Table 23) investigates a different QTEA implementation period, and shows that there is a QTEA effect, but that it is only detectable in 2009-10 and beyond; a lack of effect in 2008-09 could be why Model 1 (in which all three years are combined) does not show an effect. This approach indicates that the proportion of new-hires in the targeted group did in fact increase, but that there was a lagged effect. In the time period before QTEA implementation, 48.8% of the new-hires were in the targeted group, and in 2009-10 and beyond, 53.5% of the new-hires were in the targeted group (a statistically significant difference).

[Insert Table 23 here.]

Building off of the results in Model 2, I include a specification check in Model 3 that tests the varied implementation period (2010/2010) using the restricted sample of teachers with 2-15 years of prior experience. I find that the effect remains strong and positive for 2009-10 and beyond when limiting the sample in this way, indicating that the increasing proportion of new-hires is not driven by applicant experience (or lack thereof); before QTEA, 50% of new-hires were in the targeted group, and in 2010 and beyond, 57% are in this group (an increase of 7 percentage points). The increase in the proportion of new-hires in targeted areas provides an indication that these applicants were higher-quality, since they were ultimately hired. Now, in the next question, I seek to understand if the quality of new-hires increased as well.

Change in the quality of new-hires. In order to study whether the quality of new-hires increased after QTEA, I test whether the value-added scores in ELA and/or Math increased after the policy's implementation. Overall, I find that the quality of new-hires increased after QTEA when using value-added scores in ELA but not Mathematics.

Table 24 presents the results when using value-added scores in Engligh Language Arts. The basic model (Model 1) shows that new teachers over the entire time period (2004-05 to 2009-10) have value-added scores that are -0.115 lower than the reference group. However, for new teachers hired after QTEA, their scores were 0.061 higher than new teachers hired before. This means that after QTEA, the quality of new-hires increased by 0.24 standard deviation units.[37]

[Insert Table 24 here.]

Again, I include a specification that tests a varied definition of the QTEA implementation period; it appears that these findings in ELA are being driven by new-hires in 2009-10 (rather than in 2008-09). As shown in Model 2 (Table 24), new–hires over the entire time period (2004-05 to 2009-10) have value-added scores that are -0.115 lower than the reference group. For new teachers hired in 2008-09, their scores were not significantly different than new teachers in the time period before. However, for teachers hired in 2010, their scores were 0.088 higher than new teachers hired before. This means that in 2010, the quality of new-hires increased by 0.34 standard deviation units compared to the time period 2004-05 through 2007-08.

Finally, I include an additional specification in which I add indicators into the ELA model for whether teachers had 1-2 years of prior experience at the time they were hired or if they had more than 15 years of prior experience. The results presented in Model 3 (Table 24) show that new teachers over the entire time period (2004-05 to 2009-10) have value-added scores that are -0.080 lower than the reference group. For teachers hired after QTEA, their scores were 0.059 higher than new teachers hired before. This estimate remains essentially unchanged from the basic model, indicating that this is a true increase in quality that is not explained by a

[37] Recall that the standard deviation for all teacher-by-year value-added scores in this time period is 0.258.

change in teachers' prior experience levels. In this model, the quality of new-hires increased by 0.23 standard deviation units compared to the time period 2004-05 through 2007-08.

However, these results are not robust across specification of teacher value-added score. When I use mathematics scores as the outcome, the quality of new-hires does not appear to have increased after QTEA. As shown in Model 1 (Table 25), new teachers over the entire time period (2004-05 to 2009-10) have value-added scores that are -0.158 lower than the reference group. For new teachers hired after QTEA, their scores were 0.016 higher than new teachers hired before, but not significantly different from before QTEA. The additional specifications in Models 2 and 3 produce similar (non-statistically significant) results.

[Insert Table 25 here.]

Change in the quality of new-hires in targeted areas. Here I test whether the quality of new-hires in targeted areas increased relative to non-targeted new-hires after QTEA. At this time, I do not find that there has been a significant increase in the quality of new-hires as measured by either ELA or Math value-added scores.

The results for ELA are presented in Table 26. As shown in Model 1, new teachers over the entire time period (2004-05 to 2009-10) have value-added scores in ELA that are -0.126 lower than the reference group. For new teachers hired after QTEA, their scores were 0.024 higher than new teachers hired before (not significant), and targeted teachers both before and after QTEA had scores 0.023 higher than before (not significant). However, the difference-in-differences estimator and our coefficient of interest indicates that these targeted teachers did not have higher value-added scores after QTEA than non-targeted teachers. While this is not a significant difference, the coefficient is positive (0.077) and is close to being significant (p=0.14), which suggests that there may have been an increase in the quality of teachers in the targeted group, but that it is not being captured statistically because the demands of this model are too high given the limitations of the data. If there is a true effect here, it is possible that it can be detected if additional years of data are included in follow-up analyses. (Again I tested a varied definition of the QTEA implementation period and included controls for teacher experience; neither of these specifications presented in Table 26 show significant results, so they are not discussed here.)

[Insert Table 26 here.]

The results for Mathematics are presented in Table 26. My investigations into whether teacher quality increased in Mathematics after QTEA particularly for targeted teachers are somewhat perplexing. As shown in Model 1 (Table 27), new teachers over the entire time period (2004-05 to 2009-10) have value-added scores that are 0.211 lower than the reference group. For new teachers hired after QTEA, their scores were 0.086 higher than new teachers hired before (not significant). Targeted teachers both before and after QTEA had scores 0.102 higher than before ($p<0.01$). The difference-in-differences estimator and our coefficient of interest is the indicator for targeted teachers after QTEA; this model indicates that these targeted teachers had value-added scores 0.134 *lower* ($p<0.10$). This would indicate that targeted applicants were actually lower quality in mathematics after QTEA, which would be a disappointing outcome indeed. However, as shown in Model 2 (Table 27), it appears that this effect may be driven by 2008-09. When I test a varied definition of the implementation period (separating 2008-09 from future years of implementation), the difference-in-differences estimator in 2009 indicates that targeted teachers had value-added scores 0.221 lower than before QTEA implementation ($p<0.01$), but the effect for 2010 is positive (0.106). Although the coefficient for 2010 is not significant, it is significantly different than the coefficient in 2009 ($p=0.01$). This indicates that the negative finding may be isolated to 2009; if the same patterns hold for 2011 as for 2010, perhaps this result will be significant when the additional year of data is available and integrated into this analysis. Again, this question should be revisited when additional years of data can be included in follow-up analyses. (Note, in Model 3, I tested included controls for teacher experience, but results are similar to Model 1 and will not be discussed.)

[Insert Table 27 here.]

Conclusions – How QTEA Affected Teacher Recruitment

In this paper, I study how teacher recruitment changed in the San Francisco Unified School District (SFUSD) as a result of the Quality Teacher and Education Act of 2008 (QTEA). QTEA introduced an overall salary increase ($500-$6,300, varying by placement on the salary schedule) and a $1,000 bonus for teaching in a hard-to-fill subject. I explore in this paper both how the applicant pool changed as a result of QTEA and how the quality of new-hires changed as a result of changes to the applicant pool. Because my approach looks at both changes to the applicant pool and the cohorts of new-hires, taken as a whole, this investigation provides strong evidence that a district-level salary increase can have a positive effect on teacher recruitment in an urban school district.

To study how QTEA changed the applicant pool, I exploit natural variation in the distribution of teacher salary increases. Teachers with five or fewer years of prior experience stood to gain more than 6% salary increase as a result of QTEA, whereas teachers with six or more years of experience gained nearly nothing. In order to isolate the "QTEA effect," I exclude from my analyses applicants with fewer than two years of prior experience or more than 15. Because QTEA corresponded with a downturn in the economy, this approach ensures that I compare applicants before and after QTEA who would be similarly affected by economic changes but are differently affected by the policy. I consider applicants to be "targeted" by QTEA if they stood to gain a 6% or larger salary increase as a result of QTEA.

First, I explore whether QTEA drew additional teachers who were "targeted" for salary increases; an increase in the proportion of targeted applicants would indicate that QTEA had been successful in recruiting teachers who stood to benefit from the policy. I show that before QTEA, 26.8% of applicants were in this targeted group, and after QTEA, 36.7% of applicants were in this targeted group. I also find that the effect is larger after the first year of implementation.

Next, I demonstrate that applicants in hard-to-fill subjects who are also targeted by QTEA's overall salary increases responded by applying in higher proportion than those in hard-to-fill subjects who were not targeted by overall salary increases. The proportion of targeted applicants in hard-to-fill subjects increases after QTEA by a factor of 1.47 compared to non-targeted applicants in hard-to-fill subjects. Here, the effect is stronger in the first year of implementation, but there is an effect across all implementation years.

I then tested whether the quality of teacher applicants increased after the introduction of QTEA. In order to study changes in quality in the applicant pool, I use a non-traditional measure of quality capturing teachers' opportunities outside of teaching in San Francisco. A stated goal of district leaders in SFUSD was to attract applicants that, in the absence of QTEA, might only have applied to higher-paying districts. Because there is economic theory to suggest that applicants to higher-paying districts could be higher-quality applicants (Weiss, 1980), I use the average salary of other districts applied to as a proxy for teacher quality. Specifically, I investigate whether the average salary of other districts applicants applied to was higher after QTEA Using a difference-in-differences approach, I show that the average salary of other school districts applied to is $2,255 higher after QTEA for targeted applicants than it would have been in the absence of QTEA. Again, I find that the effect is larger after the first year of implementation.

Finally, I investigate if there was a differential effect in attracting applicants in hard-to-fill subjects who applied to other higher-paying school districts. Again, using a difference-in-differences approach, I show that those applicants in hard-to-fill subjects who were also targeted for overall salary increases applied to districts with an average salary $1,910.81 higher than those who were targeted for overall salary increases but not in hard-to-fill subjects. This indicates that targeted applicants are drawn from higher-paying districts after QTEA, and that this effect is even stronger for those targeted applicants in hard-to-fill subjects.

Taken together, these results indicate that there were substantial changes in the applicant pool as a result of QTEA. Teachers who were targeted for QTEA salary increases applied in higher proportion, providing an indicating that the size of the pool increased. In addition, I show that QTEA was effective in recruiting teachers who would have only applied to higher-paying districts in the absence of QTEA, which provides an indication that these applicants are higher-quality. The fact that these results hold for teachers in hard-to-fill subjects shows that QTEA has also been effective in improving the quantity and quality of applicants in positions that are historically difficult to fill. Finally, a variety of specification checks demonstrate the robustness of these findings. Most importantly, in all models, the findings hold when I limit the sample to applicants with 3-10 years of prior experience, which provides a more rigorous test; teachers in this range of experience are *very* likely to experience changes in the economy similarly, yet they are still differently affected by QTEA.

To study how QTEA changed the cohorts of new-hires, I build upon these results, seeking to understand whether the improvements to the applicant pool resulted in an increase in the quality of new-hires. First, I investigate whether an increase in the quantity and quality of teachers in the pool led to an increase in the proportion of targeted teachers who were ultimately hired. An increase in the proportion of new-hires in the targeted group would provide an indication that the targeted applicants were higher quality, since they were ultimately hired. I find that there is a lagged effect; the proportion of targeted new-hires increases in 2009-10 and beyond but not in 2008-09. In the time period before QTEA implementation, 48.8% of the new-hires were in the targeted group, and in 2009-10 and beyond, 53.5% of the new-hires were in the targeted group.

In order to measure whether the quality of new-hires increased after QTEA, I use a teacher “value-added” score, or an estimation of the amount that an individual teacher contributes to student achievement. Such scores, while imperfect, are widely used in education for both accountability and research purposes, and are one of the only measures of teacher quality that can be calculated using existing data sources (McCaffrey, Koretz, Lockwood, & Hamilton, 2003). I use these teacher-by-year value-added scores to investigate whether teacher quality (as measured in this way) increased after the implementation of QTEA. I find that teacher quality did increase in English Language Arts; for new teachers hired after QTEA, their scores 0.24 standard deviation units higher than before. However, I do not find any effect on the overall quality of teachers in Mathematics. Finally, I employ a differences-in-differences approach to explore specifically whether the quality of new-hires in targeted areas increased. Results in both ELA and Mathematics are inconclusive in this model, although results in ELA suggest positive trends.

This paper adds substantially to the research conducted on teacher response to salary incentives. These results shed light on how an individual district can be affected by a salary increase, whereas the existing research investigates the effect of state-level or nationwide salary increases (see, for example, Clotfelter, et al., 2008; Fowler, 2003; Loeb & Page, 2000; Manski, 1987; Reed, et al., 2006; Steele, et al., 2010). Even more importantly, existing research looks only at teachers' ultimate placement, not at the whole application process, thus confounding teacher and district preferences. Because teacher recruitment involves both applicants looking for positions and districts hiring teachers, studies aiming to understand teacher recruitment should look at changes both in the applicant pool and in the cohorts of new-hires.

In this paper, I am able to observe both changes in the applicant pool, and changes in the cohorts of new-hires, providing a more complex investigation of the way that teacher recruitment could be improved in an urban school district as a result of a teacher salary increase. I hypothesize that the quantity and quality of the applicant pool could improve as a result of the salary increase, and that (in either scenario) these improvements in the applicant pool could lead to an increase in the quality of new-hires. I show in this paper that a differential salary increase can improve a school district's attractiveness within the local teacher labor market and increase both the size and quality of the teacher applicant pool, and that such changes to the applicant pool have the potential to increase the quality of new-hires. Because my approach looks at both changes to the applicant pool and new-hires, taken as a whole, this investigation provides strong evidence that a district-level salary increase can have a positive effect on teacher recruitment in an urban school district.

My method also highlights the limitations of looking just at the final outcome (the quality of new-hires), which is the most commonly used approach. My results indicate only a minor improvement in the quality of new-hires as a result of QTEA; while there is a substantial improvement in the quality of new-hires as measured by English Language Arts scores, there is not an equal improvement as measured by Math scores. Thus, if I had looked only at the quality of new-hires, I would have detected only a moderate (and not entirely robust) effect. However, by looking at both changes to the applicant pool *and* changes to the quality of new hires, I am able to see that substantial changes in the applicant pool have led to moderate changes in the quality of new-hires.

The fact that substantial improvements in the applicant pool have led only to moderate improvements in the quality of new-hires raises questions about the use of value-added scores as a measure of teacher quality. I have acknowledged the limitations of using teacher value-added scores to measure teacher quality; scores are only available for a small number of teachers (those in tested grades and subjects), and they only measure teaching quality along one dimension. Value-added scores are widely used in research and accountability and are among the only way to measure teacher with existing data. However, it is possible that measuring teacher quality in this way limits my ability to detect improvement in the quality of new-hires. For example, the quality of new-hires in science or kindergarten could have increased dramatically, but value-added scores cannot be calculated for teachers in these groups.

Despite these possible measurement issues, the findings presented in this paper underscore the importance of district hiring in improving the quality of the teacher workforce. I have shown that a compensation increase can improve the teacher applicant pool, but the potential impact of these changes depends on a district's hiring ability. Even if compensation can improve the size and quality of the applicant pool, a district's ability to hire good teachers is central if such changes are to lead to meaningful improvements in the quality of new-hires.

These findings show that an urban school district can affect short-term improvements in their applicant pool through the introduction of relatively small salary increases. However, further research is needed to understand both long-term effects of such policies and implications if they are brought to scale. Most importantly, we need to understand how the labor market as a whole might respond in the long-term. Over time, other school districts in the local labor market could increase teacher salaries to match SFUSD's, which could diminish SFUSD's competitive advantage. While I show in this paper that a differential salary increase can improve teacher recruitment in an urban school district, it is unclear from this work *how much* higher salaries need to be compared to other districts for the compensation increase to be effective. Additionally, it is unclear whether teachers value the *absolute* amount or the *relative* salary increase compared to other school districts. Better understanding the mechanisms at play can help in designing effective policies that can be employed elsewhere.

In addition, a cost-benefit analysis is appropriate as we develop a sense of the medium-term effects of this policy on the size and quality of the applicant pool and the ultimate quality of new-hires. A compensation increase such as that introduced through QTEA represents a very large investment for an urban school district. Thus, even if QTEA works, further research should investigate whether these improvements could be achieved in other more cost-effective ways.

While the analyses presented here raise questions about the potential long term effects of a compensation increase in an urban district, these findings nonetheless provide evidence that policies like QTEA can be effective in improving teacher recruitment, specifically for urban school districts. This paper shows that salary can be used as a lever for redistributing teachers, which is particularly important given the substantially unequal sorting of teacher quality across schools and districts, and the particular challenges of urban school districts. Given the known importance of teacher quality in improving student outcomes, if policies like this are employed strategically, it will have huge implications for urban school districts and the students they serve.

Tables

Table 1. SFUSD compared to local school districts on various metrics

	Percent in SFUSD	SFUSD percentile compared to other local districts
Students who are English Learners	30.5%	76
Students eligible for Free or Reduced Price Lunch	55.5%	83
Schools in deciles 1-3 of performance	38.5%	83
Students not proficient in ELA	43.6%	69
Students not proficient in Math	39.2%	53
Teachers lacking full credentials	4.9%	75
Teachers with fewer than 2 years of experience	6.5%	79

Source: Analysis of Ed-Data files (www.ed-data.k12.ca.us) for the 2008-09 school year. Includes the 186 public school districts in the Combined Statistical Area (CSA) of San Jose-San Francisco-Oakland.

Table 2. SFUSD salaries compared to local school districts, before and after QTEA

	2007-08		2009-10		% Change	
District Name	Step 3	Step 10	Step 3	Step 10	Step 3	Step 10
San Francisco Unified	$47,370	$63,272	$54,400	$65,300	15%	3%
Oakland Unified	$43,012	$54,328	$43,765	$54,328	2%	0%
San Jose Unified	$53,740	$71,772	$53,740	$71,772	0%	0%
Palo Alto Unified	$61,068	$79,863	$62,595	$81,860	3%	3%

Source: District Salary Schedules for 2007-08 and 2009-10.
Note: Salary information at both Step 3 and Step 10 is for teachers with a BA plus 60 units of continuing education.

Table 3. Population, sample and response rates for Applicant[38] and Teacher Surveys

	2008 Applicant	2010 Applicant	2010 Teacher
Total population	4508	5180	3116
Sampled	4508	1600	3116
Respondents	1440	776	1650
Response rate	31.94%	48.50%	52.95%
Month administered	June	April	April

[38] The 2008 Applicant Survey was administered in June 2008 to all applicants in the past three years up to that point, and the 2010 Applicant Survey was administered to a sample of all applicants who applied between June 2008 and June 2010.

Table 4. Composition of the Applicant Database

	C2005	C2006	C2007	C2008	C2009[39]	C2010	C2011[40]	Total
Not hired					2008-A			
Survey taken	2008-A	2008-A	2008-A	2008-A	2010-A	2010-A	2010-A	-
Number	35	95	165	314	223	223	288	1,343
Weighted % of total	1%	4%	6%	12%	10%	18%	23%	73%
Hired								
Survey taken	2010-T	2010-T	2010-T	2010-T	2010-T	2010-T	-	-
Years experience in SFUSD at time of survey[41]	6	5	4	3	2	1	-	-
Number	87	103	102	145	160	173	-	770
Weighted % of total	5%	4%	4%	5%	5%	4%	-	27%
Total								
Number	122	198	267	459	383	396	288	2,113
Weighted % of total	6%	8%	10%	16%	14%	22%	23%	100%
Analytic sample (includes only applicants for whom salary can be calculated)								
Number	106	181	237	412	224	220	231	1,611
Weighted % of total	7%	9%	11%	18%	12%	20%	23%	100%

Table 5. Survey sampling, response rates and weights, with new hire cohort

	2008-A	2010-A	2010-T (C2005)	2010-T (C2006)	2010-T (C2007)	2010-T (C2008)	2010-T (C2009)	2010-T (C2010)
Total population	4508	5180	415	368	342	387	397	332
Sampled	4508	1600	151	180	166	216	258	268
Respondents	1440	776	87	103	102	145	160	173
Response rate	31.94%	48.50%	57.62%	57.22%	61.45%	67.13%	62.02%	64.55%
Weight	3.13	6.68	4.77	3.57	3.35	2.67	2.48	1.92

Table 6. Number of applicants in hard-to-fill subjects, by cohort

	C2005	C2006	C2007	C2008	C2009	C2010	C2011	Total
Total number of applicants	106	181	237	412	224	220	231	1,611
Applicants in hard-to-fill subjects	33	56	80	131	59	67	82	508
Weighted % of total	32%	31%	34%	32%	26%	30%	36%	32%

[39] SFUSD's data system changed before the 2008-09 school year; some applicants applied prior to this change and some after. For this reason, applicants in this cohort were captured in both the 2008 and 2010 survey. I am confident that I did not duplicate survey respondents, both because of the change in data systems, and because I excluded from the 2010 sample any applicants who had the same email address or name as those who applied in 2008.

[40] The 2010 Applicant Survey includes 21 people that were hired to teach in SFUSD. Because I did not survey teachers in this time period, new-hires are included with applicants in the weighting for this cohort.

[41] Note: due to breaks in service and other anomalies, not all teachers actually have this number of years of experience, but most do.

Table 7. Construction of variables determining whether applicants were "targeted" by QTEA

	Percentage Increase as a result of QTEA					
	Mean	SD	Min	Max	"Targeted"	N
Bachelor's degree						
None	0.0421	.	0.0421	0.0421	No	428
1	0.0395	.	0.0395	0.0395	No	104
2	0.0391	.	0.0391	0.0391	No	90
3	0.0408	.	0.0408	0.0408	No	64
4	0.0426	.	0.0426	0.0426	No	40
5	0.0443	.	0.0443	0.0443	No	30
6-10	0.0477	0.0022	0.0452	0.0506	No	86
11-15	0.0122	0.0149	0.0017	0.0227	No	31
Master's degree or higher						
None	0.1016	0.0106	0.0942	0.1091	Yes	163
1	0.1084	0.0171	0.0964	0.1205	Yes	62
2	0.1151	0.0235	0.0984	0.1317	Yes	89
3	0.1144	0.0196	0.1005	0.1283	Yes	58
4	0.1035	0.0013	0.1026	0.1045	Yes	38
5	0.0936	0.0154	0.0828	0.1045	Yes	40
6-10	0.0404	0.0277	0.0125	0.0976	No	119
11-15	0.0240	0.0111	0.0127	0.0375	No	64
16-20	0.0311	0.0015	0.0300	0.0328	No	50
20+	0.0379	0.0036	0.0328	0.0409	No	55
Total	-	-	-	-	-	1,611

Note: Dotted lines indicate inclusion in the restricted sample.

Table 8. Number of new-hires, with targeted status

	# New teachers	# Teachers with salary information	Targeted teachers #	Targeted teachers %
2004-05	415	410	226	55%
2005-06	368	367	168	46%
2006-07	341	341	157	46%
2007-08	387	387	183	47%
2008-09	396	396	168	42%
2009-10	332	332	170	51%
2010-11	223	223	127	57%
Total	2,462	2,456	1,199	49%

Table 9. Number of teachers by year, with teacher-by-year value-added scores

	2004-05		2005-06		2006-07		2007-08		2008-09		2009-10		2010-11	
All teachers	3,730		3,507		3,444		3,437		3,491		3,588		3,437	
With either ELA or Math score	875	23%	861	23%	820	22%	792	21%	760	20%	757	20%	0	--
With ELA score	722	19%	707	19%	667	18%	642	17%	626	17%	614	16%	0	--
With Math score	676	18%	679	18%	648	17%	603	16%	590	16%	595	16%	0	--
New teachers	415		368		341		387		396		332		223	
With either ELA or Math score	111	27%	100	24%	80	19%	93	22%	85	20%	42	10%	0	--
With ELA score	94	23%	76	18%	61	15%	77	19%	64	15%	37	9%	0	--
With Math score	81	20%	76	18%	60	14%	63	15%	67	16%	33	8%	0	--

Table 10. Population, sample and response rates for Principal Surveys

	2008 Principal	2010 Principal
Total population	112	105
Sampled	112	105
Respondents	89	88
Response rate	79.5%	83.8%
Month administered	June	July

Table 11. Case study and hard-to-staff schools, by school level

	Hard-to-Staff		Not Hard-to-Staff	
	Total	Case Study	Total	Case Study
Elementary	10	2	53	1
K-8	3	1	5	0
Middle	6	3	8	1
High	6	2	11	1
Total	25	8	77	3

Table 12. Student demographics in case study schools compared to the district overall

	Case study	District-wide
Average API rank	2	5
Percent African American students	17	11
Percent Asian students	30	43
Percent Filipino students	10	6
Percent Hispanic students	34	23
Percent students learning English	35	32
Percent students eligible for Free or Reduced Price Lunch	69	56

Table 13. Districts in the MSAs in the San Jose-San Francisco-Oakland CSA

Metropolitan Statistical Areas	Number of School Districts
Napa, CA	5
San Francisco-Oakland-Fremont, CA	79
San Jose-Sunnyvale-Santa Clara, CA	41
Santa Cruz-Watsonville, CA	13
Santa Rosa-Petaluma, CA	42
Vallejo-Fairfield, CA	6
Total	186

Table 14. Analytic sample for studying change in average salary of other districts applied to, by cohort

Cohort	C2005	C2006	C2007	C2008	C2009	C2010	C2011	Total
Overall								
Number	23	41	67	129	80	52	62	454
Hard-to-fill								
Number	6	16	25	41	20	19	22	149
Weighted Percent of Total	25%	39%	38%	27%	37%	35%	34%	34%

Table 15. Average salary of other districts applied to, by cohort

Cohort	Mean	Standard deviation	N
C2005	63,866.96	4,711.02	23
C2006	65,418.55	5,616.05	41
C2007	65,079.54	6,247.03	67
C2008	65,571.13	5,272.05	129
C2009	65,713.37	5,162.30	80
C2010	65,407.21	5,436.23	52
C2011	63,155.83	4,683.19	62
Total	65,074.91	5,392.01	454

Table 16. Change in the proportion of "targeted" applicants, before and after QTEA

	Basic model (limiting to teachers with 2-15 years of prior experience) **Model 1**	Varied definition of implementation period **Model 2**	Including a cohort trend **Model 3**	Restricted model (limiting to teachers with 3-10 years of prior experience) **Model 4**	Limited to cohorts after 2006 **Model 5**
QTEA implementation period					
QTEA-2009/2011	0.099*		0.139	0.089~	0.097
	(0.039)		(0.137)	(0.044)	(0.051)
QTEA-2009		0.082			
		(0.063)			
QTEA-2010/2011		0.106**			
		(0.027)			
Constant	0.268***	0.268***	0.294**	0.259***	0.270***
	(0.027)	(0.027)	(0.058)	(0.019)	(0.038)
Number	749	749	749	475	634
Weighted Number	3,065.7	3,065.7	3,065.7	1944.0	2,660.6
Specifications					
Restricted sample		X	X	X	X
Cohort trend			X		
Cohorts after 2006					X

p<0.10~, 0.05*, 0.01**, 0.001***

Table 17. Change in proportion of teacher applicants in hard-to-fill subjects after QTEA

	Teaches in a Hard-to-fill subject
QTEA-2009/2011	0.007
	(0.025)
Constant	0.328***
	(0.021)
N	749
Weighted N	3065.7

p<0.10~, 0.05*, 0.01**, 0.001***

Table 18. Applicants in hard-to-fill subjects and targeted by QTEA overall salary increase

	Number	Weighted percent of total
Non-HTF & Non-Targeted	358	46%
HTF & Non-Targeted	166	22%
Non-HTF & Targeted	151	21%
HTF & Targeted	74	11%

Table 19. Change in the proportion of “targeted” applicants in hard-to-fill subjects, before and after QTEA

	Basic model (limiting to teachers with 2-15 years of experience)			Varied definition of implementation period			Including a cohort trend			Restricted model (limiting to teachers with 3-10 years of prior experience)			Limited to cohorts after 2006		
	Model 1			**Model 2**			**Model 3**			**Model 4**			**Model 5**		
	Non-HTF & Non-Targeted	Non-HTF & Targeted	HTF & Targeted	Non-HTF & Non-Targeted	Non-HTF & Targeted	HTF & Targeted	Non-HTF & Non-Targeted	Non-HTF & Targeted	HTF & Targeted	Non-HTF & Non-Targeted	Non-HTF & Targeted	HTF & Targeted	Non-HTF & Non-Targeted	Non-HTF & Targeted	HTF & Targeted
QTEA implementation period															
QTEA-2009/2011	0.939	1.546~	1.470*				1.245	2.000	2.695*	1.127	1.710	1.553*	1.081	1.572	1.684*
	(0.160)	(0.294)	(0.222)				(0.391)	(0.987)	(1.073)	(0.097)	(0.501)	(0.230)	(0.205)	(0.570)	(0.334)
QTEA-2009				1.345	1.846*	1.753*									
				(0.300)	(0.345)	(0.395)									
QTEA-2010/2011				0.827***	1.46	1.392~									
				(0.037)	(0.322)	(0.217)									
Number		749			749			749			475			634	
Weighted Number		3,065.7			3,065.7			3,065.7			1944.0			2,660.6	
Specifications															
Restricted sample					X			X			X			X	
Cohort trend															
Cohorts after 2006														X	

p<0.10~, 0.05*, 0.01**, 0.001***

Table 20. Change in the average salary of other districts applied to after QTEA

	Basic model (limiting to teachers with 2-15 years of prior experience)	Varied definition of implementation period	Including a cohort trend	Restricted model (limiting to teachers with 3-10 years of prior experience)	Limited to cohorts after 2006
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Targeted applicants	-1005.289*	-1005.289*	-1018.408*	-946.220*	-694.056~
	(295.642)	(295.642)	(316.482)	(305.789)	(324.102)
QTEA implementation period					
QTEA-2009/2011	-1491.098~		-494.691	-1399.728*	-1547.279~
	(739.854)		(389.122)	(305.789)	(735.286)
QTEA-2009		-351.022			
		(862.721)			
QTEA-2010/2011		-1894.242***			
		(250.818)			
Targeted applicants after QTEA					
Targeted applicants, QTEA-2009/2011	2254.745**		2217.609**	1920.971***	1943.512*
	(494.710)		(454.252)	(264.015)	(500.954)
Targeted applicants, QTEA-2009		1751.436*			
		(500.825)			
Targeted applicants, QTEA-2010/2011		2391.617***			
		(296.672)			
Constant	65576.849***	65576.849***	66269.103***	65275.300***	65633.030***
	(249.598)	(249.598)	(750.181)	(275.400)	(260.892)
Number	454	454	454	284	390
Weighted Number	1855.13	1855.13	1855.13	1173.91	1637.29
Specifications					
Restricted sample		X	X	X	X
Cohort trend			X		
Cohorts after 2006					X

p<0.10~, 0.05*, 0.01**, 0.001***

Table 21. Change in the average salary of other districts applied to for targeted applicants in hard-to-fill subjects

	Basic model Model 1	Varied implementation period Model 2	Including a cohort trend Model 3	Restricted model Model 4	Limited to cohorts after 2006 Model 5
Targeted applicants ($\beta_{Targeted}$)	-792.80*	-792.796*	-806.658*	-520.68*	-595.404~
	(278.24)	(278.241)	(300.294)	(190.260)	(235.441)
Applicants in hard-to-fill subjects (β_{HTF})	-428.98	-428.979	-432.620	-433.190	-709.468
	(234.25)	(234.253)	(240.456)	(300.190)	(425.129)
Targeted applicants in hard-to-fill subjects ($\beta_{HTF*Targeted}$)	-716.75	-716.749	-716.095	-1253.59**	-323.472
	(397.34)	(397.343)	(404.408)	(298.210)	(812.696)
QTEA implementation period (β_{QTEA})					
QTEA-2009/2011	-1811.57~		-806.586*	-1815.05*	-1960.735~
	(880.82)		(290.047)	(620.380)	(838.864)
QTEA-2009		-580.041			
		(866.297)			
QTEA-2010/2011		-2356.789***			
		(267.685)			
Targeted applicants after QTEA ($\beta_{Targeted*QTEA}$)					
Targeted applicants, QTEA-2009/2011	1953.37**		1941.083**	2292.12***	1755.982**
	(469.49)		(441.919)	(166.260)	(346.397)
Targeted applicants, QTEA-2009		1596.235**			
		(303.357)			
Targeted applicants, QTEA-2010/2011		2145.571***			
		(281.550)			
Applicants in hard-to-fill subjects after QTEA ($\beta_{HTF*QTEA}$)					
Hard-to-fill applicants, QTEA-2009/2011	943.22~		1013.326~	1256.91*	1223.712*
	(430.76)		(430.578)	(370.540)	(462.303)
Hard-to-fill applicants, QTEA-2009		797.636			
		(567.730)			
Hard-to-fill applicants, QTEA-2010/2011		1266.044**			
		(238.980)			
Targeted applicants in hard-to-fill subjects after QTEA ($\beta_{HTF*Targeted*QTEA}$)					
Targeted, hard-to-fill applicants, QTEA-2009/2011	967.81~		890.221~	-1051.82~	574.531
	(420.86)		(418.951)	(482.420)	(853.867)
Targeted, hard-to-fill applicants, QTEA-2009		411.707			
		(921.254)			
Targeted, hard-to-fill applicants, QTEA-2010/2011		920.803~			
		(400.148)			
Constant	65725.91***	65725.908***	66441.658***	65427.42***	65875.072***
	(264.20)	(264.202)	(736.569)	(361.630)	(272.167)
Number	454	454	454	284	390
Weighted Number	1855.13	1855.13	1855.13	1173.91	1637.29

Table 22. Interpretation of coefficients comparing targeted teachers in hard-to-fill subjects with each reference group

Reference group	Dif-in-Dif estimators	Calculation	Final result
Non-HTF & Non-Targeted	$\beta_{QTEA*TARGETED}$ + $\beta_{HTF*QTEA}$ + $\beta_{HTF*TARGETED*QTEA}$	\$1,953.37 + \$943.22 + \$967.81	\$3,864.40*** (915.663)
HTF & Non-Targeted	$\beta_{QTEA*TARGETED}$ + $\beta_{HTF*TARGETED*QTEA}$	\$1,953.37 + \$967.81	\$2,921.18*** (638.534)
Non-HTF & Targeted	$\beta_{HTF*QTEA}$ + $\beta_{HTF*TARGETED*QTEA}$	\$943.22 + \$967.81	\$1,911.03*** (535.437)

Table 23. Proportion of new-hires in targeted areas, before and after QTEA

	Basic model (including all new-hires) **Model 1**	Basic model w/ varied definition of implementation period **Model 2**	Restricted model (2-15 years of prior experience) with varied definition of implementation period **Model 3**
Implementation period			
QTEA-2009/2011	0.001		
	(0.021)		
QTEA-2009		-0.063	0.020
		(0.028)	(0.050)
QTEA-2010/2011		0.047~	0.070~
		(0.025)	(0.040)
Constant	0.488***	0.488***	0.50***
	(0.013)	(0.013)	(0.020)
Number	2456	2,456	754
Specifications			
Limited sample			X

p<0.10~, 0.05*, 0.01**, 0.001***

Table 24. Increase in the quality of new-hires – ELA

	Basic model (including all new-hires) **Model 1**	Varied definition of implementation period **Model 2**	Controls for years of prior experience **Model 3**
New teachers	-0.115***	-0.115***	-0.080**
	(0.015)	(0.015)	(0.025)
New teachers after QTEA			
QTEA-2009/2010	0.061*		0.059*
	(0.030)		(0.030)
QTEA-2009		0.044	
		(0.036)	
QTEA-2010		0.088*	
		(0.044)	
Number	1,627	1,627	1,627
Specifications			
Prior experience			X

p<0.10~, 0.05*, 0.01**, 0.001***

Table 25. Increase in the quality of new-hires – Math

	Basic model (including all new-hires) **Model 1**	Varied definition of implementation period **Model 2**	Controls for years of prior experience **Model 3**
New teachers	-0.158***	-0.158***	-0.201***
	(0.020)	(0.020)	(0.033)
New teachers after QTEA			
QTEA-2009/2010	0.016		0.024
	(0.039)		(0.039)
QTEA-2009		0.046	
		(0.046)	
QTEA-2010		-0.037	
		(0.059)	
Number	1,640	1,640	1,640
Specifications			
Prior experience			X

p<0.10~, 0.05*, 0.01**, 0.001***

Table 26. Increase in the quality of new-hires in targeted areas – ELA

	Basic model (including all new-hires) **Model 1**	Varied definition of implementation period **Model 2**	Controls for years of prior experience **Model 3**
New teachers	-0.126***	-0.126***	-0.094**
	(0.021)	(0.021)	(0.030)
Targeted teachers	0.023	0.023	0.026
	(0.026)	(0.026)	(0.026)
New teachers after QTEA			
QTEA-2009/2010	0.024		0.030
	(0.040)		(0.040)
QTEA-2009		0.028	
		(0.045)	
QTEA-2010		0.008	
		(0.068)	
Targeted teachers after QTEA			
Targeted teachers, QTEA-2009/10	0.077		0.059
	(0.053)		(0.053)
Targeted teachers, QTEA-2009		0.049	
		(0.064)	
Targeted teachers, QTEA-2010		0.117	
		(0.083)	
Number	1,627	1,627	1,627
Specifications			
Prior experience			X

p<0.10~, 0.05*, 0.01**, 0.001***

Table 27. Increase in the quality of new-hires in targeted areas – Math

	Basic model (including all new-hires) **Model 1**	Varied definition of implementation period **Model 2**	Controls for years of prior experience **Model 3**
New teachers	-0.211***	-0.211***	-0.257***
	(0.028)	(0.028)	(0.039)
Targeted teachers	0.102**	0.102**	0.109**
	(0.035)	(0.035)	(0.036)
New teachers after QTEA			
QTEA-2009/2010	0.086		0.090~
	(0.053)		(0.053)
QTEA-2009		0.149*	
		(0.058)	
QTEA-2010		-0.122	
		(0.095)	
Targeted teachers after QTEA			
Targeted teachers, QTEA-2009/10	-0.134~		-0.124~
	(0.069)		(0.070)
Targeted teachers, QTEA-2009		-0.221**	
		(0.081)	
Targeted teachers, QTEA-2010		0.106	
		(0.114)	
Number	1,640	1,640	1,640
Specifications			
Prior experience			X

p<0.10~, 0.05*, 0.01**, 0.001***

Figures

Figure 1. Conceptualization of applicant response to a salary increase

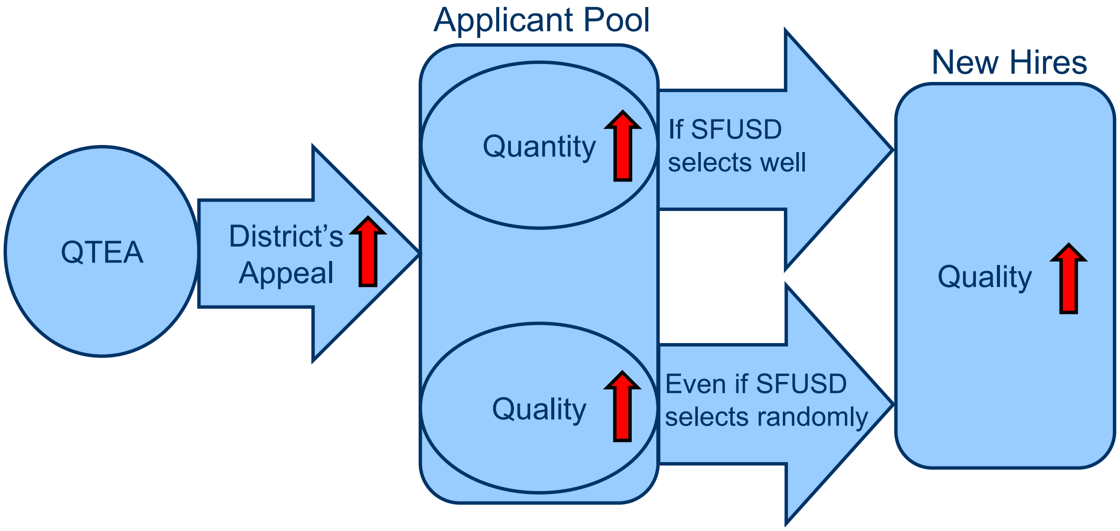


Figure 2. QTEA implementation timeline

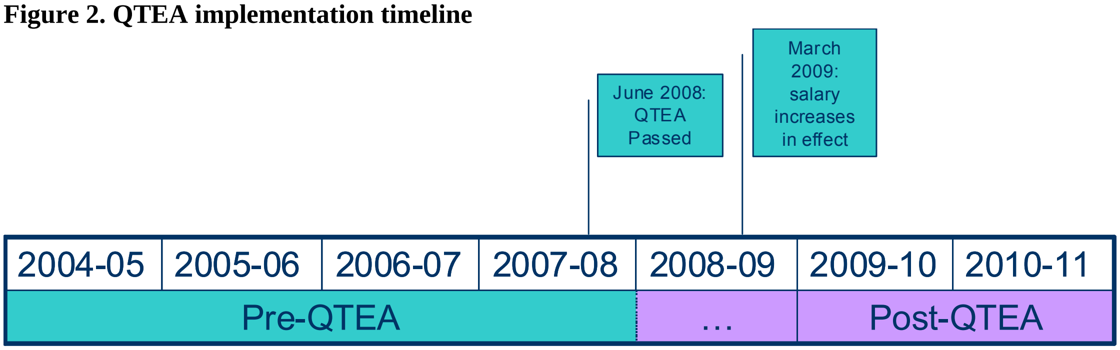


Figure 3.

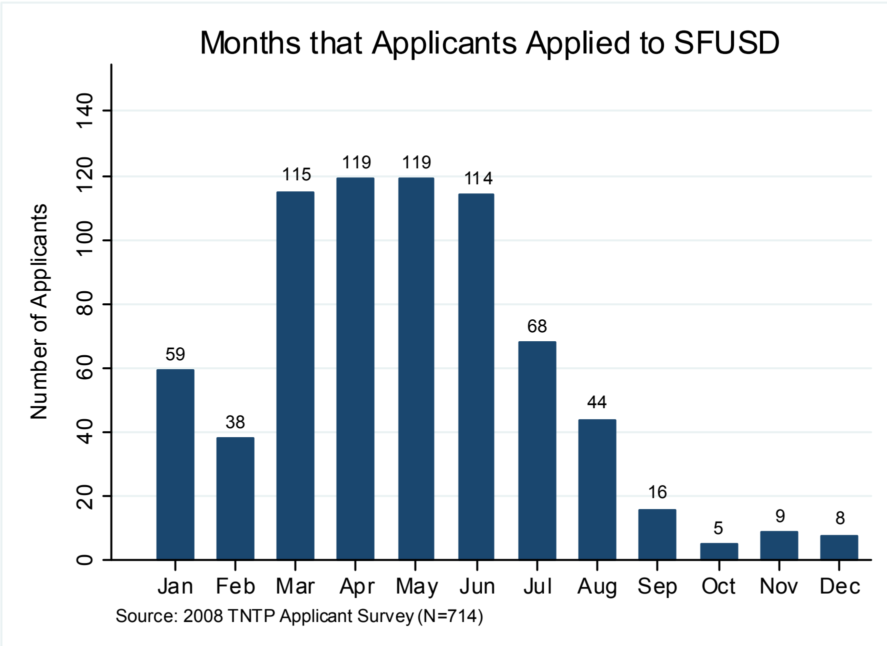


Figure 4.

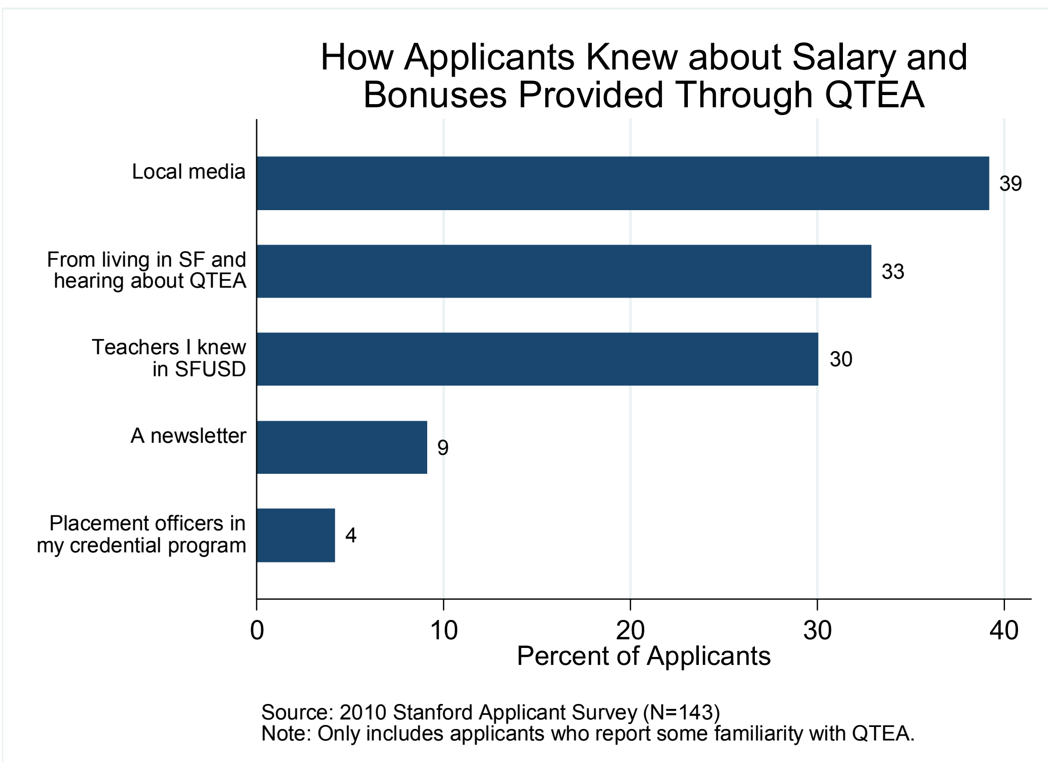


Figure 5.

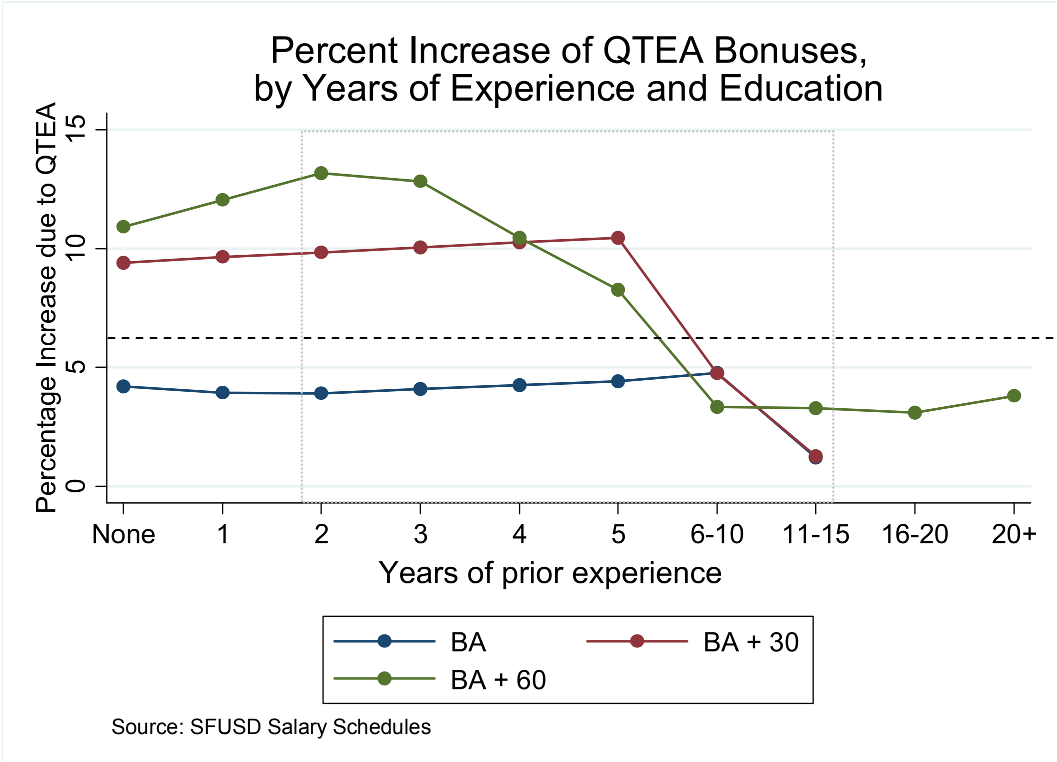


Figure 6.

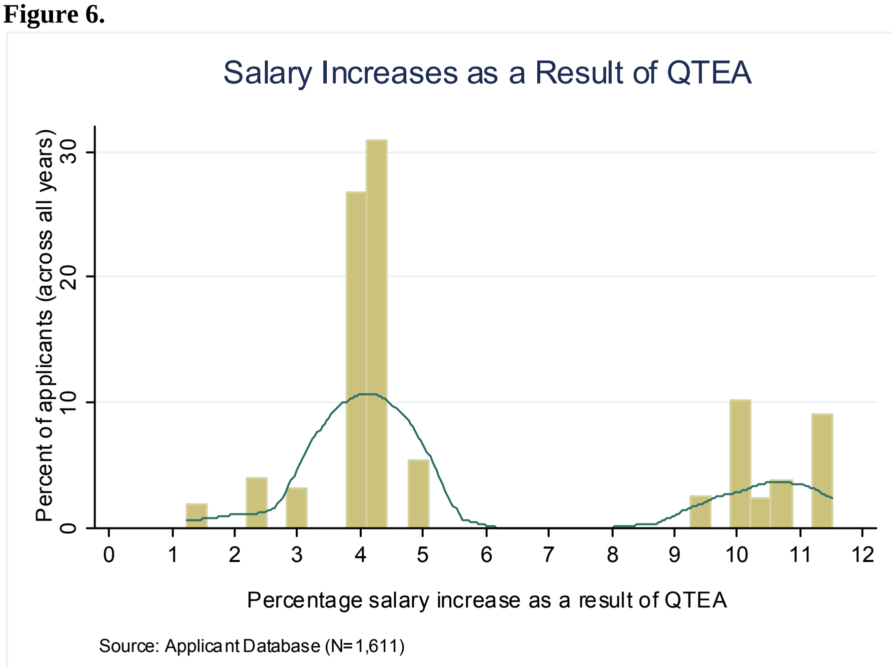


Figure 7.

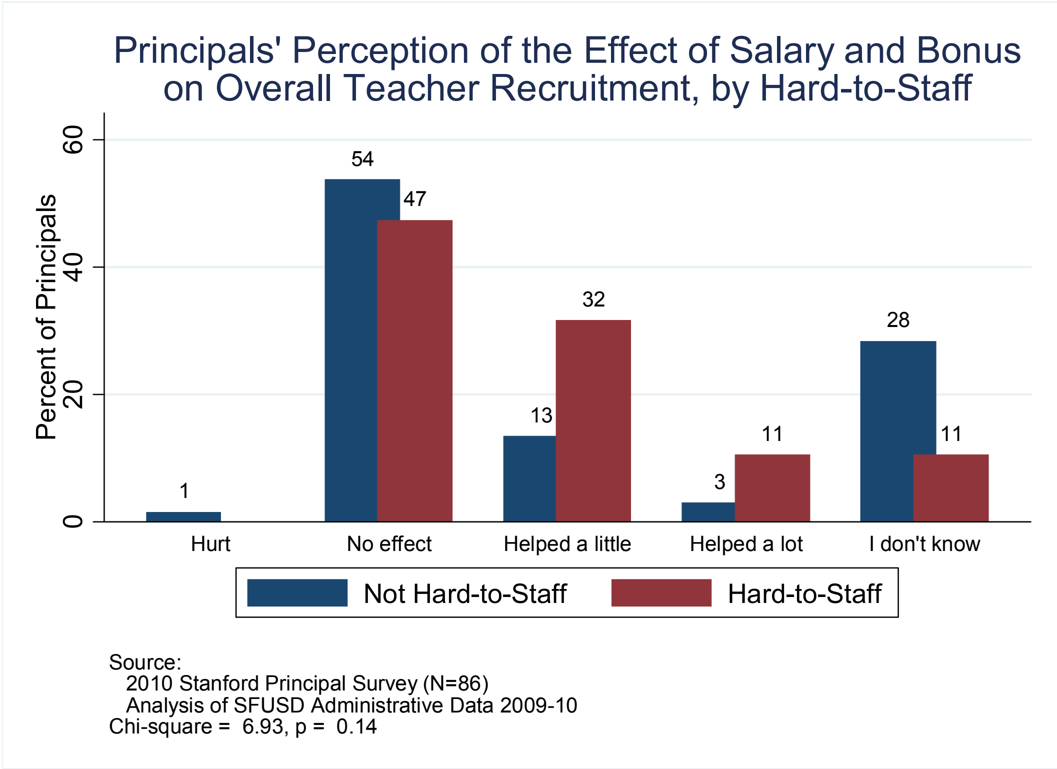


Figure 8.

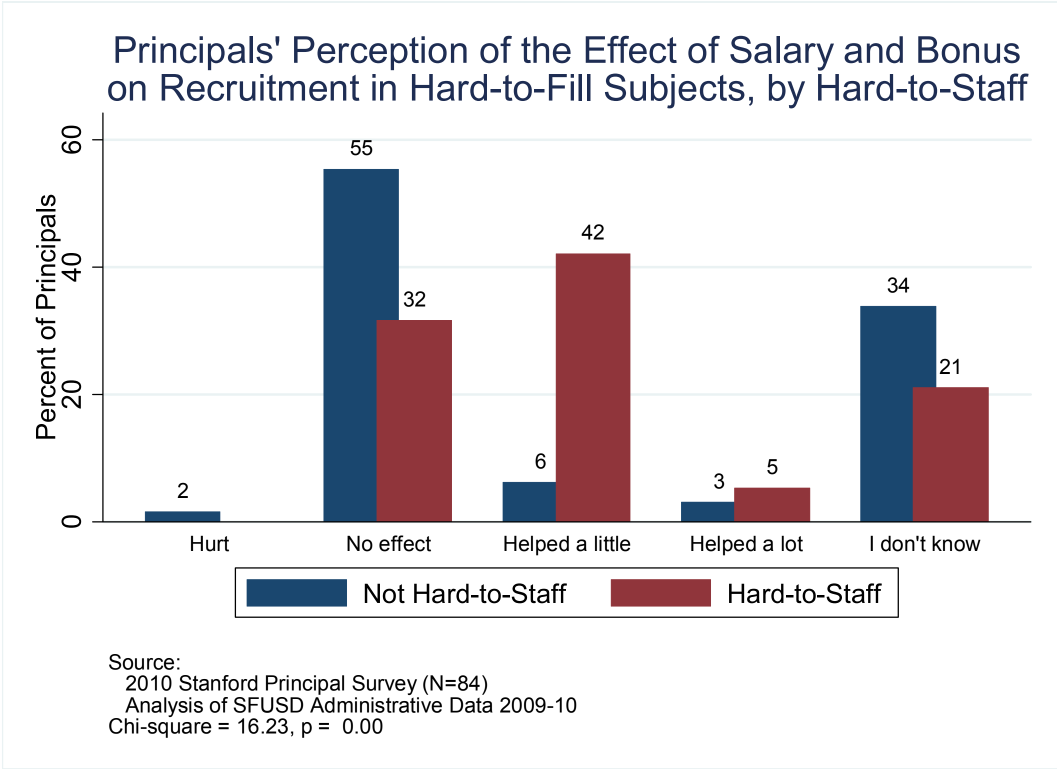


Figure 9

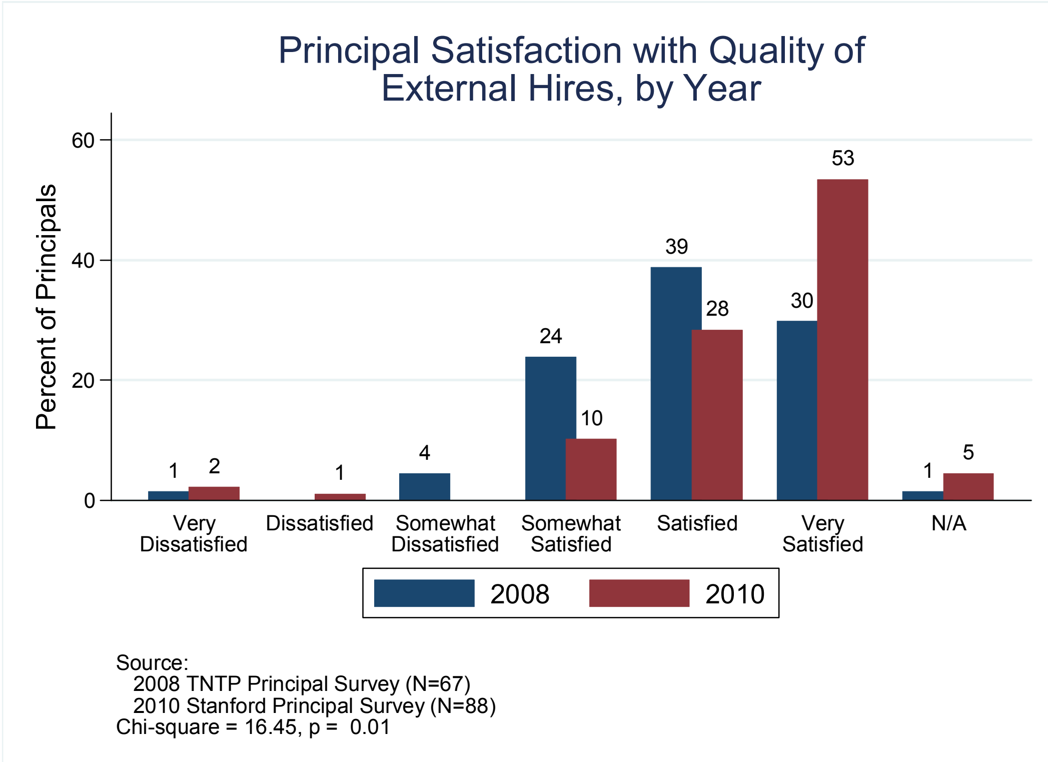


Figure 10.

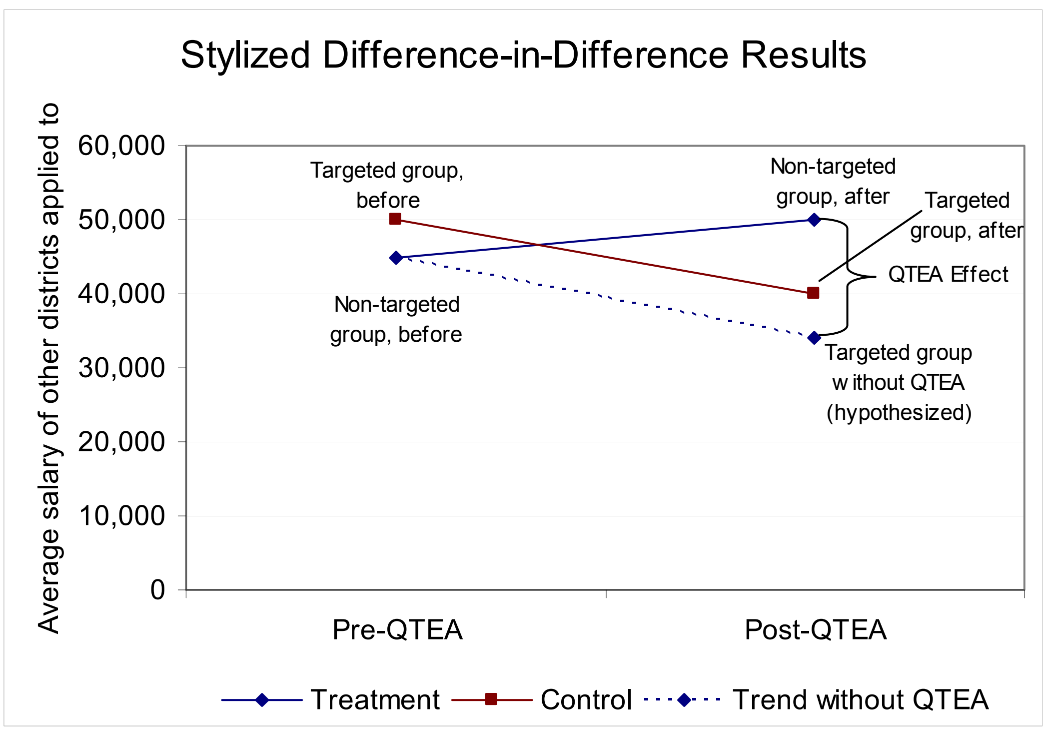


Figure 11.

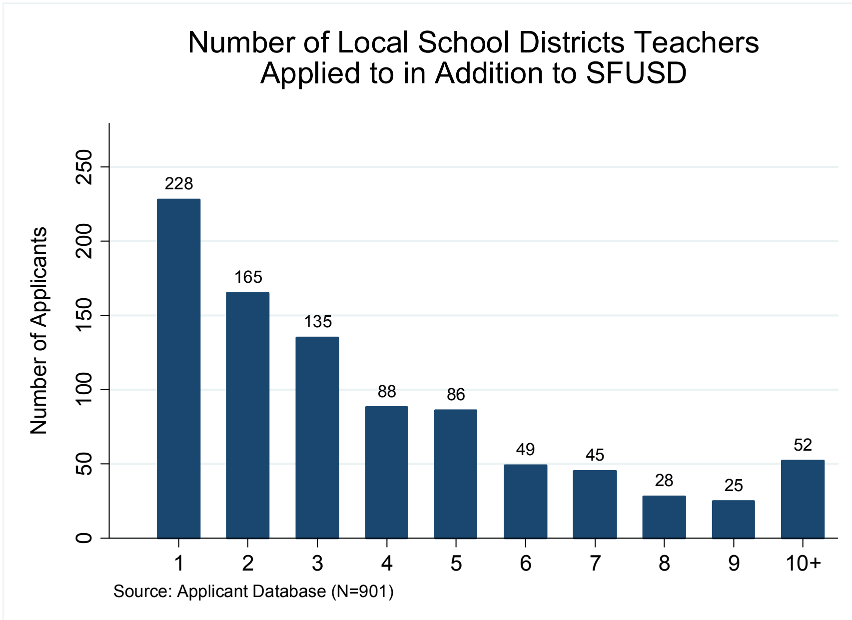


Figure 12.

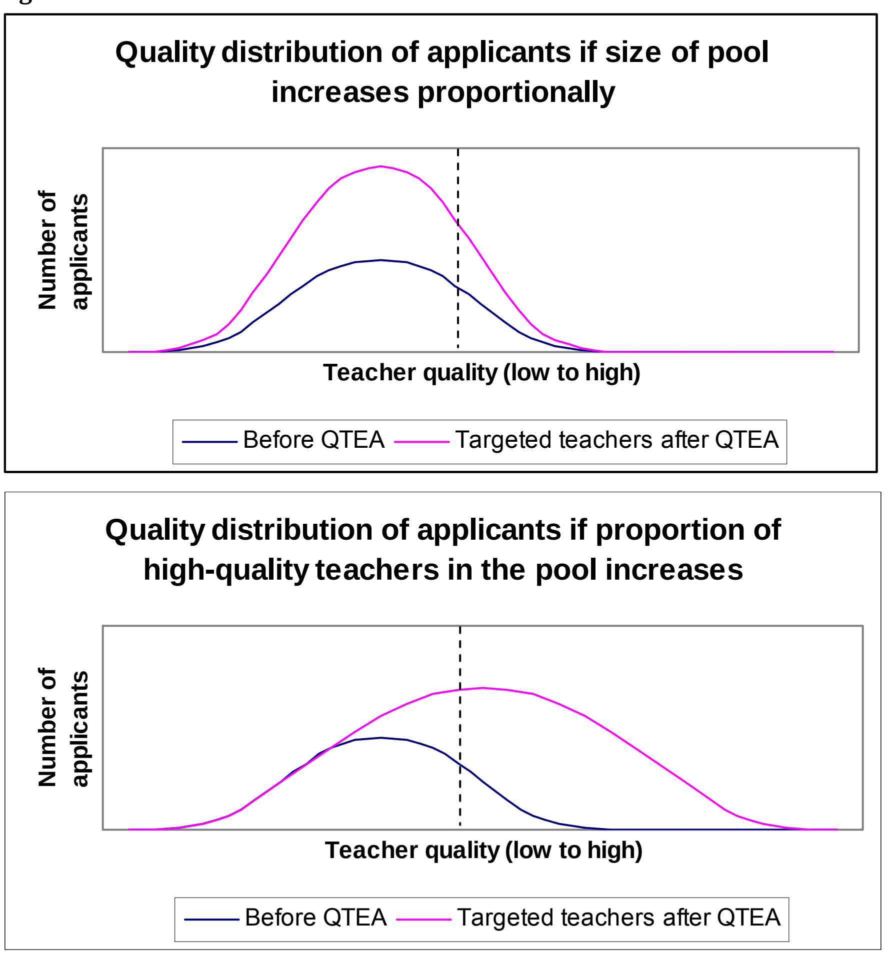
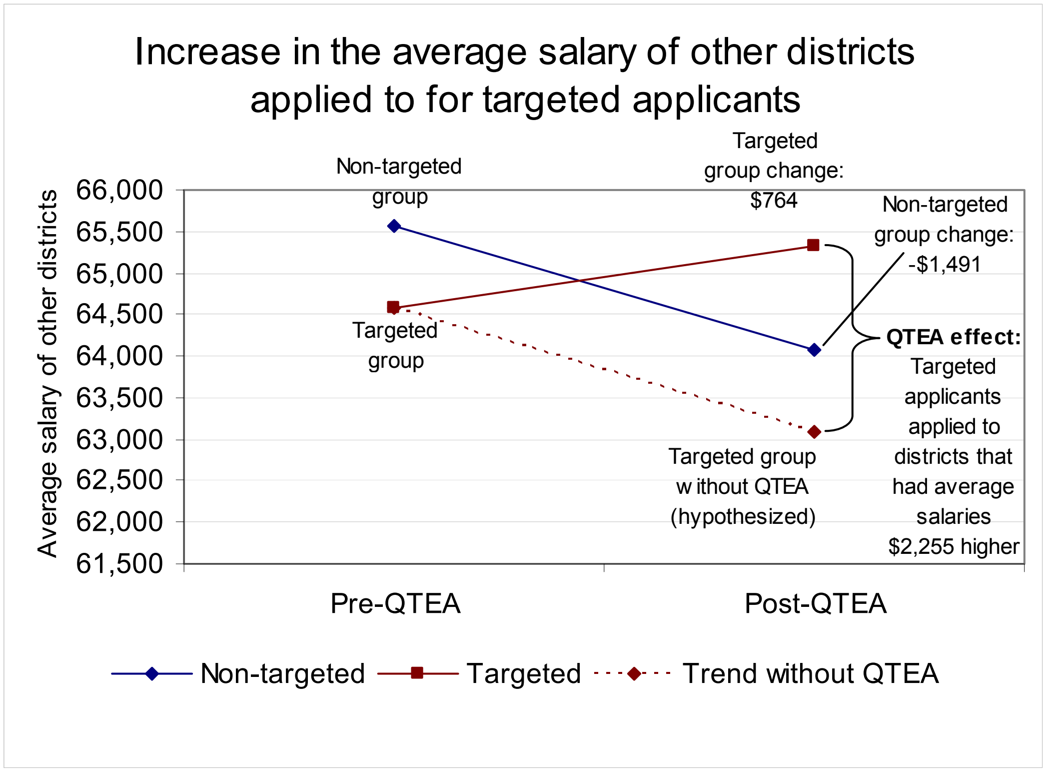


Figure 13.



Increase in the average salary of other districts applied to for targeted applicants
Average salary of other districts
66,000
65,500
65,000
64,500
64,000
63,500
63,000
62,500
62,000
61,500
Non-targeted group
Targeted group
Targeted group change: $764
Non-targeted group change: -$1,491
QTEA effect: Targeted applicants applied to districts that had average salaries $2,255 higher
Targeted group w ithout QTEA (hypothesized)
Pre-QTEA
Post-QTEA
Non-targeted
Targeted
Trend without QTEA

Appendix A. Additional Descriptive Information on Applicants and New-Hires

Table A.1. Composition of the Applicant Database, by sample subsets

	Sample for analyzing change in proportion of targeted applicants		Sample for Q2 analyzing change in average salary of other districts applied to	
	Full analytic sample	Restricted to applicants with 2-15 years of prior experience	Full analytic sample	Restricted to applicants with 2-15 years of prior experience
Not hired				
Number	1,161	604	752	405
Weighted % of total	77.3%	84.3%	86.9%	91.3%
Hired				
Number	450	145	149	49
Weighted % of total	22.7%	15.8%	13.1%	8.7%
Number	1,611	749	901	454

Table A.2. Subjects taught for applicants and new-hires

	Applicants	New-hires
Multiple Subject	44%	22%
Special Education	16%	14%
Mathematics	10%	12%
Art	5%	6%
English	16%	14%
Foreign Language	6%	3%
Physical Education	3%	6%
Science	9%	9%
Social Science	11%	8%
N	1,611	2,462

Table A.3. Years of prior experience for applicants and new-hires

	Applicants	New-hires
None	37%	53%
1	10%	15%
2	11%	7%
3	8%	4%
4	5%	4%
5	4%	3%
6-10	13%	10%
11-15	6%	2%
16-20	3%	0%
20+	3%	1%
N	1,611	2,462

Table A.3. Race/ethnicity of applicants and new-hires

	Applicants	New-hires
African American	5%	4%
Hispanic	11%	12%
Asian	16%	11%
N	1,489	2,239

Table A.3. Top 20 Districts applied to, by percentage of applicants that applied

District	Number applied	Percent Applied
Alameda City Unified	290	32.2%
Oakland Unified	276	30.6%
San Mateo-Foster City Elementary	239	26.5%
South San Francisco Unified	235	26.1%
Berkeley Unified	230	25.5%
San Jose Unified	174	19.3%
Santa Clara Unified	136	15.1%
Hayward Unified	120	13.3%
Palo Alto Unified	114	12.7%
San Rafael City Elementary	109	12.1%
Fremont Unified	96	10.7%
Burlingame Elementary	96	10.7%
West Contra Costa Unified	94	10.4%
Mill Valley Elementary	90	10.0%
Jefferson Elementary	87	9.7%
Redwood City Elementary	79	8.8%
Mt. Diablo Unified	78	8.7%
San Leandro Unified	77	8.5%
Sunnyvale	68	7.5%
Castro Valley Unified	68	7.5%

Appendix B. QTEA Principal Interview Topic Guide

1st meeting (week of September 28, 2009)

- Please tell me about your background
  - How did you become a principal in this school?

- What are your goals for the school?
  - How do these goals fit into the district's strategic plan?
  - How are you pursuing these goals in the short-run?
    - What about for the longer-term?
  - How can you tell if you are making progress towards achieving your vision?
  - Are there barriers to success in pursuing your vision? What are they?
  - Are there supports either within the school or outside of the school that are particularly helpful to you?
  - What does the district, in particular, do either to support or hinder your goals?

- Changing gears a bit, I would like to ask about the staff configuration in this school.
  - In middle/high school: How are staff configured? (Probe for planning periods, PD days, Small Learning Communities, grade- or subject-level teams.)
  - Now I would like to talk a little about the specific kinds of staff working in your school:

	How Many?	Notes (i.e., what subject? or what do they do? What are their roles?)
Number other administrators		
Support staff (master teachers, resource teachers, IRFs, etc.)		
Total number of teachers		
Number of New (Certified) Teachers		
Number of Interns		
Number of Tenured Teachers participating in PAR		

- I would like to talk a bit about each of the teachers that you hired for positions in your school this year. (For each teacher):
    - What position was open?
    - What was the process for hiring the teacher currently in the role?
        - When did you post the position?
        - How many applications did you get?
        - How did you find the teachers? (Internal application, new applicant, consolidated, etc.)
        - When did you meet with the candidates?
        - What characteristics were you looking for? How did you determine if this teacher was a good fit?
        - Did you end up getting the teacher you wanted?
            - If yes, how did you convince him/her to come to your school?
            - If no, do you have a sense for why?
        - Are you happy with the person who is currently teaching in that role?

- Do you have any teachers currently whose performance you are unhappy with, or that you would prefer don't come back? (For each teacher):
    - In what subject?
    - How many years of teaching experience?
    - How many years has s/he been in the school?
        - What were the circumstances under which the teacher came to the school? (Probe for recruitment process)
    - Why are you unhappy with this teacher's performance?
    - How do you deal with this teacher? (Probe for extra support, counseling out, PAR referral, evaluation.)

- We've talked about your specific personnel challenges in this year, but stepping back:
    - Are there some teaching positions that you have a particularly hard time filling?
        - Are you ultimately able to fill these positions to your satisfaction? How?
    - Is teacher retention a problem in your school?
        - Is the problem worse in particular subjects or grade levels?
        - What do you do to retain teachers?
        - Do you target your retention efforts at certain teachers?
        - Which teachers? In what way do you target these efforts?

- Has this year been any different from last year in your ability to recruit and retain teachers?

2nd meeting (week of November 16, 2009)

- Have there been any big changes in the school since the last time we met, or any major challenges you have been facing?

SUPPORT

- Professional development
  - What is your school's professional development plan?
    - Probe for detail on specific plans, targeted efforts, meeting times, etc.
    - Generally how useful is it?
    - How was it decided what would be covered?
    - Do all teachers receive the same PD? If not, how is it different? How is it determined?
  - Can you talk about positive experiences with PD when it has been effective?
  - How about experiences with PD that have not been as effective?
  - What would you like to see more of?
  - What are some of your constraints to providing this?
  - To what extent do you control the types of PD at your school?
  - To what extent is it decided by the district?
  - How is your school using the additional PD hours allocated under Prop A?
    - Is the additional PD perceived as useful? Is it helping you reach instructional goals that we talked about last time?

- Master teachers
  - Do you have master teachers working in this school? How many? Who?
  - How were they hired? Were you involved? What was the process like?
  - What are they doing in the schools?
  - Is the work of the master teacher perceived as useful? How are they contributing to your school's improvement plan?
  - Does the master teacher help you address the needs of your struggling teachers? Your new teachers?

- Support for new teachers
  - What are the various supports for new teachers?
  - How effective are each?
  - Do you think new teachers have the supports they need?
  - Are these systems well aligned?

- Evaluation
    - What do you perceive is the role of formal evaluations?
    - Comfort level with evals
    - Role for underperforming teachers
    - How many do you have on this cycle?
    - What determines the schedule for evaluation?
    - How do you decide what summary rating to give teachers?
    - What do you hope to happen as a result of the evals?
    - Have there been any changes in the time you have been in this school or district in the way you use evaluation?

SALARY INCREASES

- Salary changes
    - Are you aware of the salary increases provided by Prop A?
        - How knowledgeable do you think the teachers in your school are of the salary increases provided by Prop A?
    - To your knowledge, do teachers talk about the district-wide salary increases?
    - Do you think the salary increase will help you retain high quality teachers in this school?

- Targeted bonuses
    - (If school is hard-to-staff) Are teachers inside this school aware of the bonuses? How have they been made aware?
    - Are teachers in your school eligible for the hard-to-fill subjects bonuses? How many? Which subjects/teachers?
        - Are the eligible teachers aware that they will receive the bonuses?
    - Do you have teachers who will receive the retention bonuses this year? How many? To your knowledge, are they aware of the incentives?
    - Do teachers talk about the incentives? Did your new hires this year talk about the incentives? How do they know?
    - Do you think the incentives will help you retain high quality teachers in this school?

3rd meeting (week of January 18, 2010)

- What has the focus of your school been since the last time we met?
    - Anything big events capturing your attention?
    - Have you worked at all on issues of staffing? (hiring, firing, planning for next year?)
        - Municipal secretary problem

- Evaluations – how did they go?
    - For new teachers
    - For the teachers you have identified as needing additional support
    - Are you happy with teachers' performance?
    - What was the distribution of ratings and how did you decide to rate teachers that way?
        - Do principals feel confident evaluating teachers? Sending them to PAR? How are evaluations being used and is this changing over time? (Principals' use of the "needs improvement" rating)
    - What kind of support do you get around evaluation?
    - Are there teachers in your school that will now be referred to PAR due to your summary evaluation rating?
    - With teachers that are not performing at a high level, how do you use the evaluation process to help?
        - Suggest additional PD or support? In school/external?
        - Do you consider referring a teacher to PAR?
        - Do you consider suggesting that a teacher participates in PAR on a voluntary basis?
        - Do you try to encourage ineffective teachers to leave? How do you do this?

- PAR
    - Have you ever referred teachers to PAR?
        - Do you have any teachers participating now?
        - Would you consider referring teachers?
        - What are your general thoughts on the program
            - As a rehabilitation strategy?
            - To remove teachers
        - There have been some changes this year (easier entry, harder to successfully complete, no re-entry); do you think these changes will help you?
    - Has the UBC school site referred teachers? If so, what are the circumstances under which this happens?

- Budget for 2010-11
    - What are you expecting? How are you preparing?

- School site council
    - How does it work?
    - Who is on it? What are meetings like?

- School improvement incentives
    - Are you aware of the program elements?
        - Are teachers aware of the program elements?
    - Were you involved in creating the program elements?
    - How likely do you think it is that your school would win the award?
    - Is your school working toward winning the award? What?
    - How will you decide how to use the award if you win it? Have there been discussions about this yet?

- Any awareness of new positions for next year?
    - March deadline for announcing?
    - What are you doing to prepare, if you know that there are vacancies on the horizon?

Final meeting (week of May 3, 2010)

- Budget
    - What will be cut next year?
        - Positions? Programs?
        - How did you decide?
            - District? School site council?

- Staffing
    - Layoff notices?
        - Did you have any say?
        - Are these teachers that you would not/like to leave?
        - Actual layoffs
    - Teachers leaving – why?
    - Targeted subjects
        - Hard-to-staff
        - Hard-to-fill
        - Do teachers in this school get bonuses? In what subjects?
        - Retention bonus

- Update on status of previously identified underperforming teachers
    - Will they be returning next year
    - What is your long-term plan for these individuals?

- PAR
    - Easier entry
    - Higher standard? Do you know about it?
    - No reentry
    - Voluntary participation

- Professional development
    - APD
    - Are some kinds of PD better than others?
    - Prop A PD – are teachers using the hours?
        - What is it good for?

- Stepping back, what is needed in your district/school?
    - What would you need to improve teacher quality and student achievement?

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