Public and Private Learning in the Market for Teachers: Evidence from the Adoption of Value-Added Measures*

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Abstract

Previous research finds that effective teachers have significant impacts on their students' later outcomes. Yet, determining good teachers at the point of hire is difficult. Over time, principals may accumulate information allowing better discernment between more and less effective teachers. Meanwhile, teachers may draw on their experience to bolster their resumés. However, in the event that a teacher seeks to move schools, the degree to which new information influences another principal's decision is unclear. To address this question, this study develops a model of employer learning, which allows for the accumulation of both public and private information. It then takes advantage of the adoption of teacher value added measures by two large school districts in North Carolina to offer a rare direct, empirical test of public and private employer learning. Consistent with a shock to public information, for job moves within the district, I find that the adoption of value-added measures increases the probability that good teachers move to better schools. For moves out of the district, I find that the policy leads teachers with lower value added measures to become more likely to move to better schools. This adverse selection to plausibly less informed principals is consistent with asymmetric employer learning. Further, I find some evidence that these moves lead to an increase in the sorting of teachers across schools, exacerbating the inequality in access to high quality teaching.

1 Introduction:

Gaps in information hinder the efficient allocation of workers across employers in many of the most entrenched economic models [Spence, 1973, Gibbons and Katz, 1991, Farber and Gibbons, 1996, Altonji and Pierret, 2001]. While a large literature focuses on informational asymmetries between workers and employers, a more recent literature focuses on asymmetric information between current and prospective employers. This

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prior work fits models asymmetric employer learning to empirical facts, such as wage dynamics with respect to job tenure versus experience, variability of wages after a job loss, and selection of mobile or promoted workers on easy or difficult to observe characteristics [Kahn, 2013, Pinkston, 2009, Schoenberg, 2007]. Despite its important implications and intuitive appeal, there is little direct evidence of asymmetric employer learning. This is in part due to the absence of direct measures of productivity, and more importantly due to a lack of exogenous variation to informational landscape in which employers operate. This work takes advantage of micro-level administrative data from North Carolina to formulate value-added measures (VAMs) of teacher productivity. More importantly, it exploits the adoption of VAMs by two of the largest school districts in the state, as a shock to the available information for some, but not all, potential employers.

In the primary education context, questions of efficiency and equity carry additional weight. Previous research finds wide variation in the quality of teachers [Chetty et al., 2011a,b, Rivkin et al., 2005]. Yet, at the point of hire, detecting good teachers is difficult, since easily observable teacher characteristics are not highly correlated with teacher effectiveness Rivkin et al. [2005]. Informational gaps may lead schools and districts to hire relatively ineffective teachers, while passing on more capable ones. This can have significant ramifications for the students they serve [Chetty et al., 2011a,b].

After the date of hire, while principals typically do not observe a direct measure of a teachers' effectiveness, they may observe their teachers in action and inspect student outcomes. However, the quality of a teacher may remain difficult for the employing school to uncover and harder still for other schools to learn. The amount of uncertainty in the market and with whom the uncertainty lies can differentially effect the sorting and resorting of teachers across schools.

Given the difficulty to identify good teachers at the beginning of their careers, persistent informational gaps may lead schools to undervalue effective teachers and allow ineffective teachers to impede the progress of their pupils. In contrast, complete and public information allows better teachers more choice over where to teach. There is a large body of work, such as Boyd et al. [2008, 2013] and Jackson [2009], which examines teacher preferences. They find that teachers in general prefer to teach in schools that are closer in proximity to their homes, higher performing, and for white teachers, schools with a lower percentage of black students. Consequently, while providing good teachers more choice, better information may also exacerbate the divide in access to high quality education. The degree to which learning is asymmetric theoretically mitigates these effects.

The adoption of statistical measures of teacher effectiveness by some, but not all employers, provides a unique test of these hypotheses. Guilford County Schools (GCS) and Winston-Salem/Forsyth Community Schools (WSF) each independently adopted teacher level VAMs ahead of the rest of the state, which they released to principals and teachers within their district. Using differences-in-differences, this study first examines how the relation of teacher quality to the probability of moving schools changes with the adoption of value-added measures of teacher effectiveness. Careful attention to how these changes differ between moves within and out of treated districts provides evidence of public and private learning. Secondly, by examining changes in the sorting of teachers, I evaluate the impact of the information on the distribution of teacher quality across schools. Lastly, by examining the comparative statics of the policy by experience and tenure, this work illuminates the learning environment that previously prevailed.

I find that by releasing VAMs to teachers and principals, both districts increase the probability that high VAM teachers will move to higher performing schools. I estimate that on average a one standard deviation decrease in a teachers VAM increases the probability of moving out of district to better schools by about 10%. I find that the effects are much smaller for teachers moving outside the treatment districts. In GCS, the policy leads to adverse selection of teachers moving outside the district, as a teacher one standard deviation below average becomes 15% more likely to leave to a better school away from GCS. The fact that we see positive selection to principals with access to the information and much smaller effects and even negative selection for moves to those without access to the VAMs is consistent with asymmetric employer learning. Further, I find that in WSF in particular, the adoption of VAMs exacerbates the inequity of the distribution of high VAM teachers across schools.

2 Literature Review:

This work straddles two disparate literatures: the labor literature focusing on employer learning and economics of education literature focused on teacher mobility. There is a robust extant literature building models of employer learning and fitting them to stylized empirical facts. Farber and Gibbons [1996] provides the seminal model and test for employer learning. It presumes that worker ability is heterogeneous. Employers cannot directly observe the ability of potential workers and must rely on correlates to infer workers' expected value to the firm. Further, they treat a subset of worker characteristics as easily observable to all, another as easily observable to the market (and not to researchers), and yet another subset of potential correlates with productivity as easily observable to the econometricians (but not the market). This literature typically uses the percentile from a cognitive ability assessment, the Armed Forces Qualification Test (AFQT) from the National Longitudinal Survey of Youth of 1979 (NLSY79), as this relatively strong correlate with productivity that is veiled to the the market at the time of hire. By assuming a competitive marketplace and that employers all learn at the same rate, wages perfectly track the employers' learning process. Altonji and Pierret [2001] adopt a similar foundation in their examination of statistical discrimination as does Lange [2007] in his study of the speed at which employers learn.

Schoenberg [2007], Pinkston [2009], Kahn [2013] each relax the symmetric learning assumption in building private information into their own employer learning models, and each use the NLSY79 to test their models against empirical features of the data. While those assuming symmetric learning find evidence that wages follow the predictions of the model, the evidence regarding asymmetric learning is more mixed. Examining wage dynamics with regard to experience and tenure, as well as selection in job separations, Schoenberg [2007] finds that learning is largely symmetric. Pinkston [2009] adopts a learning framework more closely tied to the symmetric learning literature. In an important contrast to Schoenberg [2007], his model also allows information to pass through job-to-job transitions. In keeping with asymmetric learning, Pinkston [2009] finds that the correlation between wages and ability as measured by the AFQT exams moves more closely with respect to continuous working spells than with experience.

More recently, Kahn [2013] extends Schoenberg's framework to test whether job movers experience more volatile wages after a transition than do those who remain in place. She considers differences between workers who enter a position during recessions as opposed to economic expansions, with the idea that there is less variation in the ability of entrants during recessions. She also uses variation in the amount of exposure an occupation has outside the firm, assuming that learning is more symmetric in more exposed occupations. In support of asymmetric employer learning, Kahn finds that movers' wages are more volatile in the immediate aftermath of a transition than are the wages of those who remain in place. Also, the effects are larger for those who enter a job during an economic expansion and for those in more insular occupations.

Only DeVaro and Waldman [2012] depart from the use of the NLSY. They use administrative personnel files from a large firm to examine promotion decisions based on private and public information. In support of asymmetric employer learning, they find that conditional on private performance reviews, those with more education are more likely to be promoted than are those with less education. They also present evidence that larger wage increases accompany promotions of less educated workers than accompany promotions of better educated workers. This, they argue, is due to the fact that promotions are a stronger public signal for those with worse easily observable characteristics.

A common criticism of much of the earlier literature asks what AFQT scores are really telling us. There is little evidence that AFQT scores are related to productivity in many jobs held by the largely low-skilled respondents of the NLSY. Similarly, if employers care greatly about AFQT scores, they would simply administer the test themselves. By using a direct measure of productivity rather than an assumed correlate, this study avoids such criticism. More importantly, the stylized empirical facts given as evidence of asymmetric learning are consistent with the theoretical model, but are susceptible to alternative explanations. This study directly tests a general model of public and private learning by exploiting information shocks to a large, relevant labor market.

The second literature into which this study fits is similarly large. Much of the teacher mobility literature focuses on which teachers move, where they go, and the effects on the distribution of educational resources. Guarino et al. [2006] provides a detailed overview of earlier work on the subject. More recent work such as, Boyd et al. [2008], examines differential mobility patterns based on teacher VAMs. Using mobility records from New York State, they find that ineffective teachers are more likely to leave the profession only in their first year of teaching. They also find evidence of teachers resorting across schools; the teachers with higher VAMs transfer to better schools. This analysis interprets these results as illustrative of teacher preferences but gives little discussion to the employer side of the moves.

Jackson [2009] examines evidence of teacher preferences from the resorting of teachers in Charlotte-Mecklenburg Schools around the discontinuation of the district's integrative busing program. Jackson finds that as the composition of schools became more black, the teaching force in those school became less experienced, lower performing on state qualification exams, and less effective as measured by VAMs in math and reading. Further, he presents evidence that these changes in the teaching force were driven by teacher supply, motivated by their preferences.

Boyd et al. [2013] provides further evidence of teacher preferences. Analyzing personnel data from New York state, they estimate a two-sided matching model to distinguish teacher preferences from employer preferences. As does Jackson, they find that on average white teachers prefer not to teach in schools with a large proportion of black students. They also find that teachers prefer schools that are closer, are suburban, and have a smaller proportion of students in poverty. Employers show preferences for teachers with stronger academic achievement, measured by having more than a bachelor's degree, the selectivity of their undergraduate college, and their score on the basic-knowledge teacher certification exam, and teachers living in closer proximity to the school. Presumably some of these traits matter only insofar as they are suggestive of the effectiveness of the teacher.

The body of work that at least tangentially relates to both the employer learning and the teacher mobility literature is smaller, but helpful. For example, Jacob and Lefgren [2008] presents evidence that principals evaluations are correlated with VAMs of teacher effectiveness, but not perfectly. They find that principals can identify the most and least effective teacher, but have trouble sorting the teachers in the middle. The fact that they observe slightly higher correlations for principals who have known their teachers for longer is suggestive of a gradual learning process. Chingos and West [2011] provide further evidence that principals hone in on the effectiveness of their teachers. They find that principals classify their teachers on the basis of effectiveness, and move them accordingly. They find that principals of schools under accountability pressure are more likely to move effective teachers into and less effective teachers out of high stakes teaching assignments.

Rockoff et al. [2012] provide the closest examination to the subject of this paper. They present experimental evidence that principals who receive VAMs of their teachers update prior beliefs about teachers' efficacy in ways that are consistent with a Bayesian learning model. It is important to note that in this experiment, only teachers' current principals receive VAM reports not the teachers themselves or principals of Surveys of participating principals show that those who randomly received more precise VAM reports were more responsive to the information, than were principals receiving noisier VAM reports. They also find that providing VAMs to principals cause less effective teachers to leave at a higher rate. While the survey and retention results together provides strong evidence that VAMs provide actionable information to principals in this setting, the lack of a public component to the release of information makes it difficult to interpret the results as a true test of either asymmetric or symmetric employer learning models. Further, the limited scope of the experiment disallows it from estimating the effects of providing VAMs to principals on which teachers move and where they go in equilibrium.

3 Model

This section describes a simple model to provide predictions for which workers move, where they go, and how each may change in response to an information shock. The following learning framework builds on the model of asymmetric employer learning presented in Pinkston [2009], which in turn builds upon the canonical models of symmetric learning presented in Farber and Gibbons [1996], Altonji and Pierret [2001].

3.1 Structure

It is important to understand the context of this labor market for teachers. In formulating the model, I will highlight areas in which this market is peculiar and the model structures that accompany them. However, the information structure is standard, based upon a simple Bayesian updating model with the modification that employers receive two signals rather than one. I assume that teachers know their effectiveness (μ), but cannot credibly reveal it. As a teacher begins her career, principals begin with the prior belief that she is as good as the average teacher with her same characteristics (m). Employers then receive a private signal (P_0^h) signal of teacher effectiveness similar to an interview. Overtime, teachers may draw on their experience to bolster their resumé and network of references. If the information is credible (public learning), their public signals (R_x) become more precise with increases in teacher experience. In other words, the variance of the public signal ($\sigma_x(x)$) shrinks as teachers gain experience $\left(\frac{\partial \sigma_x(x)}{\partial x} < 0\right)$. Through interactions, observations, and/or attention to student outcomes, principals may obtain private information unavailable to prospective employers. If such private learning occurs, while prospective principals' private signals from interviewing the teacher have a constantly high variance ($\sigma_t(0)$), current principals' signals (P_t^r) become more precise the longer a teacher works in the school. If there is private learning, $\sigma_t(t) < \sigma_t(0)$ for all $t > 0$. In order to nest symmetric learning within the more flexible model, I maintain that that even in this special case, employers receive a private signal each period, but the variance of the signal is constant over tenure ($\sigma_t(t) = \sigma_t(0)\, \forall\, t > 0$). I assume that the error of the signals are orthogonal. To formalize the description above, I itemize the assumptions below:

1. True effectiveness,$\mu = m + \epsilon$, where m is the population mean of productivity among a worker's reference group and $\epsilon \sim N(0, \sigma_\mu)$.[1]
2. The public signal, $R_x = \mu + \xi$, where $\xi \sim N(0, \sigma_x(x))$, and $\frac{\partial \sigma_x(x)}{\partial x} < 0$.
3. Principals gain private information, $P_t^s = \mu + \tau_t^s$ where $\tau_t^s \sim N(0, \sigma_t(t))$, $s \in h,\ r,\ t \in [0,\ \infty]$, and $\frac{\partial \sigma_t(t)}{\partial t} < 0$.
4. $\epsilon \perp \xi \perp \tau^r \perp \tau^h$

Initially, teachers take the position that offers the highest total compensation (C_{isd}), which is comprised of salary (w_d), school characteristics (S_{sd}), and position characteristics (J_{isd}). In the public schooling sector, salaries are largely set at the district level. In many public education systems, strict salary schedules determines teachers' pay. In North Carolina, the state sets a base salary schedule that depends exclusively upon easily observable characteristics, such as education and experience. Districts typically supplement this base amount with a percentage of the base schedule. In general, this means that a given teacher will earn the same salary regardless of where and what he is teaching within the district.[2] Further, cumbersome dismissal processes result in teachers initiating much of the mobility. While principals cannot adjust salaries to influence whether a teacher stays, principals may influence school staffing through non-pecuniary position attributes, such as planning time, teaching assignments, or additional requirements.Boyd et al. [2008, 2013], and Jackson [2009] each provide evidence that teachers have strong preferences over non-wage job attributes. Yet, it seems unrealistic to suppose that substantial differences in pay or school quality or both could be compensated through perks. Consequently, I assume that all job benefits lie below an upper bound ($\overline{J_{isd}}$) forcing a maximum bid for each school, $\overline{b_{sd}} = \overline{J_{isd}} + S_{sd} + w_d$. For tractability, I assume that schools openly offer continuous bids in C_{isd}, which allows the adoption of optimal bidding strategies from Milgrom and

[1]The normality assumptions are not necessary, but are useful in deriving the comparative statics.

[2]In Section 6, I discuss strategic staffing policies deviate from this general case by offering incentives to teach at hard-to-staff schools. The bonuses attached to such positions varied formulaically and outside principals' discretion.

Weber [1982]. This allows each school to learn that the other values the teacher at least as much as it does during bidding. Each school accordingly affords the private signal double weight. A hiring principal's the optimal maximum bid (b^{*h}_{isd}) is given by equation 1.

$$b^{*h}_{isd} = min\left\{\frac{\sigma_t(0)\sigma_x(x)}{Z}m + \frac{\sigma_t(0)\sigma_\mu}{Z}R_x + \frac{2\sigma_\mu\sigma_x(x)}{Z}P^h_0,\ \overline{b^h_{sd}}\right\} \tag{1}$$

where $Z = \sigma_t(0)\sigma_x(x) + \sigma_t(0)\sigma_\mu + 2\sigma_\mu\sigma_x(x)$. First, schools offer bids reflecting the expected effectiveness of the teacher until the point that the expectation meets their maximum bid. Beyond that point, the principal can only offer $\overline{b_{sd}}$. For bids less than $\overline{b_{sd}}$, principals weight each signal by its relative precision. As the public information becomes more complete, principals give less weight to their prior beliefs and private signals and more weight to the public signal.

A principal seeking to retain her teacher has an optimal maximum bid (b^{*r}_{isd}) given by equation 2.

$$b^{*r}_{isd} = min\left\{\frac{\sigma_t(t)\sigma_x(x)}{Z'}m + \frac{\sigma_t(t)\sigma_\mu}{Z'}R_x + \frac{2\sigma_\mu\sigma_x(x)}{Z'}P^r_t,\ \overline{b^r_{sd}}\right\} \tag{2}$$

where $Z' = \sigma_t(t)\sigma_x(x) + \sigma_t(t)\sigma_\mu + 2\sigma_\mu\sigma_x(x)$. For bids less than $\overline{b_{sd}}$ beyond the initial period, principals provide more weight to their private information, if they obtain more useful information than is publicly available.

The teacher labor market generally moves in the summer between school years. Between each school year, she may sample offers. I assume that teachers change schools when a new position affords a large enough increase in overall compensation to off-set a fixed cost of moving. Accordingly, the probability of a move is:

$$P(M) = P\left[b^{*h}_{isd} - b^{*r}_{isd} > c_m\right] \tag{3}$$

There are two ways the model predicts moves to occur. Type 1 moves take advantage of the heterogeneity of $\overline{b_{sd}}$ and the probability of such moves is expressed in equation 4.

$$P(M1) = P\left(\frac{\sigma_t(0)\sigma_x(x)}{Z}m + \frac{\sigma_t(0)\sigma_\mu}{Z}R_x + \frac{2\sigma_\mu\sigma_x(x)}{Z}P^h_0 - \overline{b^r_{sd}} > c_m\right) \tag{4}$$

In general, schools that are on average more desirable to teachers have a higher maximum bid than do less desirable schools. As the public information hones in on teachers' true ability, better schools are likely to skim away the teachers for whom $\mu > \overline{b^r_{sd}}$. For these type of moves, better teachers are more likely to move, all else equal $\left(\frac{\partial P(M)}{\partial \mu} > 0\right)$.

The Type 2 moves are composed of moves in which a hiring principal values the teacher more so than does the retaining principal. Letting ψ stand for the composite error term, equation 3 simplifies to equation 5 assuming neither principal is at the boundary of possible bids.[3]

$$P(M2) = P\left[\psi - c_m > \sigma_x(x)\left(\sigma_t(0) - \sigma_t(t)\right)(\mu - m)\right] \tag{5}$$

While such moves may occur due to extreme private signals, the differences in how each principal weights the signals she receives implies this may happen even if both principals received the same private signal. For these second type of movers, it is apparent from equation 4 that all else equal, the probability of a move is inversely related to true effectiveness. Intuitively, due to their additional knowledge of teacher effectiveness, the current school should value the true effectiveness of the teacher relatively more than the outside market does. Because the outside market has less information about true effectiveness, the outside schools should place more weight on the easily observed correlates with teacher effectiveness than the current school. It is also worth noting from equation 4 that the probability of moving decreases with increases in tenure. Changes in the precision of the public signal produce ambiguity for these interior moves.[4] Lastly, these dynamics do not hold for the symmetric learning case, as $\sigma_t(t) = \sigma_t(t)$ for all t. All interior moves would be motivated by noise in the private signals, which would mostly occur early in a teacher's career. With more experience, principals would rightly place little weight on such noise. Consequently, I base all predictions for symmetric learning off the first type of move. While the model gives a clear prediction of positive selection among movers, such an empirical result does not reject the asymmetric learning hypothesis. However, negative selection on effectiveness of movers all else equal clearly contradicts symmetric employer learning.

3.2 Information Shocks

The availability of VAMs to some prospective employers, but not others, provides a rare test for the model laid out above. In 2000, Guilford County Schools (GCS), contracted with SAS to receive teacher EVAAS measures of teacher effectiveness. The district gave teachers, principals, and prospective hiring principals direct access to the teacher VAMs. In 2008, the rest of the state of North Carolina adopted EVAAS measures of school effectiveness. Winston-Salem/Forsyth Community Schools (WSF) took an additional step, providing SAS with student-teacher matches in order to receive the same teacher specific measure of effectiveness already present in GCS. In WSF, only the teachers and their principals directly received the VAM reports. Because all hiring principals may directly access a teacher's VAM, for within-district moves in GCS, the introduction of VAMs theoretically provides a shock to the precision of the public signal ($\sigma_x(x)$)

[3] See Appendix (Section 8.1).
[4] See Appendix (Section 8.1).

. Whether the information influences principals' and teachers' mobility decisions depends on whether the actors perceive it to contain information that was previously unavailable.

The introduction of VAMs in WSF is theoretically also public. Here, because prospective hiring principals cannot directly access the reports, they must rely on someone else to reveal a teacher's EVAAS report. From the perspective of a teacher's current principal, the optimal strategy is not to reveal her teachers' VAMs to another prospective principal. In the case of a teacher with a higher VAM than would otherwise be expected, the principal would likely wish to keep him. Revealing his VAM would increase the probability that he leaves. For a teacher who is worse than otherwise expected, the current principal who cannot easily fire him would like the teacher to take another position elsewhere. Here, revealing his VAM may hurt the chances of the teacher leaving. In either case the principal has the incentive to keep the information private.

Teachers have different incentives. As in Akerlof [1970], each teacher contemplating moving within the district has as incentive to reveal his score, as the pooling equilibrium unravels. Because all principals in the district know that the VAM score exists, if a teacher chooses not to reveal his score, the hiring principals will assume that he is as good as the average teacher who chooses not to reveal his score. Consequently, all teachers with above average scores should reveal their scores. In so doing, they further drive down the average score of those who do not reveal until only teachers with the minimum possible score are indifferent between revealing and keeping the information private. If teachers act as predicted, all teachers reveal their EVAAS reports, and the VAMs shock the precision of the public signal ($\sigma_x(x)$), as in GCS.

For both Type 1 and Type 2 moves, decreases in $\sigma_x(x)$ leads to an increase in the probability a good teacher moves and a decrease in the probability a bad teacher moves.[5] Given the indirect route through which prospective principals must obtain the information, the results may be larger for GCS than WSF.

While the incentives of principals remain constant, the incentives for teachers may differ when moving out-of-district. There are two main difference between within- and out-of-district moves. Perhaps most importantly, it is possible that hiring principals in the rest of the state are unaware of the existence of an applying teacher's VAM. Consequently, a teacher may withhold his signal and leave the principal's expectation of his ability unchanged. In which case, only those with VAMs above the unconditional average would choose to reveal–and only principals hiring those teachers would be aware of the VAMs presence. Furthermore, for teachers whose VAM is worse than would be expected by their resumés, moving out of district may be an attractive choice. In accordance with the model, this means that the variance of the private signal of the current principal ($\sigma_t(t)$) shrinks relative to the variance of the out-of-district principals' signals. While that has no implications for Type 1 moves, the decrease in $\sigma_t(t)$ leads to an increase in the adverse selection of movers from Type 2 moves. This informational asymmetry may be avoided by principals

[5] See Appendix (Section 8.1).

thoroughly researching from where their applicants are coming. In which case the same predictions as were formulated for within districts would apply. Thus, the test between symmetric and asymmetric learning is whether the results on selection of movers for out-of-district moves are significantly less than the effects of adopting VAMs for within-district moves.

Secondly, since principals in both GCS and WSF received training about the measures, VAMs may serve as a more salient signal for principals within the district than for those in the rest of the state. This is particularly likely for teachers moving from GCS in the early years. In 2000, when GCS contracted with SAS, the EVAAS system had only been out for a couple years, and No Child Left Behind with its additional emphasis on using standardized test scores was still a year away from passage. The salience of the signal may have been less of issue for teachers moving from WSF, considering school-level EVAAS measures were implemented across the entire state the same year. This may lead the learning results for out-of-district moves to more pronounced for GCS than they are for teachers leaving WSF.

4 Data and Estimation:

While there are other valuable dimensions of teaching, many schools and districts care a great deal about teachers' abilities to raise their students' performance on standardized assessments. This study relies on student and teacher linked longitudinal data generously provided by the North Carolina Education Research Data Center (NCERDC). Though a robust source of data, unfortunately, the NCERDC does not contain the exact VAMs issued to each teacher within the treatment districts. Rather, this study will measure the student gains on the North Carolina End of Grade exams attributable to each teacher, and use these VAMs to proxy for each teacher's underlying ability. Given that research into the most robust and effective methods to estimate VAMs is ongoing, the methods used by this study are subject to change. However, my preferred current measure is what Guarino et al. [2012] call the Dynamic OLS (DOLS) estimator presented in equation 6, due in part to the robustness that they find it to have and in part because Henry, Rose, & Lauren (2012) estimate .91 correlation between DOLS and the EVAAS measure believed to have been used by the districts.

$$A_{ijt} = \tau_{\mathbf{t}} + \mathbf{A_{ijt-1}}\boldsymbol{\beta_0} + \mathbf{X_{it}}\boldsymbol{\beta_1} + \boldsymbol{VAM_j} + e_{it} \tag{6}$$

Here, A_{ijt} represents student i's mathematics achievement in teacher j's class in year t. Including $\mathbf{A_{it-1}}$ allows for the correlation of previous math and reading test performances with current performance. Additionally, $\mathbf{X_{it}}$ is a vector including demographic attributes of individual students, such as grade, race, gender, special needs, and gifted status. It is $\mathbf{VAM_j}$, a vector of teacher indicators, which is of primary interest for this study. Acknowledging that VAMs can be somewhat unstable in any single year, my preferred estimates use data from each year a teacher is teaching 4^{th} through 8^{th} grade during my sample period. This allows me to gain the most precise estimate of teachers' true underlying ability, μ. I check the robustness of my results with other constructions of VAMs

This study restricts attention to the 5,986,132 elementary and middle school student, year observations from 1997 through 2011 to construct the VAMs for 134,219 teachers who teach 4^{th} through 8^{th} grade. I link these data to education, licensing, and work history data of 67,062 lead teachers without teaching assistants for whom the records are complete. These teachers are dispersed across the 2,966 schools in 117 school districts. I further restrict the sample to only those teachers currently teaching 4^{th} through 8^{th} grade, since they are the only elementary teachers to receive VAMs parring down my sample from 416,135 teacher, year observations to 236,018. At the teacher level, the data includes the teachers' race, gender, institution of higher education, degrees earned, experience, and tenure at a given school. Each of these are easily observable to all schools and many are likely used to filter job candidates. I use performance at the school in which the teacher currently works as an additional, easily observable, possible correlate with effectiveness. Table 1 provides summary statistics for my estimation sample.

The districts which received treatment do not differ substantially from state averages in achievement or percent of student receiving proficiency on the state standardized exams. Given that both districts include urban centers, they do have a higher proportion of Black students and teachers than does an average district in the state. While teachers come colleges of comparable selectivity, across districts, in WSF the a larger share of the teaching-force holds an advanced degree. However, on the basis of VAMs, teaching quality in both districts is very close to the state average.

This study follows earlier studies of employer learning in supposing that the research, may access information unavailable to market participants. Whereas Farber and Gibbons [1996], Altonji and Pierret [2001], Lange [2007], Schoenberg [2007], Pinkston [2009] use AFQT score as a strong correlate with productivity about which employers must learn, I use the VAM described above in this capacity. For the purpose of this study, VAMs need not totally encompass a teacher's effectiveness. Here, VAMs only need to be stronger correlates with teacher effectiveness than are other correlates with productivity, such as educational attainment and level of certification. The extant literature supports this claim. Firstly, as Rivkin et al. [2005] show, easily observed teacher characteristics are not highly correlated with teacher effectiveness. Experimental evidence from Hinrichs [2013] suggests that GPA matters little to schools in hiring decisions, and that the strongest determinant of receiving a positive response from a school is whether the teacher holds an in-state

Table 1: Sample Summary Statistics

	GCS		WSF		Rest of North Carolina	
	Mean	SD	Mean	SD	Mean	SD
Scaled Score	250.38	71.71	249.23	68.86	252.36	70.49
Percent Proficient	0.75	0.14	0.74	0.15	0.76	0.13
Share of Black Students	0.42	0.24	0.36	0.24	0.29	0.24
Share of Black Teachers	0.25	0.43	0.21	0.41	0.15	0.36
Share of Hispanic Teachers	0.01	0.09	0.00	0.04	0.00	0.06
Share of Teachers with Advanced Degrees	0.30	0.46	0.36	0.48	0.29	0.45
College Selectivity (Barron's)	3.95	1.43	3.92	1.68	3.93	1.44
Experience	11.59	9.76	13.36	9.71	12.19	9.85
Tenure	3.23	3.05	3.59	3.26	3.68	3.35
Job Moves	0.09	0.28	0.08	0.28	0.08	0.27
Within-District Moves	0.06	0.24	0.06	0.24	0.05	0.22
Out-of-District Moves	0.03	0.16	0.02	0.14	0.03	0.16
Left NCPS	0.06	0.23	0.04	0.20	0.06	0.24
VAM	0.02	1.01	0.01	0.99	0.00	1.00
N	11,239		8,295		216,484	

certificate. Recent work has shown significant correlation between teachers' VAMs and many important future outcomes for their students, including education, earnings, and probability of incarceration [Chetty et al., 2011a,b]. Furthermore, Jacob and Lefgren [2008] find large agreement between principal evaluations of teachers and VAMs, in tails of the distributions. Accordingly, it seems reasonable to suggest that these measures are also closely tied to teachers effectiveness.

Accordingly, the release of VAMs by Guilford County Schools (GCS) and Winston-Salem/Forsyth Community Schools (WSF) likely altered the informational landscape of the market for the teachers involved. To summarize the basic intuition of the model described in Section 3, if VAMs provide meaningful information to all principals in the district, and teachers in general prefer to teach at better schools, after districts release VAMs, good teacher should become more likely to move to better schools. With public learning, this is mainly due to more proficient schools being more able to identify teachers who are better than their current, more difficult schools could hope to retain. It is also possible that current principals become less able to keep quiet which teachers are really good, while passing off the worse teachers to unwitting prospective employers. Consequently, I examine moves to better schools separately from moves to worse schools. Given that teachers initiate most moves, it is generally difficult to explain the rationale of moves to worse schools through this framework. Meanwhile, easily observable, lower correlates with effectiveness may become less tied to the probability of moving after the introduction of VAMs. This gives the following base estimating equation:

$$y^*_{jdt} = \boldsymbol{T_t} + \mathbf{d_d} + VAM_{jd}\mathbf{G_1} + \mathbf{X_{jdt}}\mathbf{G_2} + \xi_{jdt} \tag{7}$$

$$\mathbf{G_h} = \gamma_{h1} + \mathbf{TreatDist_{jd}}\boldsymbol{\gamma_{h2}} + \mathbf{Post_t}\boldsymbol{\gamma_{h3}} + \mathbf{TreatDist_{jd}} \times \mathbf{Post_t}\boldsymbol{\gamma_{h4}}$$

where y^*_{jdt} may be the latent probability of a move for teacher j in district d and in year t. I only observe when a move occurs. $\mathbf{T_t}$ is a vector of year effects, $\mathbf{d_d}$ represents district fixed effects, and $\mathbf{X_{jdt}}$is a vector of teacher and school characteristics. Interactions with treatment district indicators separate permanent differences in the impacts of VAMs and other characteristics from confounding the effect of treatment, while interactions with indicators for post years do the same for statewide changes in the effects at the times the policies take effect. Due WSF's incentives to teachers in hard-to-staff schools, the indirect mechanism by which hiring principals obtain teachers' VAMs, and the potential additional salience of VAM signals to principals outside the district, I separate treatment by district. Each prediction may be more pronounced in GCS than in WSF. Furthermore, because there would be more information available on more experienced teachers if there previously been some degree of public learning, the model predicts the effects to diminish with teacher experience. Likewise, if there had previously been private learning, the learning model predicts the shock to public information to have larger ramifications for teachers with more tenure at a given school all else equal. In later specifications, I interact VAM with experience and the difference-in-differences, $\mathbf{G}$, interactions.

Given how the districts distributed VAMs, it seems clear that the new information would be public between two principals in GCS. Perhaps to a lesser extant the same holds for WSF. Accordingly, regardless of whether information had previously been more symmetric or asymmetric, the model predicts $\boldsymbol{\gamma_{14WD}} > 0$. When comparing the expectations of a retaining principal within one of the treatment districts to a hiring principal in another district there is some ambiguity as to whether VAMs provide a more precise expectation for both principals or only the current one. If principals in other districts find out about the signal's existence and meaning, they can require teachers to reveal just as in the WSF case. Thus, the symmetric learning model for out-of-district moves predicts $\boldsymbol{\gamma_{14ODS}} > 0$. If current principals can keep information from employers in other districts, the signal improves the precision of the current principal's signal about the true quality of the teacher, while the expectation of the out-of-district principal is unaffected. In which case, the asymmetric learning model would apply predicting $\boldsymbol{\gamma_{14WD}} > \boldsymbol{\gamma_{14ODA}}$ and possibly $\boldsymbol{\gamma_{14ODA}} < 0$

for out-of district moves.

This type of movement may have important implications for the distribution of teacher quality across schools. If better teachers are more able to signal their true quality, and do so in general to move to better schools, the divide in teacher quality between the worst and best schools may widen. Accordingly, I estimate equation 7 substituting percent of students proficient in the school taught at the subsequent year, for the binary variable of whether teachers move. Again, if VAMs are informative and teacher do in general prefer to teach at better schools, $\gamma_{\mathbf{14SQ}} > 0$ in this regression as well. Similar to the probability of moving to a better school, we may expect these effects to be somewhat muted for teachers moving later in their careers, in which case hiring principals may already have more complete information.

5 Results

Table 2 presents estimated impact of revealing EVAAS reports of teacher effectiveness on the correlation between teachers' VAMs and the probability a teacher moves to another school. The primary evidence for whether the introduction of VAMs alters the informational landscape of the teacher labor market comes from the probability of a teacher moves schools.[6] The test between symmetric and asymmetric employer learning focuses on how the effect of VAMs on the probability of moving within-district differ from the effects of VAM on the probability out-of-district after the treatment districts adopt the measures of teacher quality. Panel A restricts attention to within-district moves and Panel B presents evidence from out-of-district moves.

The first row presents the the relationship between VAM and the probability of each type of move in the rest of the state prior to any districts adopting the policy. In general, there is little relationship between VAMs and the probability of moving within or out of the district. However, when discerning between moves to more and less proficient schools a familiar pattern emerges. From columns 2 and 3 of Panel A, a teacher with a standard deviation higher than average VAM is about 0.3 percentage points more likely to move to a better school and 0.2 percentage points less likely to move to worse school within the district. Panel B exhibits the same pattern regarding moves to schools outside of the current district. A one standard deviation raises the probability of moving to a better school by about a tenth of a percentage point and lowers the probability of moving to worse school by about the same magnitude.

In both GCS and WSF the adoption of VAMs make the pattern discussed above much more prominent for within district moves. From the coefficient on the interactions between policy treatment and VAMs, a

[6] A move to a higher (lower) performing school is defined as a move in which the school taught at the following year has a higher (lower) percentage of students who achieve proficiency than the current school. Proficiency rates are demeaned by year statewide averages.

standard deviation increase in a teacher's VAM leads to about a half of a percentage point increase in the probability of moving within district. For both districts, the effects are significant beyond the 99% confidence level. Column 2 illustrates that these results are driven mostly by moves to better schools, as the model predicts. These point estimates translate to more than a 10% increase in the probability of moving to a better school in either district. There are essentially no effects on the probability of moving to a worse school within district. The similarity of the point estimates on the impact of VAMs post-treatment between GCS and WSF is also worth noting, as they provide no evidence that relying upon teachers to voluntarily disclose their VAMs to hiring principals mitigates the effects.

From section 3, the effect of the policy should be no different whether teachers move to schools within or outside of the district, were all principals fully informed about the existence of the additional information. If the policy gives principals in GCS and WSF an informational advantage over principals in other districts, asymmetric employer learning predicts that the selection of teachers to other districts would be smaller than for within-district moves, and may even be negative. The second column of Panel B presents changes in the effect of teacher quality on the probability of moving to a better school, out-of-district school after the adoption of VAMs. I find evidence in support of the asymmetric learning model. In GCS, a teacher who is a full standard deviation below average in her VAM, is about half a percentage point more likely to move to a better school out-of-district. In WSF, the difference between within- and out-of-district moves is less pronounced. While in WSF, a teacher with one standard deviation higher VAM is more likely to move to a better school out-of-district after the policy takes effect, the point estimate is only 38% of that from moving within-district. Each estimate lies outside the 95% confidence interval of the other coefficient. Were outside principals informed of the signal, we would expect the same positive effects found in the second column of Panel A. This statistically significant finding of adverse selection of teachers moving away from GCS in addition to the significantly mitigated effects for those moving out of WSF evidences informational asymmetries between types of potential employers.

Turning to the implications of such mobility for educational equity in general, Table 3 presents the results of how the sorting of teachers to schools changes with the implementation of the policy. The coefficient on VAM describes the relationship between teachers' VAMs and the proficiency level of the school they teach at the subsequent year in the rest of the state prior to the policy adoption. Across both columns, a one standard deviation increase in a teacher's VAM leads to about a quarter of a percentage point increase in the percent of students who are proficient in the school he teaches at the subsequent year. The result that students in better schools also get better teachers is consistent with findings in Boyd et al. [2005, 2008].

Column 1 examines the effect of the policy on sorting for all teachers in the sample who remain teaching

Table 2: Changes in the correlation of VAMs with the probability of within- and out-of-district moves

	Panel A: Within-District Moves			Panel B: Out-Of-District Moves		
VARIABLES	Total	To a higher performing school	To a lower performing school	Total	To a higher performing school	To a lower performing school
VAM	0.0016	0.0032***	-0.0016*	0.0002	0.0014**	-0.0012**
	(0.00139)	(0.00091)	(0.00083)	(0.00084)	(0.00057)	(0.00050)
VAM x Treatment GCS	0.0058***	0.0051***	0.0007	-0.0103***	-0.0054***	-0.0049***
	(0.00168)	(0.00115)	(0.00091)	(0.00090)	(0.00061)	(0.00057)
VAM x Treatment WSF	0.0052***	0.0060***	-0.0008	0.0009	0.0023***	-0.0014***
	(0.00147)	(0.00094)	(0.00125)	(0.00084)	(0.00068)	(0.00051)
Treatment GCS	-0.0040	-0.0050	0.0010	-0.0162***	-0.0232***	0.0070***
	(0.00829)	(0.00608)	(0.00537)	(0.00402)	(0.00319)	(0.00214)
Treatment WSF	0.0555***	0.0475***	0.0080**	-0.0020	0.0147***	-0.0167***
	(0.00579)	(0.00417)	(0.00311)	(0.00258)	(0.00199)	(0.00184)
Observations	236,018	236,018	236,018	236,018	236,018	236,018

District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include district and year fixed effects.
Teacher covariates and their interactions with treatment are suppressed.

in North Carolina the following year. Column 2 restricts the sample to those who remain within their current district. The second column may be more informative as to what will happen in the rest of the state after the adoption of EVAAS VAMs becomes statewide, though it is possible that the effects may be more pronounced for the state as a whole, because the costs of moving out of state are higher than those of moving out of a school district. The difference in results from Table 2 between within- and out-of-district moves imply more positive correlations between teacher VAMs and school performance among those who remain in district than overall, as a result of the policy. Table 3 reflects those patterns. Overall, it seems that releasing VAMs of teacher effectiveness does little to change the distribution of teacher quality across schools. In column 2, while there is no evidence of sorting in general rising in GCS as a result of the policy, in WSF, on average I find a teacher with one standard deviation above VAM will be at a school that has 0.2 percentage points higher proficiency rates after the district releases VAMs. In WSF, this translates to about a 70% increase in the correlation between teacher quality and student performance as a result of the policy. This strong result for WSF taken together with the mobility patterns from Table 2 evidence rising inequality in the distribution of highly effective teachers as an unintended consequence of VAM adoption.

The final piece of analysis examines the effects of the policy on the correlation between teacher VAMs and the probability of moving with respect to years of experience and tenure. If teachers are able to draw

Table 3: Changes in the correlation of VAMs with the percent of students who are proficient in the school taught at the following year

VARIABLES	Total	Within District
VAM	0.0028***	0.0024***
	(0.00038)	(0.00036)
VAM x Treatment GCS	-0.0005	-0.0000
	(0.00038)	(0.00037)
VAM x Treatment WSF	0.0007	0.0017**
	(0.00070)	(0.00071)
Treatment GCS	-0.0195***	-0.0157***
	(0.00230)	(0.00234)
Treatment WSF	0.0290***	0.0231***
	(0.00172)	(0.00175)
Observations	209,424	202,943

District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include district and year fixed effects.
Teacher covariates and their interactions with treatment are suppressed.

upon each year of experience to better demonstrate how good they are through resumés or references, or any other device, the release of VAMs would not serve as much of a shock for teachers about whom there already exists a great deal of information. The model predicts that if there is substantial public learning prior to VAM adoption, the effects of the policy should be less dramatic for more experienced teachers. While Table 4 exhibits this relationship for teachers moving out of the district, the same is not true for teachers moving within district. Taking the point estimates literally, a teacher with 5 more years of experience and one standard deviation higher than average VAM is twice as likely to move within GCS to a better school after the release of VAM, than is an otherwise similar teacher. In WSF, the point estimates imply that better than average teachers only have a higher probability of moving to a better school after they have obtained more than 2 years of experience. While the observed pattern of stronger effect for more experienced teachers may seem strange, this pattern may occur if it takes time to realize that moving is worthwhile or if releasing VAMs allow a built up stock of more experienced teachers who could not previously signal their quality to move. From columns 3 and 4, in both districts, each additional year of experience mitigates the adverse selection of inexperienced teachers moving out of the district. For GCS and WSF, 5 years of additional experience cuts the effect of VAM on the probability of moving to a better school outside the district by 15 and 20%, respectively. The same general pattern holds with regard to interactions with tenure, though the standard errors on the coefficient estimates for interactions with tenure are larger. Were private learning already prevalent in the market, the model predicts the effects of the policy to be larger for those who have taught at the same school for longer, all else being equal. This is consistent with the results in columns 1 and 2. The fact that the effect of the policy is very similar regardless of whether a teacher is relatively more

Table 4: Differential effects with respect to experience and tenure

VARIABLES	Moves Within District: Total	Moves Within District: To higher performing schools	Moves Out of District: Total	Moves Out of District: To higher performing schools
VAM	-0.0001	0.0028*	-0.0001	0.0023
	(0.00219)	(0.00151)	(0.00232)	(0.00164)
Experience x VAM	-0.0000	0.0000	-0.0000	-0.0000
	(0.00012)	(0.00009)	(0.00009)	(0.00007)
Tenure x VAM	0.0020**	0.0006	0.0006	0.0005
	(0.00090)	(0.00060)	(0.00068)	(0.00053)
VAM x Treatment GCS	0.0033	0.0050***	-0.0181***	-0.0095***
	(0.00265)	(0.00177)	(0.00235)	(0.00167)
Experience x VAM x Treatment GCS	0.0016***	0.0010***	0.0002**	0.0003***
	(0.00014)	(0.00010)	(0.00011)	(0.00008)
Tenure x VAM x Treatment GCS	0.0056***	0.0004	0.0008	0.0014***
	(0.00090)	(0.00063)	(0.00065)	(0.00052)
VAM x Treatment WSF	-0.0003	-0.0010	-0.0073***	-0.0051***
	(0.00228)	(0.00125)	(0.00144)	(0.00114)
Experience x VAM x Treatment WSF	0.0003	0.0005***	0.0002**	0.0002***
	(0.00018)	(0.00014)	(0.00010)	(0.00008)
Tenure x VAM x Treatment WSF	0.0028***	0.0009***	0.0004	0.0004**
	(0.00047)	(0.00029)	(0.00022)	(0.00017)
Observations	236,018	236,018	236,018	236,018

District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include district and year fixed effects.
Teacher covariates and their interactions with treatment are suppressed.

experienced or tenured, provides little information as to which type of learning previously dominated the information landscape or whether either type of learning occurs.

6 Robustness

6.1 Sensitivity to VAM Construction

The possibility that teachers may have different VAMs after moving to other schools, may present issues for using VAMs constructed from student data from a teacher's entire career. This could result from moves leading to higher match quality between teachers and schools as Jackson [2013] finds. Consequently, in

Table 5: Results using all previous years in constructing VAMs

	Panel A: Within-District Moves			Panel B: Out-Of-District Moves			Panel C: Lead of % Proficient	
VARIABLES	Total	To a higher performing school	To a lower performing school	Total	To a higher performing school	To a lower performing school	Total	Within District
VAM	0.0003	0.0011	-0.0008	-0.0013	-0.0006	-0.0007	0.0005	0.0004
	(0.00115)	(0.00120)	(0.00065)	(0.00086)	(0.00064)	(0.00045)	(0.00034)	(0.00034)
VAM x Treatment GCS	0.0034***	0.0030***	0.0004	-0.0027***	-0.0016**	-0.0011**	-0.0015***	-0.0010**
	(0.00125)	(0.00115)	(0.00084)	(0.00100)	(0.00079)	(0.00054)	(0.00045)	(0.00041)
VAM x Treatment WSF	0.0061***	0.0099***	-0.0038***	0.0019**	0.0025***	-0.0005	0.0025***	0.0037***
	(0.00134)	(0.00143)	(0.00114)	(0.00095)	(0.00077)	(0.00059)	(0.00093)	(0.00093)
Treatment GCS	-0.0034	-0.0042	0.0008	-0.0137***	-0.0220***	0.0082***	-0.0196***	-0.0156***
	(0.00829)	(0.00600)	(0.00538)	(0.00397)	(0.00312)	(0.00216)	(0.00231)	(0.00235)
Treatment WSF	0.0555***	0.0486***	0.0068**	-0.0017	0.0151***	-0.0168***	0.0299***	0.0241***
	(0.00578)	(0.00417)	(0.00310)	(0.00259)	(0.00198)	(0.00185)	(0.00175)	(0.00177)
Observations	236,018	236,018	236,018	236,018	236,018	236,018	209,424	202,943

District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include district and year fixed effects.
Teacher covariates and their interactions with treatment are suppressed.

Table 4, I allow teachers VAM scores to vary each year, using only data from the current and previous years to construct a teacher i's VAM in year t. The main effects hold, though they are in general somewhat exaggerated in WSF and smaller in GCS. Still, the adoption of VAMs raises the probability that good teachers move to better schools. Whereas in WSF, the effect grows to a full percentage point, in GCS, a teacher with a VAM one standard deviation above the mean becomes 0.3 percentage points more likely to move to better school post-policy. From the middle column of Panel B, the adverse selection of teachers moving out of GCS falls to just 30% of the estimate given in Table 2. From Panel C, while the effect on teacher sorting doubles in WSF, the results become more negative and statistically significant in GCS. While it is possible subsequent match quality increases for teachers from GCS and decreases for teachers in WSF, I believe measurement error may provide a more plausible explanation. In GCS, the effect of VAM prior to the their release is identified off of just two years of data. As a result, the estimates of teachers VAMs are noisier for this period as well as in the immediate aftermath of the policy. Measurement error in the primary variable of interest may attenuate the estimates in GCS where there is little data prior to the adoption of the policy, while the effects in WSF become relatively stronger.

One way of getting around this issue is to use a fixed number of years prior to the current period when constructing VAMs. Unfortunately, the adoption of VAMs by GCS comes just three years into the student data sample. Since the construction of VAMs requires at least one prior year of student data, this gives just two years at which I could fix my VAM estimate. Not only would this force a noisier estimate of VAM for the entire sample, it also provides merely one year of data prior to the adoption of the policy in GCS.

Table 6: Effect of VAMs constructed using various number of years on the probability of moving to a school with a higher percentage of proficient students

VARIABLES	2yr VAM	3yr VAM	4yr VAM	5yr VAM	6yr VAM	7yr VAM	8yr VAM
VAM	0.0020***	0.0023***	0.0024***	0.0023**	0.0025***	0.0027***	0.0040***
	(0.00074)	(0.00061)	(0.00059)	(0.00092)	(0.00095)	(0.00090)	(0.00095)
VAM x Treatment WSF	0.0103***	0.0087***	0.0076***	0.0064***	0.0099***	0.0118***	0.0150***
	(0.00145)	(0.00131)	(0.00131)	(0.00168)	(0.00173)	(0.00167)	(0.00181)
Treatment WSF	0.0555***	0.0540***	0.0550***	0.0480***	0.0427***	0.0457***	0.0407***
	(0.00427)	(0.00425)	(0.00422)	(0.00439)	(0.00447)	(0.00488)	(0.00508)
Observations	207,673	189,531	170,598	151,067	131,567	111,786	94,884

District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include district and year fixed effects.
Teacher covariates and their interactions with treatment are suppressed.

To demonstrate the changes of the estimates with varying the number of years of data used in constructing VAMs, I drop GCS from the analysis and vary the number of prior years of data I use to construct the VAMs from 2 to 8. Table 6 demonstrates that though the relationship between years used and the effect of the interaction of the policy in WSF and VAM is not monotonic, as the sample used varies, the estimates using more years of data are clearly the largest.

6.2 Strategic Staffing

A possible complication arises due to district strategic staffing policies, which aim to attract more capable teachers to teach in and stay at hard-to-staff schools.[7] Charlotte-Mecklenburg School District (CMS) and WSF were by far the earliest adopters of these initiatives with CMS beginning its Equity Plus program in 1999 and WSF following suit in 2000. By 2012 each major district in North Carolina adopted some program to attract teachers to hard-to-staff schools. In CMS, teachers received a signing bonus to enter a targeted school and teachers with a masters degree could receive up to $2,500 per year to remain in the school. A smaller incentive was offered to teachers enrolled in masters programs though the district also offered tuition reimbursement. WSF awarded 20% of the district salary supplement ($500-$1,500) to each teacher in targeted schools. Furthermore the entire state offered $1,800 bonuses to math, science, and special education teachers who taught in high poverty or low achieving schools during the three year period 2002-2004. In 2007, Guilford adopted its own strategic staffing program, in which bonuses ranged from $5,000-$25,500 depending

[7]"Strategic Staffing" is the official term for later policies with the same objectives. Earlier policies had a variety of different names; Equity Plus (1 and 2), Focus School, Mission Possible

Table 7: Changes in the correlation of VAMs with the probability of within- and out-of-district moves to non-strategic staffing schools

	Panel A: Within-District Moves			Panel B: Out-Of-District Moves		
VARIABLES	Total	To a higher performing school	To a lower performing school	Total	To a higher performing school	To a lower performing school
VAM	0.0014	0.0031***	-0.0018**	0.0002	0.0013**	-0.0011**
	(0.00143)	(0.00092)	(0.00086)	(0.00084)	(0.00056)	(0.00050)
VAM x Treatment GCS	0.0043**	0.0041***	0.0002	-0.0111***	-0.0054***	-0.0057***
	(0.00169)	(0.00117)	(0.00091)	(0.00090)	(0.00060)	(0.00056)
VAM x Treatment WSF	0.0100***	0.0103***	-0.0004	-0.0007	0.0014**	-0.0021***
	(0.00140)	(0.00094)	(0.00104)	(0.00076)	(0.00066)	(0.00045)
Treatment GCS	-0.0118	-0.0084	-0.0034	-0.0158***	-0.0238***	0.0079***
	(0.00817)	(0.00601)	(0.00562)	(0.00397)	(0.00320)	(0.00199)
Treatment WSF	0.0241***	0.0390***	-0.0149***	-0.0027	0.0114***	-0.0141***
	(0.00579)	(0.00406)	(0.00318)	(0.00248)	(0.00195)	(0.00172)
Observations	236,018	236,018	236,018	236,018	236,018	236,018

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

on subject taught, grade level, and VAM. Cumberland County Schools gave stipends to 30 "master teachers" across their 10 most difficult school. In 2008, CMS began tailoring their plan more towards targeting better teachers and WSF, followed suit in 2012. These programs may reverse which schools are most desirable to teachers. With large enough incentives, high VAM teachers may opt to work at low performing school, which is in fact the intent of the policy.

Table 7 reports similar information as is provided in Table 2, with the difference that the binary dependent variable in Table 7 is equal to one if a move occurs and the receiving school is not classified as strategic staffing. As might be expected, the results are quite similar to those in Table 2, as teachers teaching in strategic staffing schools comprise just 4% of the sample. However, the policy has a much larger effect on the correlation between VAMs and the probability of moving within WSF. Column 2 shows that releasing VAMs raises the probability that a teacher with one standard deviation higher VAM will move within WSF by a full percentage point, which is nearly double the effect found when examining all schools together. Also, the effect of the policy on the correlation between VAMs and the probability of moving out of WSF drops by 40%, when restricting analysis to moves to non-strategic staffing schools. Both changes serve to widen the gap in the estimates between moves within and out of WSF, providing further evidence of private learning.

Table 8 presents the impacts of the policy on teacher sorting within-district and within-district among non-strategic staffing schools. Column 1 in Table 8 is identical to column 2 in Table 3. I include it here

Table 8: Changes in the correlation of VAMs with the percent of students who are proficient in the school taught at the following year considering separately teachers in and out of strategic staffing schools

VARIABLES	Total	Excluding Strategic Staffing Schools
VAM	0.0024***	0.0025***
	(0.00036)	(0.00037)
VAM x Treatment GCS	-0.0000	0.0002
	(0.00037)	(0.00039)
VAM x Treatment WSF	0.0017**	0.0066***
	(0.00071)	(0.00070)
Treatment GCS	-0.0157***	-0.0144***
	(0.00234)	(0.00244)
Treatment WSF	0.0231***	0.0269***
	(0.00175)	(0.00178)
Observations	202,943	194,497

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

for ease of comparison. The second and third columns restrict the sample further to non-strategic staffing and strategic staffing schools respectively. Moving from column 1 to 2, in both districts, the point estimated effect of the policy on the degree to which high VAM teachers sort into high performing schools becomes more positive. For GCS, the coefficient becomes positive, though neither practically nor statistically significantly so. In WSF, the point estimate of the sorting effects more than triple. Table 8 provides no evidence that strategic staffing policies are driving the earlier results.

7 Conclusion

If employers are unable to learn accurate information about their teaching force over time, their subsequent personnel decisions regarding teachers would be no better at identifying effective teachers than at the point of hire. If learning is entirely asymmetric, that is other schools are no better able to tell the effectiveness of an experienced applicant than of a novice applicant, effective teachers become trapped in schools in which they do not wish to teach, while principals shuffle their less capable teachers to other schools in what the 2010 documentary Waiting for Superman terms “The Lemon Dance.” The release of value-added measures of teacher effectiveness does seem to provide actionable information to those who are aware of them. The evidence above suggests that the new information provides effective teachers with more mobility, while “The Lemon Dance” becomes focused on the uninformed. Additionally, the evidence from subsequent teacher sorting suggests that the increase in mobility leads to increased inequity in the distribution of teacher quality across schools. While there is also evidence that such sorting may be mitigated with financial incentives, such a remedy is likely to be expensive.

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8 Appendix

8.1 Comparative Statics

$$P(M) = P[b^{*h} - b^{*r} > c_m] = P(M1)P(\overline{b^r_{sd}}) + P(M1)\left[1 - P(\overline{b^r_{sd}})\right]$$

$$P(\overline{b^r_{sd}}) = P\left[\frac{\sigma_t(t)\sigma_x(x)}{Z'}m + \frac{\sigma_t(t)\sigma_\mu}{Z'}R_x + \frac{2\sigma_\mu\sigma_x(x)}{Z'}P^r_t > \overline{b^r_{sd}}\right]$$

Type 1 Boundary Moves:

$P(M1) = P\left[\frac{\sigma_t(0)\sigma_x(x)}{Z}m + \frac{\sigma_t(0)\sigma_\mu}{Z}R_x + \frac{2\sigma_\mu\sigma_x(x)}{Z}P_0^h - \overline{b_{sd}^r} > c_m\right]$, where $Z = \sigma_t(0)\sigma_x(x) + \sigma_t(0)\sigma_\mu + 2\sigma_\mu\sigma_x(x)$

Comparative Statics:

$\frac{\partial P_{m1}}{\partial S} < 0$, $\frac{\partial P_{m1}}{\partial m} > 0$, $\frac{\partial P_{m1}}{\partial \mu} > 0$, and for teachers whose $\mu > m$, $\frac{\partial P_{m1}}{\partial x} > 0$

Type 2 Interior Moves:

$P(M2) = P\left[\frac{\sigma_t(0)\sigma_x(x)}{Z}m + \frac{\sigma_t(0)\sigma_\mu}{Z}R_x + \frac{2\sigma_\mu\sigma_x(x)}{Z}P_0^h - \left(\frac{\sigma_t(t)\sigma_x(x)}{Z'}m + \frac{\sigma_t(t)\sigma_\mu}{Z'}R_x + \frac{2\sigma_\mu\sigma_x(x)}{Z'}P_t^r\right) > c_m\right]$, where $Z' = \sigma_t(t)\sigma_x(x) + \sigma_t(t)\sigma_\mu + 2\sigma_\mu\sigma_x(x)$

$= P\{\frac{2\sigma_x(x)}{ZZ'}[(m-\mu)\sigma_x(x)(\sigma_t(0)-\sigma_t(t)) + (\sigma_\mu\sigma_t(t) + \sigma_x(x)\sigma_t(t) + 2\sigma_\mu\sigma_x(x))\tau_0$

$-(\sigma_\mu\sigma_t(0) + \sigma_x(x)\sigma_t(0) + 2\sigma_\mu\sigma_x(x))\tau_t + \sigma_\mu(\sigma_t(0)-\sigma_t(t))\xi] > 0\}$

Let $\psi \equiv (\sigma_\mu\sigma_t(t) + \sigma_x(x)\sigma_t(t) + 2\sigma_\mu\sigma_x(x))\tau_0 - (\sigma_\mu\sigma_t(0) + \sigma_x(x)\sigma_t(0) + 2\sigma_\mu\sigma_x(x))\tau_t + \sigma_\mu(\sigma_v - \sigma_t(t))\xi$, be the composite error term.

$P(M2) = P\left\{\psi - c_m > \sigma_x(x)[\sigma_t(0) - \sigma_t(t)](\mu - m)\right\}$

Under the assumptions that τ^r, τ^h and ξ are each orthogonal to one another,

$\sigma_\psi \equiv var(\psi)$

$= var[(\sigma_\mu\sigma_t(t) + \sigma_x(x)\sigma_t(t) + 2\sigma_\mu\sigma_x(x))\tau_0^h - (\sigma_\mu\sigma_t(0) + \sigma_x(x)\sigma_v + 2\sigma_\mu\sigma_x(x))\tau_t^r + \sigma_\mu(\sigma_t(0)-\sigma_t(t))\xi]$
$= \sigma_t(t)(\sigma_\mu\sigma_t(0) + \sigma_x(x)\sigma_t(0) + 2\sigma_\mu\sigma_x(x))^2 + \sigma_t(0)(\sigma_\mu\sigma_t(t) + \sigma_x(x)\sigma_t(t) + 2\sigma_\mu\sigma_x(x))^2 + \sigma_x(x)\sigma_\mu^2(\sigma_t(0) - \sigma_t(t))^2$

Assuming normality of the error terms,

$P(M2) = \Phi\left\{\frac{-1}{\sqrt{\sigma_\psi}}\left[\sigma_x(x)[\sigma_t(0) - \sigma_t(t)](\mu - m)\right]\right\}$

$= \Phi\left\{-\beta_{xt}(\mu - m)\right\}$

$\frac{\partial\sigma_\psi}{\partial x} = \frac{\partial\sigma_x(x)}{\partial x}\{2\sigma_t(t)[\sigma_\mu\sigma_t(0) + \sigma_x(x)\sigma_t(0) + 2\sigma_\mu\sigma_x(x)](\sigma_\mu + \sigma_t(0))$
$+2\sigma_t(0)[\sigma_\mu\sigma_t(t) + \sigma_x(x)\sigma_t(t) + 2\sigma_\mu\sigma_x(x)](\sigma_\mu + \sigma_t(t)) + \sigma_\mu^2(\sigma_t(0) - \sigma_t(t))^2\}$.

Under the assumptions that $\sigma_t(0) > \sigma_t(t)$, pivotal to asymmetric learning and $\frac{\partial\sigma_x(x)}{\partial x} < 0$, which is key to employer learning in general, $\frac{\partial\sigma_\psi}{\partial x} < 0$

$\frac{\partial\sigma_\psi}{\partial t} = \frac{\partial\sigma_t(t)}{\partial t}\{[\sigma_\mu\sigma_t(0) + \sigma_x(x)\sigma_t(0) + 2\sigma_\mu\sigma_x(x)]^2$
$+2\sigma_t(0)[\sigma_\mu\sigma_t(t) + \sigma_x(x)\sigma_t(t) + 2\sigma_\mu\sigma_x(x)](\sigma_\mu + \sigma_x(x)) - 2\sigma_x(x)\sigma_\mu^2(\sigma_t(0) - \sigma_t(t))\}$
$= \frac{\partial\sigma_t(t)}{\partial t}\{[\sigma_\mu\sigma_t(0) + \sigma_x(x)\sigma_t(0) + 2\sigma_\mu\sigma_x(x)]^2 + 2\sigma_t(0)\sigma_\mu[\sigma_\mu\sigma_t(t) + \sigma_x(x)\sigma_t(t) + 2\sigma_\mu\sigma_x(x)]$
$+2\sigma_x(x)\sigma_t(0)[\sigma_\mu\sigma_t(t) + \sigma_x(x)\sigma_t(t) + \sigma_\mu\sigma_x(x)] + 2\sigma_x(x)\sigma_\mu^2\sigma_t(t)\}$

Under the assumptions that $\frac{\partial\sigma_t(t)}{\partial t} < 0$, which is key to asymmetric employer learning, $\frac{\partial\sigma_\psi}{\partial t} < 0$

Time dynamics: Change in Coefficients

$\frac{\partial -\beta_{xt}}{\partial t} = (-1)\left[\frac{\partial\sigma_\psi}{\partial t}\left(-\frac{1}{2}\right)\sigma_\psi^{-\frac{3}{2}}\sigma_x(x)[\sigma_t(0) - \sigma_t(t)] + (-1)\,\sigma_\psi^{-\frac{1}{2}}\sigma_x(x)\frac{\partial\sigma_t(t)}{\partial t}\right] < 0$, under the previous assumptions.

$\frac{\partial -\beta_{xt}}{\partial x} = (-1)\left[\frac{\partial\sigma_\psi}{\partial x}\left(-\frac{1}{2}\right)\sigma_\psi^{-\frac{3}{2}}\sigma_x(x)[\sigma_t(0) - \sigma_t(t)] + \sigma_\psi^{-\frac{1}{2}}\left[\sigma_t(0) - \sigma_t(t)\right]\frac{\partial\sigma_x(x)}{\partial x}\right]$

To evaluate the sign we compare $\frac{\frac{\partial\sigma_\psi}{\partial x}}{\frac{\partial\sigma_x(x)}{\partial x}}\left(\frac{\sigma_x(x)}{2\sigma_\psi}\right) \gtreqless 1$

After some algebra the provides;

$\frac{1}{2}\sigma_\mu^2\sigma_x(x)[\sigma_t(0) - \sigma_t(t)] + 5\sigma_t(t)\sigma_t(0)\sigma_\mu\sigma_x(x)^2 + \sigma_t(t)\sigma_t(0)^2\sigma_\mu^2 + 7\sigma_t(t)\sigma_t(0)\sigma_\mu^2\sigma_x(x)$
$+\sigma_t(t)\sigma_t(0)^2\sigma_x(x)^2 + \sigma_t(t)\sigma_t(0)^2\sigma_\mu\sigma_x(x) + 4\sigma_t(t)\sigma_\mu^2\sigma(x)^2 + \sigma_t(0)\sigma_\mu^2\sigma_t(t)^2$
$+\sigma_x(x)\sigma_t(0)\sigma_\mu\sigma_t(t)^2 + 2\sigma_I\sigma_\mu^2\sigma_x(x)^2 > 0$

This means that a shock to the precision of the public signal increases the probability that a teachers whose $\mu > m$, will move jobs.

8.2 Robustness: Year interactions with VAM

The primary threat to validity for difference-in-difference analysis is differential trends. The tables below provide year interactions with the VAM within both treatment districts as well as the rest of the state. While the estimates are too noisy to say anything conclusive, the pre-policy trends do not seem diverge in a way that would bias up my results. It is also noteworthy that is both districts there is a spike in the correlation of VAM with the probability of moving within-district soon after the policy takes effect.

Table 9: The effect of VAM on the probability of moving schools within-district by year.

	Total			To a more proficient school		
VARIABLES	Rest of NC	GCS	WSF	Rest of NC	GCS	WSF
year 1998 x VAM	0.0009	0.0012	0.0043	0.0021*	0.0006	-0.0003
	(0.00146)	(0.00709)	(0.00812)	(0.00109)	(0.00563)	(0.00630)
year 1999 x VAM	0.0022	0.0023	-0.0001	0.0044***	0.0048	0.0041
	(0.00148)	(0.00687)	(0.00849)	(0.00111)	(0.00545)	(0.00658)
year 2000 x VAM	0.0035**	0.0205***	-0.0007	0.0023**	0.0155***	-0.0042
	(0.00156)	(0.00656)	(0.00973)	(0.00117)	(0.00521)	(0.00754)
year 2001 x VAM	0.0019	0.0048	-0.0020	0.0035***	0.0030	0.0012
	(0.00149)	(0.00693)	(0.00880)	(0.00111)	(0.00550)	(0.00682)
year 2002 x VAM	0.0035**	-0.0044	0.0024	0.0055***	-0.0011	0.0107
	(0.00177)	(0.00809)	(0.01075)	(0.00132)	(0.00643)	(0.00833)
year 2003 x VAM	0.0004	-0.0054	0.0041	0.0027**	-0.0013	0.0042
	(0.00180)	(0.00860)	(0.01001)	(0.00134)	(0.00683)	(0.00776)
year 2004 x VAM	0.0010	0.0020	-0.0088	0.0016	-0.0073	-0.0043
	(0.00207)	(0.01046)	(0.01180)	(0.00155)	(0.00831)	(0.00914)
year 2005 x VAM	0.0015	0.0128	-0.0160	0.0040**	0.0190**	-0.0080
	(0.00237)	(0.01190)	(0.01181)	(0.00177)	(0.00945)	(0.00915)
year 2006 x VAM	0.0047***	0.0169*	0.0100	0.0055***	0.0158**	0.0037
	(0.00174)	(0.00912)	(0.00992)	(0.00130)	(0.00724)	(0.00769)
year 2007 x VAM	0.0027	0.0189**	-0.0133	0.0039***	0.0147**	-0.0078
	(0.00184)	(0.00867)	(0.01055)	(0.00137)	(0.00688)	(0.00818)
year 2008 x VAM	0.0029	0.0057	0.0005	0.0032**	0.0114*	0.0019
	(0.00177)	(0.00842)	(0.01057)	(0.00132)	(0.00668)	(0.00819)
year 2009 x VAM	0.0034	0.0036	0.0110	0.0032**	0.0046	0.0173
	(0.00214)	(0.01094)	(0.01374)	(0.00160)	(0.00868)	(0.01065)
year 2010 x VAM	-0.0001	0.0123	0.0002	0.0009	0.0121	0.0004
	(0.00188)	(0.00947)	(0.01185)	(0.00141)	(0.00752)	(0.00918)
Observations	216,484	11,239	8,295	216,484	11,239	8,295

District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include year effects.
Analysis only uses data from the geographic area defined in the heading.
Teacher covariates and their interactions with treatment are suppressed.

Table 10: The effect of VAM on the probability of moving schools out-of-district by year.

	Total			To a more proficient school		
VARIABLES	Rest of NC	GCS	WSF	Rest of NC	GCS	WSF
year 1998 x VAM	0.0017	0.0098**	-0.0079*	0.0023***	0.0076**	-0.0059
	(0.00111)	(0.00476)	(0.00475)	(0.00085)	(0.00363)	(0.00391)
year 1999 x VAM	-0.0004	0.0065	-0.0026	0.0011	0.0064*	-0.0033
	(0.00112)	(0.00460)	(0.00497)	(0.00086)	(0.00352)	(0.00409)
year 2000 x VAM	0.0006	0.0013	0.0063	0.0015*	0.0033	0.0033
	(0.00118)	(0.00440)	(0.00569)	(0.00091)	(0.00336)	(0.00469)
year 2001 x VAM	-0.0022*	0.0025	-0.0069	-0.0005	0.0063*	-0.0070*
	(0.00113)	(0.00465)	(0.00515)	(0.00087)	(0.00355)	(0.00424)
year 2002 x VAM	-0.0033**	-0.0025	0.0106*	0.0000	0.0015	0.0146***
	(0.00134)	(0.00543)	(0.00629)	(0.00103)	(0.00414)	(0.00518)
year 2003 x VAM	-0.0011	-0.0016	-0.0141**	0.0017	-0.0004	-0.0091*
	(0.00136)	(0.00577)	(0.00586)	(0.00105)	(0.00440)	(0.00482)
year 2004 x VAM	-0.0037**	0.0099	0.0054	-0.0005	0.0080	0.0092
	(0.00157)	(0.00701)	(0.00690)	(0.00121)	(0.00535)	(0.00568)
year 2005 x VAM	-0.0001	-0.0038	-0.0024	0.0011	0.0033	-0.0005
	(0.00180)	(0.00798)	(0.00691)	(0.00138)	(0.00609)	(0.00569)
year 2006 x VAM	-0.0011	-0.0095	-0.0001	0.0017	-0.0018	-0.0013
	(0.00132)	(0.00612)	(0.00581)	(0.00102)	(0.00467)	(0.00478)
year 2007 x VAM	-0.0016	-0.0223***	0.0011	0.0003	-0.0040	0.0063
	(0.00139)	(0.00581)	(0.00617)	(0.00107)	(0.00444)	(0.00508)
year 2008 x VAM	-0.0017	-0.0079	-0.0054	0.0006	0.0001	-0.0000
	(0.00134)	(0.00564)	(0.00618)	(0.00103)	(0.00431)	(0.00509)
year 2009 x VAM	0.0006	-0.0023	0.0047	-0.0004	0.0000	0.0047
	(0.00162)	(0.00733)	(0.00804)	(0.00125)	(0.00560)	(0.00662)
year 2010 x VAM	-0.0021	-0.0058	-0.0011	-0.0006	-0.0054	-0.0011
	(0.00143)	(0.00635)	(0.00693)	(0.00110)	(0.00485)	(0.00571)
Observations	216,484	11,239	8,295	216,484	11,239	8,295

District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include year effects.
Analysis only uses data from the geographic area defined in the heading.
Teacher covariates and their interactions with treatment are suppressed.

Table 11: The effect of VAM on teacher sorting within-district by year.

VARIABLES	Rest of NC	GCS	WSF
year 1998 x VAM	0.0025***	0.0045**	-0.0014
	(0.00034)	(0.00177)	(0.00215)
year 1999 x VAM	0.0026***	0.0013	0.0021
	(0.00035)	(0.00176)	(0.00217)
year 2000 x VAM	0.0019***	0.0041**	0.0007
	(0.00037)	(0.00170)	(0.00253)
year 2001 x VAM	0.0051***	0.0038**	0.0077***
	(0.00036)	(0.00178)	(0.00234)
year 2002 x VAM	0.0046***	0.0031	0.0072**
	(0.00041)	(0.00200)	(0.00281)
year 2003 x VAM	0.0031***	0.0043**	0.0052**
	(0.00041)	(0.00208)	(0.00265)
year 2004 x VAM	0.0023***	-0.0006	0.0005
	(0.00047)	(0.00252)	(0.00298)
year 2005 x VAM	0.0102***	0.0109***	0.0096***
	(0.00053)	(0.00302)	(0.00296)
year 2006 x VAM	0.0047***	0.0009	-0.0014
	(0.00040)	(0.00234)	(0.00259)
year 2007 x VAM	0.0046***	0.0049**	0.0031
	(0.00042)	(0.00212)	(0.00283)
year 2008 x VAM	0.0016***	0.0031	0.0005
	(0.00040)	(0.00213)	(0.00282)
year 2009 x VAM	-0.0003	0.0055**	0.0053
	(0.00048)	(0.00258)	(0.00351)
year 2010 x VAM	0.0033***	0.0050**	0.0045
	(0.00042)	(0.00224)	(0.00302)
Observations	185,977	9,616	7,350

District clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
All regressions include year effects.
Analysis only uses data from the geographic area defined in the heading.
Teacher covariates and their interactions with treatment are suppressed.