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Title
Public and Private Employer Learning: Evidence from the Adoption of Teacher Value Added

Permalink
https://escholarship.org/uc/item/8qf6611b

Journal
Journal of Labor Economics, 38(2)

ISSN
0734-306X

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Publication Date
2020-04-01

DOI
10.1086/705881

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Public and Private Employer Learning: Evidence from the Adoption of Teacher Value-Added

Michael Bates

January 22, 2019

Abstract

Informational asymmetries between employers may inhibit optimal worker mobility. However, researchers rarely observe shocks to employers' information. I exploit two school districts' adoptions of value-added (VA) measures of teacher effectiveness, informational shocks to some, but not all, employers, to provide direct tests of asymmetric employer learning. I develop a learning model and test its predictions for teacher mobility. I find that adopting VA increases within-district mobility of high-VA teachers, while low-VA teachers move out-of-district to uninformed principals. These patterns are consistent with asymmetric employer learning. This sorting from widespread VA adoption exacerbates inequality in access to effective teaching.

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1 Introduction

Incomplete information inhibits the market from achieving the optimal allocation of workers across employers (Spence, 1973; Jovanovic, 1979; Farber and Gibbons, 1996; Altonji and Pierret, 2001). While a large literature focuses on informational asymmetries between workers and employers, Waldman (1984) and Greenwald (1986) gave rise to another literature focusing on asymmetric information between current and prospective employers. If the current employer enjoys an informational advantage over other prospective employers, it becomes a monopsonist of that information, permitting persistent gaps between workers' wages and their marginal products of labor (Milgrom and Oster, 1987). Furthermore, workers may not flow to the human capital investments, positions, or employers at which they would be most productive (Waldman, 1984; Greenwald, 1986; Chang and Wang, 1996; Waldman and Zax, 2016).

Despite these important implications and the intuitive appeal of the theory, the existing evidence is mixed (Schönberg, 2007; Pinkston, 2009; DeVaro and Waldman, 2012; Kahn, 2013). Further, it is limited by an absence of direct measures of productivity, and more importantly, a lack of exogenous variation in the informational landscape in which employers operate. This work seeks to fill this gap. I use the release of worker-level performance data to some–but not all–employers as a unique natural experiment to test the degree to which the information spreads among employers.

I develop a model of public and private employer learning in the context of the market for middle and elementary school teachers. I then use statewide, micro-level, administrative data from North Carolina to formulate value-added (VA) measures of teacher productivity.[1] Lastly, I exploit the adoption of teacher VA by two of the largest school districts in the state, which provides an asymmetric shock to employers' information sets, to provide a direct test of asymmetric employer learning. Thus, this setting allows me to disentangle employer learning from other forms of human capital accumulation.

The adoption of VA in North Carolina provides a context with rich informational variation to examine employer learning. Each of the two large districts that adopted VA did so in different ways and separately from the rest of the state. This provides three different informational landscapes: one in Guilford County Schools (to be referred to as Guilford), where the teacher, the current (or retaining) principal, and any hiring principal within the district were given direct access to the teacher's VA; one in Winston-Salem/Forsyth Community Schools (to be referred to as Winston-Salem), in which only teachers and their current

[1] VA measures how much a teacher's students learn in comparison to how much they are expected to learn. I do not have access to the exact VA issued to teachers and principals. I estimate teacher VA using multiple methods. The primary specification estimates teacher fixed effects in the regression of student test scores on student covariates including past test scores. Results are robust to alternative formulations of VA.

principals received value-added reports; and lastly, in the rest of the state, where the information structure remained relatively constant. Examining how the relationship between teacher quality and teacher mobility changes within and across these settings reveals the degree to which VA provided meaningful information, and the degree to which it spread throughout the market.

The model provides two primary predictions for teacher mobility. If VA measures are informative, they provide teachers with a signal of their ability. Thus, the model predicts that VA measures increase the likelihood that effective teachers move from one school to another within the districts where the signals are public. If the information spreads easily through the market there should be no difference between the impacts of VA for moves within-district and out of Guilford or Winston-Salem. However, if retaining principals keep teachers' VA measures private, ineffective teachers may become more likely to move out-of-district after retaining principals receive their VA. Thus, the asymmetric employer learning model predicts adverse selection of teachers out-of-district.

Understanding informational asymmetries in the teacher labor market is also important in its own right, as there are currently an estimated 3.1 million teachers employed in the United States (NCES, 2016). Further, prior work finds that effective teachers have large, meaningful impacts on the lives of their students, though there is wide variation in the teachers' ability to do so (Chetty et al., 2011, 2014). While Staiger and Rockoff (2010) and Rivkin et al. (2005) illustrate the difficulty in identifying effective teachers at the point of hire, Jacob and Lefgren (2008); Chingos and West (2011); and Rockoff et al. (2012) each present evidence of principals learning about the quality of their teaching force. However, there is little understanding of how much of that information spreads to principals of other schools nor how widespread changes in available information about teacher quality may change teacher mobility.

In the teacher labor market, wage rigidities force the market to clear on other amenities, such as schools that are closer in proximity to their homes, higher performing, and for white teachers, schools with a lower percentage of black students (Boyd et al., 2008; Jackson, 2009; Boyd et al., 2013). Consequently, if VA signals provide effective teachers with more choice over where to teach, prior estimates of average teacher preferences suggest that such choice will lead to increased mobility of high-performing teachers to higher-performing schools. Such mobility may exacerbate the divide in access to high-quality education. This work provides the first examination of whether the release of VA leads to further sorting of teachers to schools. Rising inequity may be an important consequence of the policy that has been previously overlooked.

Using differences-in-differences analysis, I find that by releasing VA measures to teachers and principals, both districts increase the probability that high-VA teachers will move within district, particularly to higher-performing schools. Specifically, I estimate that the release of VA increases the probability that a teacher with a one standard deviation higher VA moves within-district to higher-performing schools by about 10 percent. This suggests that VA provided new public information into those markets.

Second, I find that the selection of mobile teachers due to adopting VA is less positive for teachers moving to schools outside of Guilford and Winston-Salem. The policy leads teachers who have a standard deviation lower VA to become roughly 30 percent more likely to move from Guilford to a school in the rest of the state. In Winston-Salem, the effect of the policy on the probability that a high-VA teacher moves schools is 60 percent smaller for teachers moving out-of-district than it is for teachers moving within-district.

This work contributes to a growing literature, which uses models of asymmetric employer learning to explain empirical facts, such as wage dynamics with respect to job tenure versus experience, variability of wages after a job loss, and selection of displaced, mobile, or promoted workers on easy or difficult to observe characteristics (Gibbons and Katz, 1991; Acemoglu and Pischke, 1998; Schönberg, 2007; Zhang, 2007; Pinkston, 2009; DeVaro and Waldman, 2012; Kahn, 2013; Bognanno and Melero, 2016; Cassidy et al., 2016). Though some of the evidence from these studies is mixed, the results are largely supportive of asymmetric employer learning playing an important role within labor markets. However, many of these empirical facts may be explained by alternative explanations (see Krashinsky (2002) and Song (2007) for examples).

These tests are mostly predicated on the theory from Greenwald (1986) that low-performing workers are more likely to change employers when asymmetries are large.[2] I offer more comprehensive tests of this fundamental hypothesis by examining whether selection of mobile workers becomes more advantageous where the information in the market becomes more symmetric, and whether selection of mobile workers becomes more adverse where informational presumably asymmetries grow. The fact that after districts released VA, I find that selection of mobile teachers became more positive to principals with access to the information and much smaller effects and even negative selection for moves to those without direct access to the VA measures is consistent with asymmetric employer learning. While the evidence from selection on observable characteristics is mixed, the fact that teachers with more tenure are the most responsive to the policy within-district offers further corroboration of the theory of asymmetric employer learning.

[2]Though closely related, DeVaro and Waldman (2012), Bognanno and Melero (2016), and Cassidy et al. (2016) provide exceptions in testing extensions of Waldman (1984). Consistent with the theory, in general they find that more educated workers, even after controlling for performance, are more likely to be promoted, though they receive smaller wage increases with promotion than their less educated counterparts.

This rising mobility of effective teachers to high-performing schools evidences an important unintended consequence of adopting VA: namely, rising inequality in the distribution of teacher quality across schools. These results are reinforced with similar teacher mobility away from schools with higher shares of black students. Further, I find that the variance of teacher-effectiveness across schools grows in VA-adopting districts, and I also find evidence that VA-adoption may lead to increased growth in school performance for high-VA teachers. Given that 38 states currently require teacher evaluations to incorporate teachers' impacts on student achievement on standardized exams, this threat to educational equity is an important and perhaps widespread consequence of the policy that has been previously overlooked.

2 Setting

Shocks to the information available on workers' productivity are rare. Shocks to the information of some, but not all, employers in a market are rarer still. I describe the details of each adoption of VA by two large school districts in North Carolina below. Hiring principals in the two adopting districts gain additional information about the teachers in the district, whereas hiring principals in outside districts generally do not. To my knowledge, this allows for the first study directly testing a general model of public and private learning by exploiting information shocks to a large, important labor market.

Guilford County Schools (Guilford) contracted with the statistical software company SAS to receive teacher Education Value-Added Assessment System (EVAAS) measures of teacher effectiveness in 2000. These measures are based on the model developed by Sanders et al. (1997) under the name "Tennessee Value-Added Assessment System" (TVAAS). The adoption of VA by Guilford accompanied the transition of TVAAS to EVAAS, as the system came under the management of SAS, which began at North Carolina State University. The district gave teachers, principals, and hiring principals within the district direct access to teacher VA measures. Consequently for moves within Guilford, the introduction of VA provides a shock to the public information.

The rest of the state of North Carolina adopted EVAAS measures of school effectiveness in 2008. Winston-Salem/Forsyth Community Schools (Winston-Salem) took an additional step, providing SAS with the student-teacher matches necessary to receive the same teacher specific measure of effectiveness already present in Guilford. In Winston-Salem, only the teachers and their own principals directly received the VA reports. The VA measures were not directly given to principals at other schools in the district.

However, the introduction of VA in Winston-Salem is theoretically also public. As in Grossman (1981) and Milgrom (1981), each teacher contemplating moving within the district has as incentive to voluntarily disclose his score. Because all principals in the district know that the VA exists, if a teacher chooses not to reveal his score, according to theory, hiring principals within the district assume that he is as good as the average teacher who chooses not to reveal his score. Consequently, all teachers with scores above that average have an incentive reveal their scores. The average score of those who do not disclose drops until only teachers with scores at the minimum are indifferent between revealing and keeping the information private. If teachers and principals act as predicted, all teachers voluntarily disclose their EVAAS reports, and VA alters the information available to both retaining and hiring principals within Winston-Salem, just as they do in Guilford.

In contrast, hiring principals in the rest of the state are not directly informed that the VA measures exist for teachers from Guilford or Winston-Salem. This informational asymmetry may be avoided by non-adopting-district principals thoroughly researching from where their applicants are coming. However, such acquisition of information about other districts' personnel policies induces as additional cost, and principals may forgo it. If an out-of-district hiring principal is uniformed of the measure, then a teacher from Guilford or Winston-Salem may decide whether to make the signal private or public. In which case, high-VA teachers may continue to reveal their VA. However, a teacher may strategically withhold disclosure, if the VA score is lower than what he expects principals would otherwise infer about his ability. Thus, the key difference between moves from and within Guilford and Winston-Salem is that some teachers moving from a treatment district may withhold their signals and leave the principal's expectation of their abilities unchanged. In contrast, every principal within the VA-adopting districts can infer a low VA from teachers' refusal to reveal their VA.

Further, principals in both Guilford and Winston-Salem received training about VA measures. Consequently, in the case that a teacher did reveal his VA to an outside principal, the VA would likely serve as a more salient signal for principals within the district than for those in the rest of the state. Out-of-district hiring principals may have placed particularly low weight on the measure early in Guilford's adoption of VA. Guilford contracted with SAS just two years after the creation of the EVAAS system, and two years before the passage of No Child Left Behind. At that time, VA were largely absent from education policy discussions. The salience of the signal was likely less of an issue for teachers moving from Winston-Salem, considering school-level EVAAS measures were implemented across the entire state the same year. This may lead the differences between within and out-of-district moves to be more pronounced for Guilford than they are for teachers leaving Winston-Salem.

3 Model

This section provides a theoretical framework characterizing how employers and employees respond to public or private information shocks about worker productivity. Principals with VA information can estimate the true effectiveness of a teacher with more accuracy than without the VA information. The implications of the introduction of VA for teacher mobility depend on the following: 1) whether the information is common across employers or is privately held by current principals, and 2) teacher characteristics including the true effectiveness of the teacher. In order to better understand the potential consequences associated with teacher VA, I integrate discrete information shocks into an asymmetric employer learning model, similar to Pinkston (2009). Below, I present the setup of the model and the general predictions. Specific details of the model are in Appendix 8.1.

3.1 Structure

There are two broad classifications of principals: those who are hiring (denoted by the superscript h); and those who are retaining teachers (denoted by the superscript r). Each period, teachers receive two offers, and move to schools that maximize their utility net of a fixed cost to moving.[3] Each subsequent period, teachers receive an offer from their retaining principal and an outside offer from a principal either within or outside of the current district with a given probability.[4] These offers reflect principals' expectations about the effectiveness of the teacher, which is based upon the information available.

As in the prior employer learning literature, I assume that teachers know their effectiveness (μ), but cannot credibly reveal it. As a teacher begins his career, all principals begin with the prior belief that he is as good as the average teacher with his same easily-observable characteristics (m). Through the application process, the teacher may privately (but noisily) signal his ability akin to an interview (denoted by P_0^h where 0 indicates no additional private information), allowing the principals to update their priors.

Over time, teachers may draw on their experiences to bolster their public signals denoted by R_x (resumés for example). If there is public learning, the variance of the public signal will shrink with teacher experience (x), as more information comes into the market.

The longer a teacher teaches within the school (t), through interactions, observations, and/or attention to outcomes, retaining principals may obtain private information unavailable to rival employers (P_t^r). If such private learning occurs, the variance of the retaining principal's signal decreases in time at the school, while hiring principals' private signals from

[3]The restriction of the number of principals is for simplification. Without this restriction, the number of principals will shrink during the bidding to the final two with the highest valuation. Allowing for more principals opens the possibility that the retaining principal is not among the final two bidders. However, I show that predictions are consistent in these cases in Appendix 8.1.12.

[4]Principals face rigid budget constraints, which translate to a fixed number of positions.

interviewing the teacher have a constantly high variance. Thus, the accumulation of private information leads current principals to receive more precise private signals than other principals.

VA enters the learning model as an additional piece of information influencing either the public or private signal. VA influences the public signal if it is accessible to both principals. As in standard Bayesian updating, the new public signal ($R_{x\nu}$) is the precision-weighted average of the old public signal (R_x) and the new VA information (V). If VA is only accessible to retaining principals, it instead enters their private signals (P^r_{tV}), updating the private signal in a similar manner.

I summarize the information structure below:

1. True effectiveness is not observable to employers, but is given by, $\mu = m + \epsilon$, where $\epsilon \sim N(0,\ \sigma_\epsilon)$ and m is observable and is the mean productivity among a worker's reference group.

2. The public signal is given by $R_x = \mu + \xi_x$, where $\xi_x \sim N(0, \sigma^2_\xi(x))$, and $\frac{\partial \sigma^2_\xi(x)}{\partial x} < 0$.

3. Private signal:

    (a) For hiring principals, the private signal is given by$P^h = \mu + \tau^h$ where $\tau^h \sim N(0, \sigma^2_\tau(0))$. $\sigma^2_\tau(0)$ is fixed over time.

    (b) For a retaining principal, the private signal is given by $P^r_t = \mu + \tau^r_t$ where $\tau^r_t \sim N(0, \sigma^2_\tau(t))$ and $\frac{\partial \sigma^2_\tau(t)}{\partial t} < 0$.

4. VA ($V = \mu + \nu$, where $\nu \sim N(0, \sigma^2_\nu)$) provides additional information that may alter the mean and variance of the public or private signal depending on whether it is available to both bidding principals.

    (a) When VA is public, the public signal becomes $R_{x\nu} = \frac{\sigma^2_\nu R_x + \sigma^2_\xi(x) V}{\sigma^2_\nu + \sigma^2_\xi(x)}$. The variance of $R_{x\nu}$ is denoted as $\sigma^2_{\xi V}(x)$.

    (b) When VA is private, the retaining principal's private signal becomes $P^r_{t\nu} = \frac{\sigma^2_\nu P^r_t + \sigma^2_\tau(t) V}{\sigma^2_\nu + \sigma^2_\tau(t)}$. The variance of $P^r_{t\nu}$ is denoted as $\sigma^2_{\tau V}(t)$.

5. $\rho^s < 1$ is a school-level, proportional constraint on principals' bids reflecting school heterogeneity. In expectation, ρ^s is increasing in school desirability (S^s) $\left[\frac{\partial E(\rho^s)}{\partial S^s} > 0\right]$.

6. $c \sim N(0, \sigma^2_c)$ represents an idiosyncratic cost paid by the teacher of moving schools.

7. The noise of each signal is orthogonal to the noise of the other signals.[5]

[5]The orthogonality assumptions are not necessary to derive the following predictions. However, relaxing these require a less restrictive, though more complicated set of assumptions, outlining the direction and magnitude of correlations between the errors of the signals. I relax this assumption is appendix 8.1.13.

3.2 Bidding

The teacher labor market generally moves in the summer between school years.[6] At that time, teachers may sample two offers, an update from their current school and one outside offer. In many public education systems, strict salary schedules determine teachers' pay. In North Carolina, the state sets a base salary schedule that depends exclusively upon easily-observable characteristics, such as education and experience.[7] Districts supplement this base amount with a percentage of the base schedule. In general, this means that principals cannot differentially pay teachers within their school on the basis of perceived performance.[8] 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.[9]

Under such a rigid pay regime, the market clears on other amenities. To respect this environment, I model total compensation as the normalized sum of salary set by the district, characteristics of the school, and characteristics of the position. I assume that teachers take the position that offers the highest total compensation net of an idiosyncratic cost of moving (c).[10] Non-pecuniary, position-specific attributes are not typically observable in available data. As a result, empirically I use differences in school characteristics (for instance moves to higher-performing schools, which prior work shows teachers typically prefer) to proxy for moves to higher total compensation.[11]

For tractability, I model bidding as principals openly offering continuous bids in total compensation, as in a standard English auction.[12] Hiring principals make an offer for a teacher to which the retaining principal may counter. Counter offering continues until one principal drops out. The remaining principal hires (or retains) the teacher at the total compensation at which the rival principal conceded, paying essentially the second highest price. This framework is similar to that used in Pinkston (2009), and permits the adoption of optimal bidding strategies from Milgrom and Weber (1982). To summarize the intuition

[6] In both Guilford and Winston-Salem there is a transfer window that allows district employees to apply for other positions within the district in the spring prior to the jobs being posted publicly, thus facilitating within-district transfers (WSF, 2001; GCS, 2005). However, the job transition still occurs during the summer.

[7] As of 2014, North Carolina will move to paying teachers in part based upon teachers' VA.

[8] In Section 6, I discuss policy exceptions to this in North Carolina school districts.

[9] Painter (2000) states that principals reference additional mandatory meetings as their most frequent response to low-performing teachers who are difficult to remove. Ladd and Zelli (2002) notes that in North Carolina at this time principals reported discretion to allocate resources across classrooms and remove teachers.

[10] The costs of moving may also take the form of idiosyncratic teacher preferences over moving.

[11] Boyd et al. (2008); Jackson (2009), and Boyd et al. (2013) provide evidence the teachers in general prefer to teach in higher performing schools.

[12] In appendix 8.1.13, I show that the predictions of the model do not hinge on this particular bidding structure. In fact, earlier drafts adopt a more restrictive second price second auction bidding structure. The predictions are consistent in both environments.

from Milgrom and Weber (1982) and adapt it to this setting, initially each principal offers her expectation of the teacher's effectiveness.[13] Principals formulate these expectations by averaging over the signals they receive (initially just m, R_x, and P_0^h or P_t^r). After viewing a rival's bid, she then updates her own expectation, incorporating the knowledge that her rival's private signal is at least as high as her own. She consequently affords her private signal double weight in her subsequent bid. I list the optimal bid of a hiring principal (b_{NV}^{h*}) in equation 1, where $Z_{NV}^h = \sigma_\tau^2(0)\sigma_\xi^2(x) + \sigma_\tau^2(0)\sigma_\epsilon^2 + 2\sigma_\epsilon^2\sigma_\xi^2(x)$. A retaining principal's bid (b_{NV}^{r*}) is given by equation 2, where $Z_{NV}^r = \sigma_\tau^2(t)\sigma_\xi^2(x) + \sigma_\tau^2(t)\sigma_\epsilon^2 + 2\sigma_\epsilon^2\sigma_\xi^2(x)$. The subscript NV indicates that the principal does not receive the teacher's VA.

$$b_{NV}^{h*} = \frac{\sigma_\tau^2(0)\sigma_\xi^2(x)}{Z_{NV}^h} m + \frac{\sigma_\tau^2(0)\sigma_\epsilon^2}{Z_{NV}^h} R_x + \frac{2\sigma_\epsilon^2\sigma_\xi^2(x)}{Z_{NV}^h} P_0^h. \tag{1}$$

$$b_{NV}^{r*} = \frac{\sigma_\tau^2(t)\sigma_\xi^2(x)}{Z_{NV}^r} m + \frac{\sigma_\tau^2(t)\sigma_\epsilon^2}{Z_{NV}^r} R_x + \frac{2\sigma_\epsilon^2\sigma_\xi^2(x)}{Z_{NV}^r} P_t^r. \tag{2}$$

Equations 1 and 2 are standard Bayesian expectations with three signals. In accordance to Bayesian updating, the bid of the hiring principal is a weighted average of the prior, the public signal, and the private signal, where the weights are inversely related to the relative variances of the signals. Employer learning manifests itself through the variances of the public and private signals indexed by experience (x) and tenure (t) respectively. If there is public learning, the variance of the public signal shrinks and principals expectations place more weight on it, while discounting their prior and private signals. If there is private learning, only retaining principals place more weight on their private signals, while placing less weight on the prior belief and public signal. This is reflected by $\sigma_\tau^2(t)$ in equation 2, which shrinks with additional private information, as opposed to $\sigma_\tau^2(0)$ from equation 1, which remains constant for hiring principals. Thus, the bids diverge with additional private information, all else equal.

3.3 Bidding with the introduction of VA

The introduction of VA alters the information available to principals, but the manner in which it does depends on which principals have access to the VA. For instance, consider the case where two rival principals serve in Guilford County, and are contemplating retaining or hiring a given teacher. The adoption of VA results in both the retaining and hiring principal gaining access to the teacher's VA. Thus, VA becomes incorporated in the public signal. I show in Lemma 1 that if VA is informative, the variance of the cumulative public signal must decrease.

[13] I introduce school heterogeneity as a proportional bidding constraint on principals' expectations below to better align the model with the empirical setting.

Lemma 1: $\sigma^2_{\xi V}(x) < \sigma^2_{\xi}(x)$.

Proof: Under the orthogonality assumptions, $var(R_{x\nu}) \equiv \sigma^2_{\xi V}(x) = \frac{\sigma^4_\nu \sigma^2_\xi(x) + \sigma^2_\nu \sigma^4_\xi(x)}{(\sigma^2_\nu + \sigma^2_\xi(x))^2} = \frac{\sigma^2_\nu \sigma^2_\xi(x)}{\sigma^2_\nu + \sigma^2_\xi(x)}$. Taking the difference of the two variances gives the following: $\sigma^2_\xi(x) - \sigma^2_{\xi V}(x) = \frac{\sigma^2_\xi(x)(\sigma^2_\nu + \sigma^2_\xi(x))}{\sigma^2_\nu + \sigma^2_\xi(x)} - \frac{\sigma^2_\nu \sigma^2_\xi(x)}{\sigma^2_\nu + \sigma^2_\xi(x)} = \frac{\sigma^4_\xi(x)}{\sigma^2_\nu + \sigma^2_\xi(x)} > 0$.

Accordingly, equation 3 provides the optimal bid of a hiring principal, where $Z^h_{HV} = \sigma^2_\tau(0)\sigma^2_{\xi V}(x) + \sigma^2_\tau(0)\sigma^2_\epsilon + 2\sigma^2_\epsilon \sigma^2_{\xi V}(x)$. The subscript HV indicates that both principals may access the teacher's VA. Equation 4 provides a retaining principal's optimal bid, where $Z^r_{HV} = \sigma^2_\tau(t)\sigma^2_{\xi V}(x) + \sigma^2_\tau(t)\sigma^2_\epsilon + 2\sigma^2_\epsilon \sigma^2_{\xi V}(x)$.

$$b^{h*}_{HV} = \frac{\sigma^2_\tau(0)\sigma^2_{\xi V}(x)}{Z^h_{HV}} m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{HV}} R_{x\nu} + \frac{2\sigma^2_\epsilon \sigma^2_{\xi V}(x)}{Z^h_{HV}} P^h_0. \quad (3)$$

$$b^{r*}_{HV} = \frac{\sigma^2_\tau(t)\sigma^2_{\xi V}(x)}{Z^r_{HV}} m + \frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{HV}} R_{x\nu} + \frac{2\sigma^2_\epsilon \sigma^2_{\xi V}(x)}{Z^r_{HV}} P^r_t. \quad (4)$$

Using the finding from Lemma 1 that the variance of the public signal declines with the introduction of VA, once hiring and retaining principals may access a teacher's VA, they shift weight from their prior beliefs and their private information, and place it onto the public information that now includes a teacher's VA (R_{xv}). We might expect the introduction of VA to be more influential for hiring principals than for current principals. Indeed, Jacob and Lefgren (2008) and Chingos and West (2011) present evidence that current principals can identify at least which teachers lie in either tail in the distribution of teacher effectiveness.[14] The model reflects this, as the variance of the hiring principal's private information is larger than the variance of retaining principals' private information. Receiving a teacher's VA results in the information of both prospective employers to become more symmetric, causing their expectations to converge.

If a retaining principal's rival is from outside of the district and uninformed of a teacher's VA, the VA enters the retaining principal's set of private information. The retaining principal's new private signal ($P^r_{t\nu}$) becomes the precision-weighted average of the prior private information and the new VA. If VA is informative, the precision of the cumulative private information must increase, as shown by Lemma 2.

Lemma 2: $\sigma^2_{\tau V}(t) < \sigma^2_\tau(t)$.

Proof: Under the orthogonality assumptions, $var(P_{t\nu}) \equiv \sigma^2_{\tau V}(t) = \frac{\sigma^4_\nu \sigma^2_\tau(t) + \sigma^2_\nu \sigma^4_\tau(t)}{(\sigma^2_\nu + \sigma^2_\tau(t))^2} =$

[14] Jacob and Lefgren (2008) find that principals can identify the highest- and lowest-VA teachers. Their observation of slightly higher correlations for principals who have known their teachers for longer suggests a gradual learning process. Chingos and West (2011) find that principals classify their teachers on the basis of effectiveness, and when under accountability pressure move high-VA teachers into high-stakes teaching assignments.

$\frac{\sigma_\nu^2\sigma_\tau^2(t)}{\sigma_\nu^2+\sigma_\tau^2(t)}$. Taking the difference of the two variances gives the following: $\sigma_\tau^2(t)-\sigma_{\tau V}^2(t) = \frac{\sigma_\tau^2(t)(\sigma_\nu^2+\sigma_\tau^2(t))}{\sigma_\nu^2+\sigma_\tau^2(t)} - \frac{\sigma_\nu^2\sigma_\tau^2(t)}{\sigma_\nu^2+\sigma_\tau^2(t)} = \frac{\sigma_\tau^4(t)}{\sigma_\nu^2+\sigma_\tau^2(t)} > 0$.

The retaining principal's optimal bid is shown in equation 5, where $Z_{RV}^r = \sigma_{\tau V}^2(t)\sigma_\xi^2(x) + \sigma_{\tau V}^2(t)\sigma_\epsilon^2 + 2\sigma_\epsilon^2\sigma_\xi^2(x)$. The subscript RV denotes that only retaining principals receive a teacher's VA. The out-of-district hiring principal's bid remains unchanged from equation 1.

$$b_{RV}^{r*} = \frac{\sigma_{\tau V}^2(t)\sigma_\xi^2(x)}{Z_{RV}^r}m + \frac{\sigma_{\tau V}^2(t)\sigma_\epsilon^2}{Z_{RV}^r}R_x + \frac{2\sigma_\epsilon^2\sigma_\xi^2(x)}{Z_{RV}^r}P_{t\nu}^r. \tag{5}$$

Equation 5 is similar to equation 2 except for the replacement of P_t^r by $P_{t\nu}^r$ and of $\sigma_\tau^2(t)$ by $\sigma_{\tau V}^2(t)$. While the change may be small, this decrease in the variance of the private signal decreases the weight retaining principals place on their prior beliefs and the public signal, and increases the relative weight they place on their now fuller private information. The degree to which VA alters a current principal's expectation of a teacher depends on the relative variances of the prior, her previous private information without VA, and of the VA measure itself. The hiring principals' initial expectations do not change, as she is unaware of the signal. Thus, the introduction of VA exacerbates informational asymmetries between prospective employers, and the two principals' bids further diverge.

I present out-of-district principals as uninformed here for simplicity. However, some out-of-district principals may learn of the existence of teachers' VA due to high-VA teachers revealing their VA or by learning the personnel practices of other districts. Accordingly, the furthering of information asymmetries between employers may not universally apply to out-of-district moves. However, the fact that out-of-district principals are not directly informed of teachers' VA produces a positive probability that an out-of-district principal is ignorant of teachers' VA, whereas the probability that a within-district principal is ignorant of a teachers' VA is zero. Appendix 8.1.5 discusses this in more detail.

3.4 Mobility with the introduction of VA

After teachers receive both bids, they transfer schools as long as the gains from moving outweigh the nominal cost of doing so. Accordingly, the probability of a move is:

$$P(M) = P\left[b^{h*} - b^{r*} > c\right]. \tag{6}$$

How does the introduction of VA change which teachers this standard model predicts to move, and where they go? To examine these questions, I consider the expected change in the differences between hiring and retaining principals' optimal bids. The exact form of the post-policy optimal bids depends on whether the hiring principal is from within or outside of the adopting district. As described in Section 2, both districts' adoptions of VA provide a shock to the information of all principals within the district. Thus, by examining within-district teacher mobility in response to the release of VA, I test whether releasing VA leads to more symmetric information between employers. However, out-of-district principals cannot directly access the new VA measures. Thus, examining mobility out of adopting districts distinguishes whether the information spreads to all employers or exacerbates informational asymmetries between them.

3.4.1 VA increases mobility of effective (or high-VA) teachers within-district

To examine which teachers' within-district mobility the model predicts to be most affected by the policy, I take the derivative of the expected change in the difference between retaining and hiring principals' bids with respect to teacher effectiveness or VA. There are two primary ways of thinking about the impact of VA in the model. The first is more in keeping with the prior employer learning literature. VA serves as a difficult-to-observe measure of teacher quality, which researchers may use to proxy for μ, and about which employers are learning. In expectation, the information shock primarily affects variances of employers' signals. Accordingly, the model predicts whether more or less effective teachers move in response to districts adopting VA. Equation 7 takes this broad view.[15]

$$\begin{aligned}\frac{\partial E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial \mu} &= \frac{2\sigma^4_{\epsilon}(\sigma^2_{\tau}(0) - \sigma^2_{\tau}(t))(\sigma^2_{\xi}(x) - \sigma^2_{\xi V}(x))}{Z^h_{NV} Z^r_{NV} Z^h_{HV} Z^r_{HV}} \times \\ &\quad [2\sigma^2_{\xi}(x)\sigma^2_{\xi V}(x)(\sigma^2_{\tau}(t)\sigma^2_{\tau}(0) + \sigma^2_{\epsilon}\sigma^2_{\tau}(0) + \sigma^2_{\tau}(t)\sigma^2_{\epsilon}) \\ &\quad + (\sigma^2_{\xi V}(x) + \sigma^2_{\xi}(x))\sigma^2_{\tau}(t)\sigma^2_{\epsilon}\sigma^2_{\tau}(0))] > 0. \end{aligned} \tag{7}$$

This result rests on whether $\sigma^2_{\tau}(0) > \sigma^2_{\tau}(t)$, which is fundamental to asymmetric employer learning. Therefore, the model predicts that relative to ineffective teachers, informing both principals of VA, as occurred within both adopting districts, should raise the probability that effective teachers move, all else equal.

Under the second interpretation, EVAAS VA enters the two districts directly as a new signal. Accordingly, the model offers predictions on the differential effects of the policy on the probability of moving for teachers receiving different signals, all else equal. Equation 8 takes this more narrow view.[16]

$$\frac{\partial E\left[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ V,\ \mu\right]}{\partial V} = \frac{2\sigma^2_{\epsilon}\sigma^2_{\xi}(x)(\sigma^2_{\tau}(0) - \sigma^2_{\tau}(t))}{Z^h_{HV} Z^r_{HV}} > 0. \tag{8}$$

While the interpretations are subtly different, the comparative statics with respect to VA after the policy takes effect are the same. In both instances, the predicted increase in

[15] See Appendix 8.1.1 for proof.
[16] See Appendix 8.1.2 for proof.

mobility of effective (or high-VA) teachers results from existing informational differences between employers.

3.4.2 VA release leads to adverse selection of teachers to uninformed principals

Recall from Section 2, that if principals in other districts know of the existence of VA for teachers from Winston-Salem and Guilford, the policy would theoretically alter their information. In this context, the previous predictions would apply to out-of-district moves as well. However, it is plausible that principals in other districts were uninformed about the policy. In which case, VA enters retaining principals' private signals in Guilford and Winston-Salem, making the balance of information more asymmetric between retaining and out-of-district hiring principals.

The same two interpretations of VA apply here. I first take the broad view of VA with equation 9 demonstrating the predicted change in the relationship between teachers' underlying abilities and the probability of moving to uninformed principals. Equation 10 presents the partial derivative of the expected difference in the differences between employers bids with respect to the VA signal itself.[17]

$$\frac{\partial E[b^{h*}_{NV} - b^{r*}_{RV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu]}{\partial \mu} = \frac{2\sigma^2_\epsilon \sigma^2_\xi(x)^2(\sigma^2_{\tau V}(t) - \sigma^2_\tau(t))}{Z^r_{NV} Z^r_{RV}} < 0. \tag{9}$$

$$\frac{\partial E\left[b^{h*}_{NV} - b^{r*}_{RV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, V,\, \mu\right]}{\partial V} = \frac{-2\sigma^2_\xi(x)\sigma^2_\epsilon \sigma^2_\tau(t)}{Z^r_{RV}(\sigma^2_\nu + \sigma^2_\tau(t))} < 0. \tag{10}$$

The predictions are consistent. Under Lemma 2, $\sigma^2_\tau(t) > \sigma^2_{\tau V}(t)$; predicting that releasing VA to only retaining principals increases the likelihood that ineffective teachers move to uninformed principals. Similarly, equation 10 shows that the policy leads to adverse selection of out-of-district moving teachers on the basis of the VA signal, all else equal.

As shown in Appendix 8.1.5, a positive probability that an out-of-district principal is uninformed of teachers' VA is sufficient to produce differences in selection between out-of-district and within-district movers. As the probability that out-of-district principals are uninformed approaches one, VA adoption leads to negative selection of mobile teachers from adopting districts. Thus, the test between symmetric and asymmetric learning is whether the effects of the policy on the selection of out-of-district movers are significantly more negative (either smaller in magnitude or strictly negative) than the effects of adopting VA on the selection of within-district movers.

3.4.3 Within-district mobility under heterogeneous school constraints

It may be unrealistic to suppose that all schools can bid for teachers in accordance with how the principal expects teachers to perform. Large differences in pay or school desirability

[17] See Appendices 8.1.3 and 8.1.4 respectively for proofs.

may be too great for a principal to overcome with position-specific, non-pecuniary benefits. In order to better customize the model and its predictions to the market for teachers, I introduce school heterogeneity using a school-level, proportional constraint on principals' bids ($\rho^s < 1$ where the superscript $s = r,\ h$ indicates retaining and hiring principals) reflecting the costs to principals of providing position-specific attributes.[18] The key feature of ρ^s is that in expectation it is increasing in school desirability (S^s), such that $\frac{\partial E(\rho^s)}{\partial S^s} > 0$.[19]

In order to gain predictions regarding the probability of moving within-district in this framework, I take the cross partials of $E\left[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\ \mu\right]$ with respect to teacher ability (μ) and both S^h and S^r below.[20]

$$\frac{\partial^2 E[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\ \mu]}{\partial\mu\partial S^h} = \frac{2(\sigma^4_\xi(x) - \sigma^4_{\xi V}(x))\sigma^2_\epsilon\sigma^2_\tau(0)}{Z^h_{HV}Z^h_{NV}}\frac{\partial E[\rho^h]}{\partial S^h} > 0. \tag{11}$$

$$\frac{\partial^2 E[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\ \mu]}{\partial\mu\partial S^r} = \frac{-2(\sigma^4_\xi(x) - \sigma^4_{\xi V}(x))\sigma^2_\epsilon\sigma^2_\tau(t)}{Z^h_{HV}Z^r_{HV}}\frac{\partial E[\rho^r]}{\partial S^r} < 0. \tag{12}$$

By Lemma 1, $\sigma^4_\xi(x) > \sigma^4_{\xi V}(x)$. Thus, $\frac{\partial E[\rho^h]}{\partial S^h} > 0$ implies that all else equal, the release of VA increases the mobility of effective teachers to high-performing schools. By the same reasoning, equation 12 is negative, implying that the release of VA is predicted to increase the mobility of effective teachers from low-performing schools. Taken together, the probability of a highly-performing teacher moving within-district increases as the hiring school desirability rises relative to the quality of the retaining school after the release of VA.[21]

3.4.4 Comparative statics for within and out-of-district moves with respect to easily-observable teacher characteristics (m)

The introduction of new information may also change the weighting principals formerly applied to easily-observable teacher characteristics such as level of education, experience, and the selectivity of their undergraduate institutions. Furthermore, how the weighting changes with the introduction of VA again depends on whether both principals are informed of teachers' VA. Throughout the model, m stands as summary measure of easily-observable correlates with teacher effectiveness.

[18] Prior drafts modeled school heterogeneity using a maximum possible bid, considering constrained and unconstrained moves separately. Basic predictions hold in under either construction.

[19] By having the expectation of ρ^s increase in S^s, I allow teachers to have differing preferences over school characteristics. To obtain comparative statics with respect to effectiveness (or VA) and school desirability, it is sufficient for teachers on average to prefer to teach at more desirable schools, which empirically are measured by student performance. I also consider heterogeneity of school desirability on the basis of school-wide bonus pay and the racial composition of the school. Boyd et al. (2008); Jackson (2009), and Boyd et al. (2013) provide evidence of teachers on average holding preferences over each.

[20] See Appendix 8.1.6 for proof. I also present the cross partial with respect to VA and S^s in Appendix 8.1.7.

[21] The model offers no predictions regarding the performance of hiring schools out-of-district.

I derive the predicted change in the relationship between a teacher's easily-observable traits and the probability of moving within-district with the introduction of VA, taking the derivative of $E\left[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu\right]$ with respect to m.[22]

$$\begin{aligned}\frac{\partial E\left[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu\right]}{\partial m} = & \frac{2\sigma^2_\epsilon(\sigma^2_\tau(0) - \sigma^2_\tau(t))(\sigma^2_{\xi V}(x) - \sigma^2_\xi(x))}{Z^r_{HV}Z^h_{HV}Z^r_{NV}Z^h_{NV}} \\ & [2\sigma^2_\tau(t)\sigma^2_\tau(0)\sigma^2_\xi(x)\sigma^2_{\xi V}(x) + 2\sigma^2_{\xi V}(x)\sigma^2_\epsilon\sigma^2_\xi(x)(\sigma^2_\tau(0) \\ & + \sigma^2_\tau(t)) + (\sigma^2_{\xi V}(x) + \sigma^2_\xi(x))\sigma^2_\tau(t)\sigma^2_\epsilon\sigma^2_\tau(0)] < 0.\end{aligned} \tag{13}$$

Under the assumptions of prior private learning, and informative VA, all else equal, the model predicts the probability of moving within-district decreases for teachers with strong observable characteristics relative to their VA after the introduction of VA.

Easily-observable characteristics may play a larger role in out-of-district mobility after the introduction of VA. I derive the predicted change in the relationship between a teacher's easily-observable traits and the probability of moving out of district with the introduction of VA by taking the derivative of $E\left[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu\right]$ with respect to m.[23]

$$\frac{\partial E\left[b^{h*}_{RV} - b^{r*}_{RV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu\right]}{\partial m} = \frac{2\sigma^2_\xi(x)^2\sigma^2_\epsilon(\sigma^2_\tau(t) - \sigma^2_\tau(t\,V))}{Z^r_{RV}Z^r_{NV}} > 0. \tag{14}$$

By Lemma 2, all else equal, the model predicts the introductions of VA to increase mobility towards uninformed principals, for teachers with relatively strong easily-observable characteristics. Again, the possibility that some out-of-district principals may be uninformed of VA leads the model to predict that the effects of the policy on the selection of out-of-district movers are significantly more positive (either less negative in magnitude or strictly positive) than the effects of adopting VA on the selection of within-district movers.

3.4.5 Comparative statics for within-district moves with respect to ability (μ) and tenure (t)

We might expect that if employer learning was previously largely asymmetric, mobility responses may be strongest for teachers who have many years of tenure in the same school, because their principals may benefit from the largest informational advantages. Taking the cross partial of $E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu]$ with respect to μ and t provides predictions

[22] See Appendix 8.1.8 for proof.

[23] See Appendix 8.1.9 for proof.

Table 1: Summary of model predictions

	Model predictions for VA adoption	Assumptions: There was prior private learning,VA is informative, and...	Table	Appendix
1.	Effective (higher-VA) teachers become more likely to move within district after the adoption of VA.		3	8.1.1 (8.1.2)
2.	Ineffective (lower-VA) teachers become more likely to move out of district after the adoption of VA.	VA may be kept private.	3	8.1.3 & 8.1.5 (8.1.4)
3.	The within-district selection effects are driven by moves to higher-performing schools.	Teachers generally prefer higher-performing schools and principals at lower-performing schools are constrained in attracting talent.	3	8.1.6 8.1.7
4.	Easily-observable characteristics become less predictive of mobility for within-district moves.		4	8.1.8
5.	Easily-observable characteristics become more predictive of mobility for out-of-district moves.	VA may be kept private.	4	8.1.9
6.	The change in the extent of positive selection within-district will be more pronounced for teachers with more tenure.		5	8.1.10

for how policy-induced changes in selection into mobility evolve with increases in tenure.[24]

$$\begin{aligned}\frac{\partial^2 E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial\mu\partial t} &= \frac{\partial\sigma^2_\tau(t)}{\partial t}\frac{2\sigma^4_\epsilon\sigma^2_\tau(t)(\sigma^2_{\xi V}(x) - \sigma^2_\xi(x))}{{Z^r_{HV}}^2{Z^r_{NV}}^2} \\ &[2\sigma^2_\xi(x)\sigma^2_{\xi V}(x)(\sigma^2_\tau(t) + 2\sigma^2_\epsilon) + \sigma^2_\epsilon\sigma^2_\tau(t)(\sigma^2_\xi(x) + \sigma^2_{\xi V}(x))] > 0.\end{aligned} \tag{15}$$

The assumptions of prior private learning $\left(\frac{\partial\sigma^2_\tau(t)}{\partial t} < 0\right)$ and informative VA $\left(\sigma^2_{\xi V}(x) < \sigma^2_\xi(x)\right)$, imply that equation 15 is positive. Thus, the growth in positive selection within-district following the introduction of VA should be more pronounced for those with more tenure.

3.4.6 Model summary

In the model described above, I develop a useful structure to demonstrate how new information may be incorporated publicly or privately into the market, and how such new information may impact teacher mobility. I present a summary of the predictions from the model in Table 1, which also lists the corresponding key assumptions and the appendices containing relevant proofs of each prediction. Further, Table 1 relates the model to the empirical analysis by listing the tables that contain evidence regarding each prediction.

While helpful for exposition, the structure of the model makes some potentially restrictive assumptions that abstract from reality. For instance, I assume that the errors of the signals

[24] See Appendix 8.1.10 for proof. I present the cross partial with respect to VA and t in Appendix 8.1.11.

are orthogonal to one another, and I model the bidding process as an open continuous English auction where rivals may update their expectations based on the actions of the other. Neither of these assumptions are necessary for the primary predictions of the model.

For instance, in a previous version of the paper the bidding was modeled in another extreme as a static second price auction. Under both bidding structures, the predictions from the model are the same. Both bidding structures belong to a more general framework in which the expectation of bids can be written as the weighted sum of a common prior (m) and true effectiveness (μ). In the full model, these weights are determined by the variances of the signals. In appendix 8.1.13, I adopt this broader framework using these general weights to derive sufficient conditions in keeping with private and public employer learning for which the primary predictions follow. This more general approach not only allows for a wider range of bid structures, but also allows for correlations between the signal errors.

To summarize the results from appendix 8.1.13, prediction 1 rests on the introduction of VA causing within-district hiring principals to shift more weight onto their signals of true effectiveness than retaining principals shift onto their signals of true effectiveness. Under the full model structure, this follows from prior private learning and VA containing some new information to hiring within-district principals. Note that this prediction does not require VA to inform retaining principals, meaning that the error in the VA and retaining principals' signals could be perfectly correlated, and the same within-district predictions would apply.

Conversely, the prediction of adverse selection out-of-district with the adoption of VA requires VA to inform retaining principals' expectations of teacher effectiveness. Naturally, VA would have no effect if it provides no information to either party. However, even without adverse selection, we would still expect VA adoption to cause more positive selection of movers on the basis of effectiveness (or VA) within-district than out-of-district, and only the assumptions above are required for this result.

No new assumptions are required to generate the predictions for within or out-of-district mobility with respect to easily observable information. The remaining predictions regarding the dynamics with respect to differences in school desirability and teacher tenure each requires additional structure. The full model presented above provides an example of one such structure which is largely in keeping with the employer learning literature.

4 Data and estimation

In this section, I describe both the data and methods used to generate VA measures of teacher effectiveness, and estimate the effects of the district policies on teacher mobility. Subsection 4.1 describes the generation of VA. Subsection 4.2 describes the estimation sample. Subsection 4.3 describes the difference-in-differences estimation approach used to identify the effects of the new information on the mobility decisions of teachers and principals.

4.1 Value-Added

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 administrative, longitudinal data, which links students to their teachers and was generously provided by the North Carolina Education Research Data Center (NCERDC) to estimate teachers' abilities to do just that. Though a robust source of data, the NCERDC does not contain the exact VA issued to each teacher, and neither VA-adopting district agreed to release them. Consequently, this study generates the student gains on the North Carolina End of Grade exams attributable to each teacher.

There are two primary ways to go about this. The first is to attempt to model the exact measures that teachers and principals receive. This is useful in taking the narrow view of VA in the theoretical model to explain the teachers' and principals' observed behavior, but may be less relevant for policy. The second is to econometrically model teacher effectiveness (μ) about which employers may be learning. In my preferred specification, I model teacher effectiveness rather than attempting to replicate the EVAAS measure.[25] This is because the policy context matters in this setting, and according to theory, the same predictions hold regarding effectiveness as hold with respect to the signal of effectiveness.

In practice, I use both Dynamic OLS (DOLS) and Empirical Bayes (EB) in Section 6 and the results do not change much as the measures are highly correlated.[26] I present my preferred DOLS measure of VA in equation 16.[27]

$$A_{ijt} = \mathbf{T_t} + \mathbf{A_{ijt-1}}\boldsymbol{\beta_0} + \mathbf{X_{it}}\boldsymbol{\beta_1} + \mathbf{I_j}\boldsymbol{VA_j} + e_{it} \tag{16}$$

Here, A_{ijt} represents student i's mathematics achievement in teacher j's class in year t. Including $\mathbf{A_{it-1}}$ controls for student ability reflected through previous math and reading test performances. $\mathbf{X_{it}}$ is a vector including demographic attributes of individual students, such as grade, race, gender, special needs, and gifted status. It is $\mathbf{VA_j}$, the coefficients on a vector of teacher indicators, which is of primary interest for this study. Acknowledging that VA measures 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

[25] An element of feasibility also enters this preference. The EVAAS system is proprietary, and the exact data and methods used are not disclosed. Furthermore, SAS uses two different proprietary models, and for large school districts it is unclear which is used.

[26] Rose et al. (2012) finds 94-95 percent agreement between the EVAAS measure and DOLS and 95-97 percent agreement between EVAAS and EB.

[27] It is unlikely that teacher effectiveness is uncorrelated with student covariates, which Guarino et al. (2012) notes leads to inconsistency in the VA estimates when using EB as opposed to DOLS.

allows me to gain the most precise estimate of teachers' true underlying ability (μ).

4.2 Estimation sample

This study restricts attention to the 5,986,132 3^{rd} through 8^{th} grade student-year observations from 1997 through 2011 to construct the VA measures for 134,219 elementary and middle school teachers. I link these data to education, licensing, and work history data of 67,062 teachers 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 observations in which teachers are teaching mathematics in grades covered by end-of-grade standardized exams at the time of observation. This restriction pares 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.[28] Each of these are easily observable to all schools and many are likely used to filter job candidates. I use characteristics of the school in which the teacher currently works as additional, easily-observable, possible correlates with effectiveness. Table 2 summarizes to relevant variables in my estimation sample.

The districts that adopt VA 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 from colleges of comparable selectivity, across districts, in Winston-Salem, a larger share of the teaching-force holds an advanced degree. However, on the basis of VA, teaching quality in both districts is very close to the state average.

4.3 Estimation strategy

I use a modification of differences-in-differences to compare changes in the relationship between teacher quality and mobility around the adoptions of VA to the changes in the same relationship over the same times in the rest of the state. I estimate the following specification:

$$y^z_{jdt} = \boldsymbol{T^z_t} + \mathbf{D^z_d} + \mathbf{TreatDist_d} \times \mathbf{Post_t}\boldsymbol{\delta^z} + VA_j\mathbf{DinD^z_{1dt}} + \mathbf{X_{jdt}}\mathbf{DinD^z_{2dt}} + \xi^z_{jdt}, \tag{17}$$

where $\mathbf{DinD^z_{hdt}} = \gamma^z_{h1} + \mathbf{TreatDist_d}\boldsymbol{\gamma^z_{h2}} + \mathbf{Post_t}\boldsymbol{\gamma^z_{h3}} + \mathbf{TreatDist_d} \times \mathbf{Post_t}\boldsymbol{\gamma^z_{h4}}, h = 1, 2.$

y^z_{jdt} is an indicator of a job change for teacher j in district d and in year t with the superscript ($z = W$, WH, WL, O, OH, OL) indicating job changes within-district, within-district to higher-performing schools, within-district to lower-performing schools, out-of-district, out-of-

[28] Because tenure is generated and censored for job matches beginning prior to 1995, an indicator of whether the current match existed in 1995 is included in all regressions.

Table 2: Sample Summary

	Guilford		Winston-Salem		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
Black share of students	0.42	0.24	0.36	0.24	0.29	0.24
Black share of teachers	0.25	0.43	0.21	0.41	0.15	0.36
Hispanic share of 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
Value added (VA)	0.02	1.01	0.01	0.99	0.00	1.00
N	11,239		8,295		216,484	

Note: VA is measured in standard deviations with the mean centered at 0. Tenure is generated, and is censored for those already working at a given school in 1995.

district to higher-performing schools, and out-of-district to lower-performing schools respectively. $\mathbf{T^z_t}$ represents year effects, $\mathbf{D^z_d}$ represents district fixed-effects, and $\mathbf{X_{jdt}}$ is a vector of teacher and school characteristics including teacher experience, tenure, race, highest degree earned and selectivity of bachelor degree granting institution, as well as percent of students who are black and percent of students testing above proficiency at the school level. $\mathbf{DinD^z_{1dt}}$ captures the differences in the effects of VA on mobility based on whether VA measures were available for teacher j in district d, at time t. Interactions between VA and treatment district indicators account for permanent differences in the relationship between VA and the probability of moving in treatment districts as opposed to the rest of the state. Interactions between VA and indicators for post years do the same for statewide changes in the same relationship for the times that the policies take effect. Thus, the identifying variation comes from differences between adopting districts and the rest of the state in the change in the regression coefficients of VA on the probability of moving from pre- to post-policy years.

Given how the districts distributed VA, it seems clear that the new information would be public between two principals in Guilford. Perhaps to a lesser extant the same holds for Winston-Salem. Due to the indirect mechanism by which hiring principals in Winston-Salem obtain teachers' VA and the potential additional salience of VA signals to principals outside the district during Winston-Salem's later adoption, I separate treatment by district. Accordingly, the parameterization of the first prediction listed in table 1 is that $\gamma_{14}^{W} > 0$ (where γ_{14}^{W} is the effect of the interaction of VA with receiving treatment on the probability of moving within-district).

Outside of the adopting districts, principals were not directly informed of teachers' VA. If learning was nonetheless symmetric, with all principals updating their beliefs in accordance to teachers' VA, regardless of district, the model would predict $\gamma_{14}^{O} = \gamma_{14}^{W}$ (where γ_{14}^{O} is the effect of the interaction of VA with receiving treatment on the probability of moving out-of-district). However, if the information spread asymmetrically, and some out-of-district principals were uninformed of VA, asymmetric learning leads to prediction 2: namely, that $\gamma_{14}^{W} > \gamma_{14}^{O}$ and possibly $\gamma_{14}^{O} < 0$ for out-of district moves. Thus, the test between symmetric and asymmetric learning is whether the effects of VA-adoption on the selection of out-of-district movers are significantly more negative than the effects of the policy on the selection of within-district movers.

These predicted mobility patterns may have important implications for the distribution of teacher quality across schools. If effective teachers are better able to signal their true quality, and do so in general to move to higher-performing schools, the divide in teacher quality across schools may widen. Accordingly, I disaggregate the mobility responses to the policy by whether the receiving school has a higher share of proficient students than does the sending school. I test this third prediction from the model by evaluating whether $\gamma_{14}^{WH} > 0$, (where γ_{14}^{WH} is the effect of the interaction of VA with receiving treatment on the probability of moving within-district to a higher-performing school). I repeat the same exercise regarding the racial composition of students at the sending and receiving schools. In order to estimate the effect of the policy on sorting overall, I estimate equation 17 using the percent of students proficient in the school taught at during the subsequent year as the dependent variable. I do the same using the share of students who identify as black.

According to predictions 4 and 5 of the model, easily-observable, lower correlates with effectiveness may become less (more) tied to the probability of moving within (out-of) the district after the introduction of VA. Thus, I relax the restriction that the coefficients on easily-observable characteristics remain constant throughout the policy adoption by interacting other teacher covariates with the differences-in-differences framework ($\mathbf{DinD^{z}_{2dt}}$) in all regressions. In order to provide a summative statistic, I generate an index of easily-observable teacher quality (TQ index) by taking the fitted values from the linear projection of teacher VA on observable teacher covariates, including an indicator for having an advanced degree, a vector of indicators for Barron's College Competitiveness index, years of experience, years of tenure, an indicator for whether tenure is censored, race, gender, and a vector of year indicators. I use the residuals from this same projection to proxy for information contained in VA that was previously more difficult for the market to uncover. I then estimate equation 17 with the VA residuals substituting for VA_j and the teacher quality index substituting for $\mathbf{X_{it}}$. Accordingly, predictions 4 and 5 can be respectively parameterized as $\gamma_{24}^{W} < 0$ and and $\gamma_{24}^{O} > \gamma_{24}^{W}$.

Furthermore, absent other forms of firm specific human capital, if there had previously been private learning, the 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 VA with tenure and the difference-in-differences interactions. Thus, according to prediction 6 the coefficient on $VA \times tenure \times treatment$ should be positive in these regressions with within-district mobility as the dependent variable.[29]

5 Results

5.1 Mobility

How does mobility change with the adoption of VA and what does that tell us about the way employers learn about their employees? Table 3 presents the estimated impact of revealing EVAAS reports of teacher effectiveness on the relationship between teachers' VA and the probability a teacher moves to another school. Given the evidence that teachers prefer to teach in schools with higher-performing students, Table 3 decomposes effects by whether the receiving school has higher or lower-performing students than the current school.[30] The test between symmetric and asymmetric employer learning focuses on how the effects of VA on the probability of moving within-district differ from the effects of VA on the probability of moving out-of-district after VA adoption. The first three columns restrict attention to within-district moves, and the last three present evidence from out-of-district moves.

The first row presents the the relationship between VA measures and the probability of each type of move in the rest of the state, regardless of any districts adopting the policy. In general, there is little relationship between VA 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, a teacher with a standard deviation higher VA is about 0.3 percentage points more likely to move to a higher-performing school and 0.2 percentage points less likely to move to a lower-performing school within the district. Columns 4-6 exhibit the same pattern regarding moves to schools outside of the

[29] I do the same with experience as we may expected muted results among teachers about whom there may already be a rich accumulation of information.

[30] The primary effects of VA further supports this distinction. I define a move to a higher performing school as a move in which the school taught at the following year has a higher percentage of students who achieve proficiency than the current school. I demean proficiency rates by year statewide averages.

current district. A one standard deviation increase in VA before the policy takes effect raises the probability of moving to a higher-performing school by about a tenth of a percentage point and lowers the probability of moving to lower-performing school by about the same magnitude.

Table 3: Probability of moving schools within and out-of district

	Within-District Moves			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
VA	0.0016	0.0032***	-0.0016**	0.0002	0.0014**	-0.0012**
	[0.00129]	[0.00091]	[0.00074]	[0.00096]	[0.00072]	[0.00058]
VA x Treatment GCS	0.0058**	0.0051**	0.0007	-0.0103***	-0.0054***	-0.0049***
	[0.00265]	[0.00199]	[0.00151]	[0.00261]	[0.00195]	[0.00156]
VA x Treatment WSF	0.0052*	0.0060***	-0.0008	0.0009	0.0023	-0.0014
	[0.00286]	[0.00229]	[0.00194]	[0.00241]	[0.00208]	[0.00129]
Treatment GCS	-0.0040	-0.0050	0.0010	-0.0162***	-0.0232***	0.0070***
	[0.00851]	[0.00571]	[0.00679]	[0.00374]	[0.00233]	[0.00268]
Treatment WSF	0.0555***	0.0475***	0.0080***	-0.0020	0.0147***	-0.0167***
	[0.00499]	[0.00372]	[0.00299]	[0.00274]	[0.00224]	[0.00178]
Observations	236,018	236,018	236,018	236,018	236,018	236,018

DiCiccio and Romano (1988) district-clustered-teacher-stratified-bootstrapped (CSB) standard errors from 500 repetitions appear in brackets.[31] All regressions use a linear functional form, year and district fixed effects, and include teacher-level covariates and interactions with treatment indicators. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Within both Guilford and Winston-Salem, the release of VA intensifies this pattern. From the coefficient on the interactions between policy treatment and VA in both districts, a standard deviation increase in a teacher's VA leads to about a half of a percentage point increase in the probability of moving within district after VA adoption. While the magnitudes of the effects are very close between districts, the estimates are more precise for Guilford. Column 2 illustrates that these results are driven by moves to higher-performing schools, as the model predicts. From column 2, the estimated coefficients imply that the adoption of VA raises the probability that a teacher with one standard deviation higher VA will move

[31] Following DiCiccio and Romano (1988), I adopt a nested sampling technique to generate the district-clustered-teacher-stratified-bootstrapped (CSB) standard errors presented above. First, I sample districts randomly with replacement just as with the standard cluster-bootstrap. I then conduct stratified sampling at the teacher-level, such that for every teacher who was originally sampled, I randomly sample student/year observations with replacement. This provides generally more conservative standard errors across estimated parameters. Table A1 in the Appendix 8.2 presents both district-clustered and student-year bootstrapped standard errors for for comparison. Throughout the remainder of this paper, I present the CSB standard errors unless noted otherwise.

to a higher-performing school by 14 percent (p-value .011) in Guilford and nearly 18 percent (p-value .009) in Winston-Salem. Column 3 reveals little change in the effects of VA on the probability of moving to a lower-performing school within district. The similarity of the point estimates on the impact of VA post-treatment between Guilford and Winston-Salem provides no evidence that relying upon teachers to voluntarily disclose their VA scores 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 under the symmetric learning hypothesis. However, asymmetric employer learning predicts the policy to give principals in Guilford and Winston-Salem an informational advantage over principals in other districts. This translates into more negative selection effects for teachers moving to other districts than for within-district moves. Again, the selection of mobile workers after VA adoption are consistent with asymmetric employer learning.

The finding that the adverse selection of teachers leaving Guilford becomes more pronounced after the adoption of VA provides the strongest evidence of growing informational asymmetries between employers. In Guilford, a teacher who has a standard deviation lower VA, is a full percentage point more likely to move out-of-district with the effect split evenly between moves to high and lower-performing schools.

In Winston-Salem, the difference between within and out-of-district moves is less pronounced, though still consistent with private employer learning. While in Winston-Salem, a teacher with one standard deviation higher VA is more likely to move to a higher-performing school out-of-district after the policy takes effect, the point estimate is only 38 percent of that from moving within-district and is no longer statistically significant. Were outside principals informed of the signal, we would expect the same positive effects found in the second column to be present in the fifth column.

The fact that effects are more negative in Guilford than Winston-Salem, may be explained by differences in the salience of the signals between teachers moving from Guilford as opposed to those moving from Winston-Salem. Given Guilford's early adoption of the policy, it is unlikely that at that time principals in other districts had much understanding of the measures, or their reliability. In contrast, the rest of the state adopted school-level EVAAS reports simultaneously with Winston-Salem's adoption of teacher-level VA. Given this difference in contexts, high-VA teachers from Winston-Salem may have been better able to use their VA to obtain positions outside of Winston-Salem, than would a comparable teacher moving earlier from Guilford. In Winston-Salem, the increase in high-VA teachers' ability to signal their effectiveness may offset any effects from relatively low VA teachers exploiting the informational asymmetry. The mitigated effects of VA for those moving out of Winston-Salem in addition to the negative selection of teachers moving away from Guilford evidences informational asymmetries between potential employers within as opposed to outside of the district.

5.2 Observable and unobservable measures of quality

While the adoption of VA provides information on all teachers, an equivalent, new VA may have different impacts on principals' prior beliefs of different teachers. A high-VA may have little impact for a teacher with easily-observable characteristics indicative of quality, while the same VA may be more impactful for a teacher who lacks such positive signals. The model in Section 3 predicts the introduction of VA to affect the weight principals place on easily-observable teacher characteristics. Specifically, principals would place less emphasis on easily-observable correlates with teacher effectiveness, such as degree attainment and college selectivity, when teacher VA becomes public to both hiring and retaining principals. In cases where VA exacerbates informational asymmetries between current and hiring principals, the same teacher characteristics expectedly receive additional emphasis on the probability of a move.

In order to test these predictions, I decompose my measure of teacher VA into parts that are initially observable and unobservable to the market. I do this by regressing my estimated VA on the easily-observable teacher covariates. The VA residuals serve as the hard-to-observe measure of effectiveness, while the fitted values form a teacher quality index to serve as a composite measure of easily-observable indicators of teacher effectiveness.

Table 4 presents these estimates for within and out-of-district moves. In the absence of VA, those with strong observable characteristics are more likely to move to better schools, while those with weak observable characteristics are more likely to move to lower-performing schools. The fact that the VA residuals also predict mobility to higher-performing schools prior to VA-adoption suggests some degree of public learning of teacher effectiveness even in the absence of VA. However, the point estimates from rows 1 and 2 imply that a standard deviation increase in easily-observable teacher quality has about two-times the impact on the probability of moving to a better school than does a standard deviation increase in hard-to-observe teacher quality.[32]

Comparing the results of rows three and four of Table 4 to the same rows of Table 3, I find larger point estimates of the effect of VA-adoption with increases in VA residuals as opposed to increases in the composite VA measure. Though the estimates are not statistically different from one another, the estimates imply that the portion of VA that is uncorrelated with easily-observable teacher covariates is driving the increase in mobility after the release

[32]Both measures of teacher quality are similarly standardized.

of VA information.

Rows five and six of the first two columns of Table 4 do not bear out the predictions regarding easily-observable characteristics for within-district moves. The point estimates of the effects of the teacher index on the probability of moving schools within-district after the adoption of VA are positive. However, whereas in the rest of the state the index of teacher quality is more predictive of teacher mobility to higher-performing schools than VA, post-policy the magnitude of the coefficients on the quality index is only 43 to 62 percent the magnitude on VA. Further, these estimates are noisy and generally not statistically different from the estimated impacts of the TQ index on within-district mobility prior to the release of VA.[33] While the point estimates are not expected, this result may be explained by the additional churn that accompanies the adoption of VA particularly for moves to better schools within Guilford. Heterogeneous openness among principals to VA may also contribute.[34] In which case, as high-VA teachers move to principals that value VA, those with other favorable easily-observable attributes move to the principals who value those characteristics.

The change in the relationship between the index and the probability of moving out-of-district with the adoptions of VA is more supportive of the model. Whereas movers out of Guilford are adversely selected on the basis of the hard-to-observe VA, they are positively selected on the basis of the index of easily-observable measures of teacher quality, whether they are moving to higher- or lower-performing schools. This finding provides further evidence that the moving teachers with a high index, but low VA were able to keep their VA private, while utilizing their otherwise strong resumés to move to uninformed principals. Given that it is plausible that more teachers moving from Winston-Salem could inform out-of-district principals of their VA, attenuated results may make sense. While the results for moves out of Guilford are reassuring, cumulatively, the evidence from changes in the relationship between the index of easily-observable teacher characteristics, and the probability of moving schools is too mixed to draw definitive conclusions.

[33] The only significant result is for moves to better schools within Guilford.

[34] Informal conversations with principals in Winston-Salem and Guilford indicate this may be the case, as two of the current lower elementary principals that I spoke with indicated that teachers' VA played a limited role in their hiring decisions.

Table 4: Effects of easy and hard-to observe measures of quality on the probability of moving

Variables	Within-District Moves: Total	Within-District Moves: To higher performing schools	Within-District Moves: To lower performing schools	Out-of-District Moves: Total	Out-of-District Moves: To higher performing schools	Out-of-District Moves: To lower performing schools
VA Residuals	0.0018	0.0039***	-0.0021***	-0.0002	0.0014**	-0.0016***
	[0.00111]	[0.00078]	[0.00073]	[0.00091]	[0.00068]	[0.00053]
Teacher Quality Index (TQ Index)	0.005**	0.0071***	-0.0021**	-0.0005	0.0031***	-0.0035***
	[0.00233]	[0.00173]	[0.00105]	[0.00186]	[0.00115]	[0.00096]
VA Residuals x Treatment GCS	0.0083***	0.0069***	0.0014	-0.0109***	-0.0053***	-0.0056***
	[0.00237]	[0.00177]	[0.0014]	[0.00249]	[0.00189]	[0.00145]
VA Residuals x Treatment WSF	0.0063**	0.0062***	0.0000	0.0001	0.0018	-0.0017
	[0.00248]	[0.00199]	[0.00193]	[0.00212]	[0.00189]	[0.00115]
TQ Index x Treatment GCS	0.0040	0.0043**	-0.0003	0.0076***	0.0061***	0.0015*
	[0.00246]	[0.00153]	[0.00145]	[0.00116]	[0.00088]	[0.00088]
TQ Index x Treatment WSF	0.0029	0.0027	0.0002	-0.0011	-0.0026***	0.0015**
	[0.00254]	[0.00192]	[0.00131]	[0.00097]	[0.00078]	[0.00063]
Treatment GCS	0.0142**	0.0253***	-0.0111***	-0.0120***	-0.0132***	0.0011
	[0.00595]	[0.00449]	[0.00405]	[0.00258]	[0.00167]	[0.00189]
Treatment WSF	-0.0015	0.0091***	-0.0106***	0.0118***	0.0177***	-0.0059***
	[0.00383]	[0.00242]	[0.00253]	[0.00251]	(0.00136]	[0.00139]
Observations	236,018	236,018	236,018	236,018	236,018	236,018

CSB standard errors from 500 repetitions appear in brackets. All regressions use a linear functional form, and include teacher-level covariates and interactions with treatment indicators. The VA residuals used in this analysis are the residuals from the projection of my standard VA measure on easily-observable teacher covariates, and the TQ index is the fitted values from the same linear projection. Though many covariates such as advanced degrees, college selectivity, tenure, and demographics are statistically significant in this linear projection, the OLS regression of VA on teacher covariates only has an R^2 of 0.013. *** p<0.01, ** p<0.05, * p<0.1

5.3 Differential effects with respect to experience and tenure

Examination of differential effects with respect to years of experience and tenure in a given school may provide insight into the type of learning that previously prevailed. Were private learning already prevalent in the market, the model predicts more advantageous change in the selection of movers who have more years of tenure. This is because the information gaps between retaining and hiring principals grows with time a teacher teaches in the same school. Public introduction of VA would be a larger shock to the information gap on these teachers.[35]

[35] Ambiguity in the model prevents me from making a formal prediction regarding experience. However, if there was previous public learning, intuitively the release of VA would serve as less of a shock for teachers about whom there already existed more information. Thus, we may expect smaller results for more experienced teachers. While Table 5 exhibits this relationship for teachers moving out of the district (though not statistically significantly so), the same is not true for teachers moving within district.

Table 5: Differential effects with respect to experience and tenure

VARIABLES	Within District Total	Within District Higher Performing	Out of District Total	Out of District Higher Performing
VA	-0.0001	0.0028*	-0.0001	0.0023
	[0.0023]	[0.00161]	[0.00244]	[0.00173]
Experience x VA	-0.0000	0.0000	-0.0000	-0.0000
	[0.00011]	[0.00008]	[0.00011]	[0.00008]
Tenure x VA	0.0020**	0.0006	0.0006	0.0005
	[0.0008]	[0.00059]	[0.00073]	[0.00058]
VA x Treatment GCS	0.0033	0.0050	-0.0181***	-0.0095*
	[0.00568]	[0.00465]	[0.00693]	[0.00514]
Experience x VA x Treatment GCS	0.0016***	0.0010***	0.0002	0.0003
	[0.00026]	[0.0002]	[0.00032]	[0.00026]
Tenure x VA x Treatment GCS	0.0056***	0.0004	0.0008	0.0014
	[0.00179]	[0.00146]	[0.00217]	[0.00178]
VA x Treatment WSF	-0.0003	-0.0010	-0.0073	-0.0051
	[0.00551]	[0.00431]	[0.00503]	[0.00452]
Experience x VA x Treatment WSF	0.0003	0.0005	0.0002	0.0002
	[0.00043]	[0.00036]	[0.00029]	[0.00025]
Tenure x VA x Treatment WSF	0.0028***	0.0009*	0.0004	0.0004
	[0.00078]	[0.00055]	[0.00053]	[0.00046]
Observations	236,018	236,018	236,018	236,018

CSB standard errors from 500 repetitions appear in brackets. All regressions use a linear functional form, year and district fixed effects, and include teacher-level covariates and interactions with treatment indicators. *** p<0.01, ** p<0.05, * p<0.1

The results in columns 1 and 2 are consistent with prior private learning. For each additional year of tenure a standard-deviation-higher-VA teacher has, he is about 0.6 a percentage point more likely to move within Guilford and 0.3 a percentage point more likely to move within Winston-Salem. From column 2, the economic and statistical significance surprisingly falls when focusing on moves to better schools. The increased within-district mobility of effective teachers following the release of VA itself implies prior information gaps between employers. The finding that mobility responses are stronger for teachers with more tenure at a given school further suggests that the prior informational environment was largely asymmetric.

5.4 Educational equity

The increases in the mobility of effective teachers to higher-performing schools is concerning for educational equality, and an increase in mobility in general may impede performance overall. In order to investigate these issues, I first continue the analysis reported in Table 3, this time considering teachers' mobility regarding the student body's racial composition. Table 6 presents these results in panel A. I then examine the effects of VA adoption on the overall sorting of teachers to schools with respect to students' race and students' performance in panels B and C.[36] In Appendix 8.3, I present the results from district-level analysis reporting the estimated effect of VA adoption on overall mobility, teacher effectiveness, and the across school variance of teacher effectiveness.

From Table 6, the coefficient on VA in column 1 of panel A demonstrates that in general more effective teachers are more likely to move to schools with smaller shares of black students than their current school. Moving down the column shows that the release of VA magnifies that sorting in both adopting districts. VA adoption in Winston-Salem leads to a 1.3 percentage point increase in the probability that a teacher with a standard deviation higher VA moves within-district to a school with a lower share of black students, and a 0.8 percentage point drop in the probability that a similarly effective teacher moves to a school with a higher proportion of black students. For moves within Guilford, the effects are smaller, but still statistically significantly positive. For out-of-district moves, there continues to be no statistically significant effect for Winston-Salem, and in Guilford there continues to be adverse selection to schools with higher and lower shares of black students.

Table 6: Students' race and teacher sorting

Panel:	A: Moves based on share of students who are black				B: Growth in percent black		C: Growth in percent proficient	
	Within-District		Out-of-District					
VARIABLES	To lower percent black	To higher percent black	To lower percent black	To higher percent black	Total	Stay Within district	Total	Stay Within district
VA	0.0021**	-0.0005	0.0009	-0.0007	-0.0018***	-0.0011***	0.0028***	0.0024***
	[0.00088]	[0.00086]	[0.00078]	[0.00059]	[0.00046]	[0.00038]	[0.00033]	[0.00033]
VA x Treatment GCS	0.0037*	0.0021	-0.0067***	-0.0035**	0.005**	0.0026	-0.0005	-0.0000
	[0.0019]	[0.00167]	[0.00217]	[0.00143]	[0.00198]	[0.002]	[0.00074]	[0.0007]
VA x Treatment WSF	0.0133***	-0.0082***	-0.0007	0.0017	-0.0034	-0.0033*	0.0007	0.0017*
	[0.00228]	[0.00188]	[0.00192]	[0.00129]	[0.00235]	[0.002]	[0.00114]	[0.00102]
Treatment GCS	0.0040	-0.0088	-0.0043*	-0.0119***	0.0354***	0.0290***	-0.0195***	-0.0157***
	[0.00513]	[0.00738]	[0.00251]	[0.00278]	[0.00319]	[0.00302]	[0.00211]	[0.00216]
Treatment WSF	0.0277***	0.0280***	-0.0041*	0.0020	-0.0198***	-0.0245***	0.0290***	0.0231***
	[0.00355]	[0.00292]	[0.00233]	[0.00164]	[0.00318]	[0.00328]	[0.00172]	[0.00168]
Observations	236,018	236,018	236,018	236,018	209,424	202,943	209,424	202,943

CSB standard errors from 500 repetitions appear in brackets. All regressions use a linear functional form, year and district fixed effects, and include teacher-level covariates, and their interactions with treatment indicators. *** p<0.01, ** p<0.05, * p<0.1.

Turning to panels B and C, the coefficient on VA describes the general relationship between teachers' VA and the share of black or proficient students at the school they teach at the subsequent year. Since all regressions control for the current share of black students

[36] Missingness of free and reduced price lunch status (FRL) data prevents me from examining the effect of the policy on mobility with respect to FRL for Guilford. However, unreported regressions show that in Winston-Salem the mobility patterns with respect to FRL are very similar to those regarding students' race.

and proficient students at the current school, it can be thought of as the relationship between teacher effectiveness and year-by-year change in school proficiency level or racial composition in the absence of observable VA. The first columns of panels B and C examine sorting for all teachers in the sample who remain teaching in North Carolina the following year. The second columns of panels B and C restrict the sample to those who remain within their current district. This analysis on the restricted sample may be more informative for predicting the effects of statewide adoption of VA, as the larger geographic policy footprint would make it more difficult to flee informed principals.

From the first row in panel B, a standard deviation increase in a teacher's VA is associated with about 0.1 percentage point decrease in the the percent of black students. Across both columns of panel C, a standard deviation higher VA is associated with 0.25 percentage point increase in the percent of students who are proficient in the school in which he teaches the subsequent year.[37]

Next, I turn to the change in sorting with VA adoption in rows 3 and 4. Including teachers who move within and out-of district, it seems from the first columns of panels B and C that releasing VA has opposite effects in the two districts on the distribution of teacher quality across schools. However, this can be explained by the adverse selection of teachers moving from Guilford after the policy takes effect.

Turning to the sample of teachers who remain in the same district, the second column of both panels provides evidence of further sorting within Winston-Salem.[38] From the second column of panel B, the release of VA leads a teacher with one standard deviation higher VA to be at a school with 0.3 percentage points lower share of black students. From the second column of panel C, the same teacher will be at a school that has 0.2 percentage points higher proficiency rates after the district releases VA. Taken literally, this translates to 70 and 300 percent increases in the sorting of teacher quality towards high achieving students and away from black students respectively. However, each estimate is noisy, and is only marginally statistically significant (respective p-values of 0.096 and 0.099), and should be treated accordingly. In Guilford, the positive coefficient estimate suggests that the policy leads better teachers to move to schools with higher proportion of black students, but has essentially no effect on sorting with regard to student performance.[39]

[37]The result that students in better schools also get better teachers is consistent with findings in Boyd et al. (2005) and Boyd et al. (2008).

[38]The degree to which VA adoption can affect the sorting of teachers across schools within the district depends on the degree of sorting already present. In the base period with respect to both race and performance, Guilford is more sorted than the average district, while Winston-Salem is slightly less sorted.

[39]Contextually, it is important to note that both districts offer teachers financial incentives to teach in lower-performing schools. Analysis in Section 6.3 examines the effects of VA adoption on the re-sorting of teachers between schools in which no compensating differentials were in place. Further, I find no evidence of

6 Robustness

In the following section, I examine the robustness of the effects of VA adoption. In Section 6.1, I perform within-district, year-by-year analysis of the changing effects of VA on mobility to examine the parallel trends assumption. Section 6.2 examines the robustness of the results when using alternate constructions of VA measures. Section 6.3 considers whether other district policies that paid teachers to work in hard-to-staff schools impact the estimated effects. Appendix 8.4 considers teacher mobility in accordance with the state ABC growth bonus-pay system. In Appendix 8.5, I use competing risks regression to examine the possibility of correlated errors between types of moves. In Appendix 8.6, I take the normality assumptions seriously, and perform normal Maximum Likelihood Estimation.[40]

6.1 Year-by-year analysis

The main assumption underpinning the evidence above is that changes in the relationship between teachers' mobility and VA around the time of VA adoption in the two adopting districts would be otherwise similar to contemporaneous changes in the relationship between teachers' mobility and their VA in the rest of the state. I first investigate this assumption by examining whether the regression coefficient of VA on the probability of moving each year

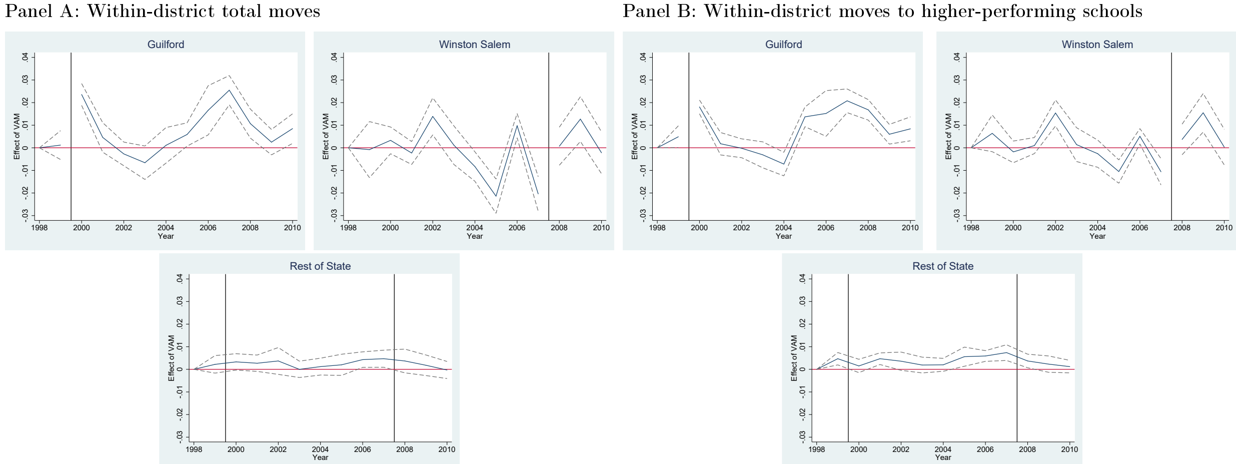
more low-VA teachers leaving teaching in response to district adopting VA. In unreported regressions, the probability of leaving North Carolina Public Schools from Winston-Salem are statistically unrelated to the teachers' VA and from Guilford, better teachers become more likely to leave.

[40]Because job mobility is often localized, I also restricted analysis to districts which share a border with Guilford and Winston-Salem. The results from this restriction were noisy and uninformative, and are unreported here.

Figure 1: The effects of VA on the probability of moving schools within-district by year.

Panel A: Within-district total moves

Panel B: Within-district moves to higher-performing schools



Note: Solid blue lines reflect the point estimates within each district or within the rest-of state on the interactions between year indicators and VA. The dotted lines indicate the 95 percent confidence interval from a within-district bootstrap with 500 replications.

in each informational environment follow parallel trends prior to the policy. More formally, I estimate the following specification separately for Guilford, Winston-Salem, and the rest of the state:

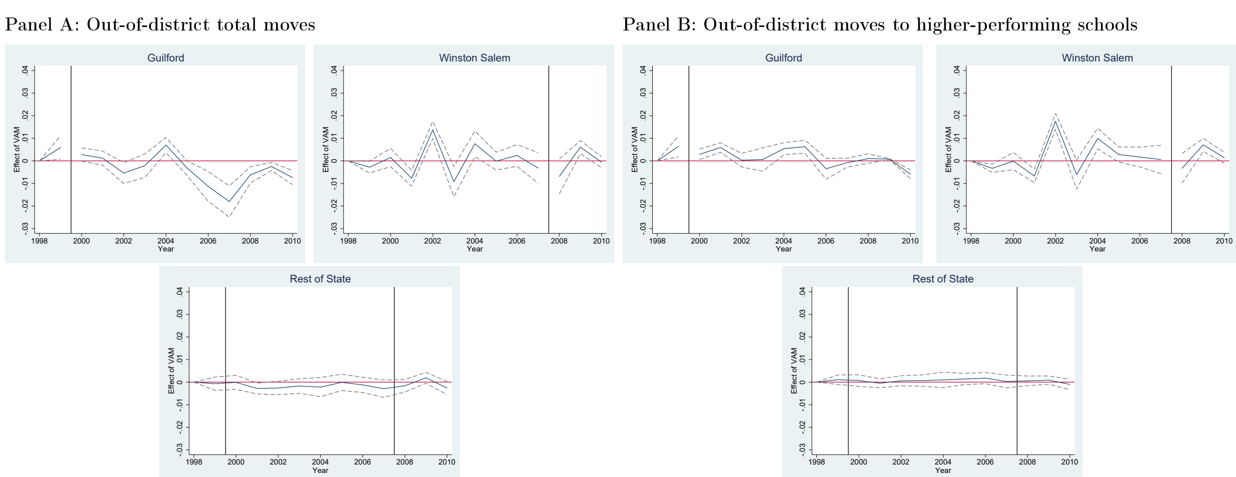
$$y_{jdt} = \boldsymbol{T_t} + VA_j\boldsymbol{\gamma_t} + \mathbf{X_{jdt}}\boldsymbol{\beta_1} + \mathbf{X_{jdt}} \times \mathbf{Post_t}\boldsymbol{\beta_2} + \xi_{jdt}, \tag{18}$$

where $\boldsymbol{\gamma_t}$ is a vector of year specific regression coefficients on VA_j in each mobility regression.[41]

Figure 1 reports these yearly VA coefficient estimates on within-district mobility with 95 percent confidence intervals and breaks at policy adoption. In panel A the dependent variable is an indicator for moving within-district, and in panel B the outcome is an indicator for moving to higher-performing schools within-district. In both districts there is a spike in the coefficient estimates of VA soon after the policy takes effect. These spikes in the estimated coefficients on VA are more pronounced for moves to higher-performing schools. Data limitations pre-policy make it difficult to draw definitive conclusions regarding Guilford, while for Winston-Salem, the yearly estimates are somewhat noisy. However, the pre-policy trends do not seem diverge in a way that would bias up the results. Figure 2, illustrates the same evolution of coefficient estimates on out-of-district mobility. In keeping with the hypothesized asymmetric spread of VA information, the spikes in the correlation between VA and mobility that accompanied VA adoption for within-district transfers are absent when examining out-of-district moves, though the same limitations persist.

[41] Regressions for the rest of the state also include district-level fixed effects.

Figure 2: The effect of VA on the probability of moving schools out-of-district by year.



Note: Solid blue lines reflect the point estimates within each district or within the rest-of state on the interactions between year indicators and VA. The dotted lines indicate the 95 percent confidence interval from a within-district bootstrap with 500 replications.

6.2 Robustness to alternate VA constructions

As discussed in Sections 4.1, when constructing VA estimates for each teacher it may make sense to set the objective of approximating the signals that teachers and principals receive as opposed to the true effectiveness of the teacher. Panel A of Table 7 reflects similar regressions as does Table 3 except that I use EB estimates of teachers' VA rather than DOLS. Using EB, the results remain remarkably similar both in magnitude and precision.

Table 7: Probability of moving schools using Empirical Bayes

	Within District			Out of District		
VARIABLES	**Total**	**To a higher performing school**	**To a lower performing school**	**Total**	**To a higher performing school**	**To a lower performing school**
			Panel A: Full sample of student test scores			
VA	0.0006	0.0028***	-0.0022***	-0.0006	0.0014**	-0.0020***
	[0.00141]	[0.00097]	[0.00079]	[0.00094]	[0.00064]	[0.00059]
VA x Treatment GCS	0.0048*	0.0059***	-0.0011	-0.0130***	-0.0078***	-0.0051***
	[0.00256]	[0.002]	[0.00135]	[0.00229]	[0.00179]	[0.00148]
VA x Treatment WSF	0.0066**	0.0085***	-0.0020	0.0009	0.0023	-0.0013
	[0.00288]	[0.00225]	[0.00178]	[0.00235]	[0.00212]	[0.00121]
Treatment GCS	-0.0048	-0.0055	0.0007	-0.0174***	-0.0245***	0.0072***
	[0.00743]	[0.00478]	[0.00652]	[0.00326]	[0.00233]	[0.00177]
Treatment WSF	0.0553***	0.0471***	0.0082***	-0.0022	0.0144***	-0.0167***
	[0.00453]	[0.0032]	[0.00282]	[0.00233]	[0.00209]	[0.0014]
			Panel B: Restricted to prior student test scores			
VA	-0.0015	0.0000	-0.0015	-0.0021**	-0.0011	-0.0010
	[0.00169]	[0.00141]	[0.00093]	[0.00098]	[0.00073]	[0.00062]
VA x Treatment GCS	0.0035	0.0037	-0.0001	-0.0063***	-0.0041**	-0.0023*
	[0.00331]	[0.00252]	[0.00221]	[0.00232]	[0.00195]	[0.00129]
VA x Treatment WSF	0.0090***	0.0129***	-0.0039**	0.0020	0.0019	0.0001
	[0.003]	[0.00236]	[0.00186]	[0.0023]	[0.00202]	[0.00113]
Treatment GCS	-0.0032	-0.004	0.0008	-0.0162***	-0.0239***	0.0077*
	[0.01311]	[0.00855]	[0.01071]	[0.00515]	[0.00281]	[0.00431]
Treatment WSF	0.0555***	0.0477***	0.0078***	-0.0021	0.0147***	-0.0167***
	[0.00496]	[0.00346]	[0.00294]	[0.00234]	[0.00208]	[0.00142]
Observations	236,018	236,018	236,018	236,018	236,018	236,018

CSB standard errors from 500 repetitions appear in brackets. All regressions use a linear functional form, and include teacher-level covariates and interactions with treatment indicators, as well as year and district fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

The possibility that teachers may have differences in VA after moving to other schools, may present issues for using VA measures 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. It may also result from transitory adjustment costs, giving a theoretically ambiguous direction of potential bias

Consequently, in Panel B of Table 7, I allow teachers VA scores to vary each year, using only data from the current and previous years to construct a teacher's VA in any given year. The main effects hold, though they are in general somewhat exaggerated in Winston-Salem and smaller in Guilford. Still, the adoption of VA raises the probability that good teachers move to better schools. Whereas in Winston-Salem, the effect grows to a full percentage point, in Guilford, the effect falls to 0.4 percentage point and loses statistical significance. From the middle column of Panel B, the negative selection of teachers moving out of Guilford falls to just 30 percent of the estimate given in Table 3, but remains statistically significant.

While it is possible subsequent match quality increases for teachers from Guilford and decreases for teachers in Winston-Salem, I believe measurement error may provide a more plausible explanation. In Guilford, the effect of VA prior to the their release is identified off of just two years of data. As a result, the estimates of teachers' VA 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 Guilford where there is little data prior to the adoption of the policy, while the effects in Winston-Salem become relatively stronger.

Table 8: Sensitivity to using various number of years of student data in VA construction

VARIABLES	2yr VA	3yr VA	4yr VA	5yr VA	6yr VA	7yr VA	8yr VA
VA	0.0010**	0.0015***	0.0017***	0.0019***	0.0021***	0.0023***	0.0035***
	[0.00032]	[0.00047]	[0.00047]	[0.00058]	[0.00063]	[0.00066]	[0.00072]
VA x Treatment WSF	0.0119**	0.0114**	0.0108**	0.0116**	0.0142**	0.0163***	0.0181***
	[0.00614]	[0.00613]	[0.00609]	[0.00621]	[0.0063]	[0.00655]	[0.00685]
Treatment WSF	0.0550***	0.0534***	0.0542***	0.0473**	0.0416**	0.0439**	0.0401*
	[0.01873]	[0.01855]	[0.01856]	[0.0181872]	[0.01911]	[0.02002]	[0.0227]
Observations	207,673	189,531	170,598	151,067	131,567	111,786	94,884

CSB standard errors from 500 repetitions appear in brackets. All regressions use a linear functional form, and include teacher-level covariates and interactions with treatment indicators. Observations from GCS are omitted from the above analysis. *** p<0.01, ** p<0.05, * p<0.1.

To shed light on this issue, I use a fixed number of years prior to the current period when constructing VA measures. Unfortunately, the adoption of VA by Guilford comes just three years into the student data sample, and thus, does not permit me to vary the number of years of data used. Consequently, I drop Guilford from the analysis, and vary the number of prior years of data I use to construct the VA measures from 2 to 8 for estimating effects of the policy on mobility within Winston-Salem. Table 8 demonstrates that though the relationship between years used and the effect of the interaction of the policy in Winston-Salem and VA is not monotonic as the sample used varies, the estimates using more years of data are clearly the largest. This further suggests correlated measurement error presents a problem for restricting VA construction to prior years of data.

6.3 Strategic staffing

A possible complication arises due to alternate teacher compensation plans. District strategic staffing policies, which aim to attract more capable teachers to teach in and stay at hard-to-staff schools could potentially alter teacher preferences over schools.[42] Charlotte-Mecklenburg Schools (CMS) and Winston-Salem were by far the earliest adopters of these initiatives with CMS beginning its Equity Plus program in 1999 and Winston-Salem following suit in 2000.[43] 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. Winston-Salem awarded 20 percent of the district salary supplement ($500-$1,500) to each teacher in targeted schools. In 2007, Guilford adopted its own strategic staffing program, in which bonuses ranged from $5,000-$25,500 depending on subject taught, grade level, and VA. Cumberland County Schools gave stipends to 30 "master teachers" across their 10 most difficult schools. In 2008, CMS also began targeting effective teachers. These programs may reverse which schools are most desirable to teachers. With large enough incentives, high-VA teachers may opt to work at low-performing schools, which is in fact the intent of the policy.

I collected data indicating hard-to-staff schools from each district in North Carolina that offered bonus pay to teachers in those schools. Panels A and B of Table 9 report similar information as is provided in Table 3, except that the binary dependent variable in Table 9 is equal to one, if a move occurs, and the receiving school is not classified as a strategic staffing school. As might be expected, the results are quite similar to those in Table 3, as teachers working in strategic staffing schools comprise just 4 percent of the sample. However, the policy has a much larger effect on the correlation between VA and the probability of moving within Winston-Salem. Column 2 shows that releasing VA raises the probability that a teacher with one standard deviation higher VA will move within Winston-Salem 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 VA and the probability of moving out of Winston-Salem drops by 40 percent, when restricting analysis to moves to non-strategic staffing schools. Both changes serve to widen the gap in the estimates between moves within

[42]"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, and Mission Possible.

[43]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.

and out of Winston-Salem, providing further evidence of private learning.

Table 9: Mobility between non-strategic-staffing schools with respect to school proficiency

	Panel A: Within-District Moves to non-strategic staffing schools			Panel B: Out-Of-District Moves to non-strategic staffing schools			Panel C: Growth in percent proficient staying within-district	
VARIABLES	Total	To a higher performing school	To a lower performing school	Total	To a higher performing school	To a lower performing school	Total	Excluding strategic staffing
VA	0.0014	0.0031***	-0.0018**	0.0002	0.0013*	-0.0011*	0.0024***	0.0026***
	[0.00127]	[0.00086]	[0.00076]	[0.00098]	[0.00072]	[0.00059]	[0.00033]	[0.00034]
VA x Treatment GCS	0.0043*	0.0041**	0.0002	-0.0111***	-0.0054***	-0.0057***	-0.0000	0.0009
	[0.00244]	[0.00197]	[0.00148]	[0.00248]	[0.00194]	[0.0014]	[0.0007]	[0.00072]
VA x Treatment WSF	0.0100***	0.0103***	-0.0004	-0.0007	0.0014	-0.0021**	0.0017*	0.0020*
	[0.00233]	[0.00176]	[0.00148]	[0.00208]	[0.00196]	[0.00113]	[0.00102]	[0.00114]
Treatment GCS	-0.0118	-0.0084	-0.0034	-0.0158***	-0.0238***	0.0079***	-0.0157***	0.0029
	[0.00848]	[0.00552]	[0.00728]	[0.00362]	[0.00221]	[0.00272]	[0.00216]	[0.00222]
Treatment WSF	0.0241***	0.0390***	-0.0149***	-0.0027	0.0114***	-0.0141***	0.0231***	0.0196***
	[0.0049]	[0.00345]	[0.00287]	[0.00255]	[0.00233]	[0.00142]	[0.00168]	[0.0018]
Observations	236,018	236,018	236,018	236,018	236,018	236,018	202,943	197,364

CSB standard errors from 500 repetitions appear in brackets. All regressions use a linear functional form, include year and district fixed effects, and include teacher-level covariates and interactions with treatment indicators. *** p<0.01, ** p<0.05, * p<0.1

Panel C of Table 9 presents the impacts of the policy on teacher sorting within-district among non-strategic staffing schools. Column 1 of panel C is identical to column 2 of panel C in Table 6. I include it here for ease of comparison. Column 2 restricts the sample further to only include non-strategic staffing schools. Moving from column 1 to 2, in both districts, the estimated effect of the policy on the degree to which high-VA teachers sort into high-performing schools becomes more positive, though only statistically significantly so for Winston-Salem.[44] Table 9 accordingly provides no evidence that strategic staffing policies are driving the earlier results. If anything, it seems that these pay policies may mute what would otherwise be larger impacts of releasing VA.

7 Conclusion

If employers are unable to learn accurate information about their workforce over time, their subsequent personnel decisions would be no better at identifying effective employees than at the point of hire. If learning is entirely asymmetric, that is other employers are no better able to tell the effectiveness of an experienced applicant than of a novice applicant,

[44] Table A7 provides a similar inspection instead focusing on the racial composition of the schools. The results are similar, except that sorting with respect to race becomes more significant in both districts when focusing only on non-strategic staffing schools and the magnitude of the mobility effects are somewhat smaller.

productive employees become trapped in positions which under-utilize their talents. Though the context is specialized and not all predictions were born out by the data, the weight of the evidence points to the existence of informational asymmetries between employers. Primarily, this is due to the finding that new public information increased mobility disproportionately for effective workers. Secondly, the adverse selection of workers to employers who were not directly informed of the new information provides further evidence that information arises unevenly in the market.

In the context of public school teachers, this means that effective teachers may be trapped in positions in which they do not wish to teach, while principals shuffle their less capable teachers to other schools. The release of value-added measures of teacher effectiveness does seem to provide actionable information to those who are aware of them. Though additional evidence is still needed, 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 may lead to increased inequity in the distribution of teacher quality across schools. Despite the fact that 38 states have adopted teacher VA, and often contentiously, this signaling role of the measures has avoided discussion. This paper provides novel evidence that adopting teacher-level VA may lead to further sorting of teachers to schools and widen the spread of teacher quality across schools. The policy implication of this finding is not to universally avoid VA. However, it would be useful to provide policy makers an estimate of the cost of retaining high-VA teachers in hard-to-staff schools. The analysis excluding strategic staffing schools implies that the sorting may have been larger without the incentives to induce teachers to work in lower-performing schools.

Clotfelter et al. (2011) and Glazerman et al. (2012) have examined the question of attracting teachers to understaffed schools. Further work is needed to estimate the costs and effectiveness of these policies in retaining effective teachers in low-performing schools, which may cost substantially less. As states and districts continue to adopt teacher VA, policy makers should be aware of the potential consequences of these policies on educational equity, as well as the costs of offsetting these effects.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Disclosure

This work was conducted under expedited IRB approval through both Michigan State University and the University of California at Riverside. The author disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The research reported here was supported by the Institute of Education Sciences, U.S. Department of Education, through R305B090011 to Michigan State University. The opinions expressed are those of the authors and do not represent the views of the Institute or the U.S. Department of Education.

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8 Appendices for online publication

8.1 Model proofs

8.1.1 Comparative statics for within-district moves with respect to teacher effectiveness (μ)

Assuming the probability of moving schools is monotonically increasing in the difference between b^{h*} and b^{r*}, the sign of $\frac{\partial P[b^{h*}_{HV}-b^{r*}_{HV}>0|m,\,\mu]-P[b^{h*}_{NV}-b^{r*}_{NV}>0|m,\,\mu]}{\partial \mu}$ is implied by the sign of $\frac{\partial E[b^{h*}_{HV}-b^{r*}_{HV}-(b^{h*}_{NV}-b^{r*}_{NV})|m,\,\mu]}{\partial \mu}$. Here, the subscript HV denotes that hiring principals may access a teacher's VA, while the subscript NV denotes that there is no VA informing the bidding. I present the conditional expectation in equation 19 below.

$$\begin{aligned}
E[b^{h*}_{HV}-b^{r*}_{HV}-(b^{h*}_{NV}-b^{r*}_{NV})|m,\ \mu] =& \frac{\sigma^2_\tau(0)\sigma^2_{\xi V}(x)}{Z^h_{HV}}m+\frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{HV}}\mu+\frac{2\sigma^2_\epsilon\sigma^2_{\xi V}(x)}{Z^h_{HV}}\mu \\
&-\left(\frac{\sigma^2_\tau(t)\sigma^2_{\xi V}(x)}{Z^r_{HV}}m+\frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{HV}}\mu+\frac{2\sigma^2_\epsilon\sigma^2_{\xi V}(x)}{Z^r_{HV}}\mu\right) \\
&-\left(\frac{\sigma^2_\tau(0)\sigma^2_{\xi}(x)}{Z^h_{NV}}m+\frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}}\mu+\frac{2\sigma^2_\epsilon\sigma^2_{\xi}(x)}{Z^h_{NV}}\mu\right) \\
&+\left(\frac{\sigma^2_\tau(t)\sigma^2_{\xi}(x)}{Z^r_{NV}}m+\frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{NV}}\mu+\frac{2\sigma^2_\epsilon\sigma^2_{\xi}(x)}{Z^r_{NV}}\mu\right).
\end{aligned} \tag{19}$$

Taking the derivative of equation 19 with respect to μ gives the following:

$$\begin{aligned}
\frac{\partial E[b^{h*}_{HV}-b^{r*}_{HV}-(b^{h*}_{NV}-b^{r*}_{NV})|m,\ \mu]}{\partial\mu} &= \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{HV}}+\frac{2\sigma^2_\epsilon\sigma^2_{\xi V}(x)}{Z^h_{HV}}-\left(\frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{HV}}+\frac{2\sigma^2_\epsilon\sigma^2_{\xi V}(x)}{Z^r_{HV}}\right) \\
&-\left(\frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}}+\frac{2\sigma^2_\epsilon\sigma^2_{\xi}(x)}{Z^h_{NV}}\right)+\left(\frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{NV}}+\frac{2\sigma^2_\epsilon\sigma^2_{\xi}(x)}{Z^r_{NV}}\right).
\end{aligned}$$

$$= \frac{2\sigma^2_\xi(x)^2\sigma^2_\epsilon(\sigma^2_\tau(0)-\sigma^2_\tau(t))}{Z^h_{NV}Z^r_{NV}}-\frac{\sigma^2_{\xi V}(x)^2\sigma^2_\epsilon(\sigma^2_\tau(0)-\sigma^2_\tau(t))}{Z^h_{HV}Z^r_{HV}}$$

$$= \frac{2\sigma^2_\epsilon(\sigma^2_\tau(0)-\sigma^2_\tau(t))[Z^h_{HV}Z^r_{HV}\sigma^2_\xi(x)^2-Z^h_{NV}Z^r_{NV}\sigma^2_{\xi V}(x)^2]}{Z^h_{NV}Z^r_{NV}Z^h_{HV}Z^r_{HV}}$$

$$
\begin{aligned}
\frac{\partial E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial \mu} = {} & \frac{2\sigma^2_\epsilon(\sigma^2_\tau(0) - \sigma^2_\tau(t))}{Z^h_{NV} Z^r_{NV} Z^h_{HV} Z^r_{HV}}[\sigma^4_\xi(x)(\sigma^2_\tau(t)\sigma^4_{\xi V}(x)\sigma^2_\tau(0) \\
& + 4\sigma^4_\epsilon \sigma^4_{\xi V}(x) + 2\sigma^2_\epsilon \sigma^4_{\xi V}(x)\sigma^2_\tau(0) + \sigma^2_\tau(t)\sigma^4_\epsilon \sigma^2_\tau(0) \\
& + 2\sigma^4_\epsilon \sigma^2_{\xi V}(x)\sigma^2_\tau(0) + 2\sigma^2_\tau(t)\sigma^2_\epsilon \sigma^2_\tau(0)\sigma^2_{\xi V}(x) \\
& + 2\sigma^2_\tau(t)\sigma^4_{\xi V}(x)\sigma^2_\epsilon) + 2\sigma^2_\tau(t)\sigma^4_\epsilon \sigma^2_{\xi V}(x)) \\
& - \sigma^4_{\xi V}(x)(4\sigma^4_\epsilon \sigma^4_\xi(x) + 2\sigma^2_\tau(t)\sigma^2_\xi(x)\sigma^2_\tau(0)\sigma^2_\epsilon \\
& + \sigma^2_\tau(t)\sigma^4_\epsilon \sigma^2_\tau(0) + 2\sigma^2_\epsilon \sigma^4_\xi(x)\sigma^2_\tau(0) + \sigma^2_\tau(t)\sigma^2_\tau(0)\sigma^4_\xi(x) \\
& + 2\sigma^2_\xi(x)\sigma^2_\tau(0)\sigma^4_\epsilon + 2\sigma^2_\tau(t)\sigma^4_\xi(x)\sigma^2_\epsilon + 2\sigma^2_\tau(t)\sigma^4_\epsilon \sigma^2_\xi(x))]
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial \mu} = {} & \frac{2\sigma^4_\epsilon(\sigma^2_\tau(0) - \sigma^2_\tau(t))(\sigma^2_\xi(x) - \sigma^2_{\xi V}(x))}{Z^h_{NV} Z^r_{NV} Z^h_{HV} Z^r_{HV}} \\
& [2\sigma^2_\xi(x)\sigma^2_{\xi V}(x)(\sigma^2_\tau(t)\sigma^2_\tau(0) + \sigma^2_\epsilon \sigma^2_\tau(0) + \sigma^2_\tau(t)\sigma^2_\epsilon) \\
& + (\sigma^2_{\xi V}(x) + \sigma^2_\xi(x))\sigma^2_\tau(t)\sigma^2_\epsilon \sigma^2_\tau(0))].
\end{aligned} \tag{20}
$$

$\frac{1}{Z^h_{HV} Z^r_{HV} Z^h_{NV} Z^r_{NV}}$ is positive, as it is purely a function of variances. As a fundamental component of asymmetric employer learning, it is assumed that $\sigma^2_\tau(0) - \sigma^2_\tau(t) > 0$. If VA is at all informative, lemma 2 shows that $\sigma^2_{\xi V}(x) - \sigma^2_\xi(x) < 0$. All other terms are positive variances, which implies that $\frac{\partial E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial \mu} > 0$, which in turn implies that the probability of moving within-district increases with increases in μ.

8.1.2 Comparative statics for within-district moves with respect to VA (V)

In determining the comparative statics with regard to the VA signal, I seek to sign $\frac{\partial E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ V,\ \mu]}{\partial V}$. Explicitly showing V allows equation 19 to be written as follows.

$$
\begin{aligned}
E[b^{h*}_{HV} - b^{r*}_{HV} - {} & (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu] = \\
& \frac{\sigma^2_\tau(0)\sigma^2_{\xi V}(x)}{Z^h_{HV}} m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{HV}} \frac{\sigma^2_\nu \mu + \sigma^2_\xi(x) V}{\sigma^2_\nu + \sigma^2_\xi(x)} + \frac{2\sigma^2_\epsilon \sigma^2_{\xi V}(x)}{Z^h_{HV}} \mu \\
& - \left(\frac{\sigma^2_\tau(t)\sigma^2_{\xi V}(x)}{Z^r_{HV}} m + \frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{HV}} \frac{\sigma^2_\nu \mu + \sigma^2_\xi(x) V}{\sigma^2_\nu + \sigma^2_\xi(x)} + \frac{2\sigma^2_\epsilon \sigma^2_{\xi V}(x)}{Z^r_{HV}} \mu \right) \\
& - \left(\frac{\sigma^2_\tau(0)\sigma^2_\xi(x)}{Z^h_{NV}} m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}} \mu + \frac{2\sigma^2_\epsilon \sigma^2_\xi(x)}{Z^h_{NV}} \mu \right) \\
& + \left(\frac{\sigma^2_\tau(t)\sigma^2_\xi(x)}{Z^r_{NV}} m + \frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{NV}} \mu + \frac{2\sigma^2_\epsilon \sigma^2_\xi(x)}{Z^r_{NV}} \mu \right).
\end{aligned} \tag{21}
$$

Taking the derivative with respect to VA (V) provides the following.[45]

[45] $\frac{\partial \sigma^2_{\xi V}(x)}{\partial V} = 0$, since the variance of the signal does not depend on the magnitude of the signal.

$$\frac{\partial E\left[b^{h*}_{HV}-b^{r*}_{HV}-(b^{h*}_{NV}-b^{r*}_{NV})|m,\ V,\ \mu\right]}{\partial V}=\frac{2\sigma^4_\epsilon\sigma^2_\xi(x)(\sigma^2_\tau(0)-\sigma^2_\tau(t))}{Z^h_{HV}Z^r_{HV}}>0$$

As a fundamental component of asymmetric employer learning, it is assumed that $\sigma^2_\tau(0)-\sigma^2_\tau(t)>0$. Meaning that releasing VA raises the probability that high-VA teachers move schools.

8.1.3 Comparative statics for out-of-district moves with respect to teacher effectiveness (μ)

Here, the subscript RV denotes that only retaining principals may access a teacher's VA, while the subscript NV denotes that there is no VA informing the bidding. The first thing to note is that hiring principals bids cancel each other. Thus, I focus on retaining principals' bids with and without VA. Letting $Z^r_{RV}=\sigma^2_\xi(x)\sigma^2_{\tau V}(t)+\sigma^2_\epsilon\sigma^2_{\tau V}(t)+\sigma^2_\epsilon\sigma^2_\xi(x)$, equation 22 gives the conditional expectation of this difference.

$$\begin{aligned}E[b^{h*}_{NV}-b^{r*}_{RV}-(b^{h*}_{NV}-b^{r*}_{NV})|m,\ \mu]=&\frac{\sigma^2_\tau(t)\sigma^2_\xi(x)}{Z^r_{NV}}m+\frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{NV}}\mu+\frac{2\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^r_{NV}}\mu\\&-\left(\frac{\sigma^2_{\tau V}(t)\sigma^2_\xi(x)}{Z^r_{RV}}m+\frac{\sigma^2_{\tau V}(t)\sigma^2_\epsilon}{Z^r_{RV}}\mu+\frac{2\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^r_{RV}}\mu\right)\end{aligned}\tag{22}$$

Taking the derivative with respect to μ gives:

$$\begin{aligned}\frac{\partial E[b^{h*}_{NV}-b^{r*}_{RV}-(b^{h*}_{NV}-b^{r*}_{NV})|m,\ \mu]}{\partial\mu}=&\frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{NV}}+\frac{2\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^r_{NV}}-\left(\frac{\sigma^2_{\tau V}(t)\sigma^2_\epsilon}{Z^r_{RV}}+\frac{2\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^r_{RV}}\right)\\=&\frac{\sigma^2_\epsilon[(\sigma^2_\tau(t)+2\sigma^2_\xi(x))Z^r_{RV}-(\sigma^2_{\tau V}(t)+2\sigma^2_\xi(x))Z^r_{NV}]}{Z^r_{NV}Z^r_{RV}}\\=&\frac{\sigma^2_\epsilon}{Z^r_{NV}Z^r_{RV}}[(\sigma^2_\tau(t)+2\sigma^2_\xi(x))(\sigma^2_\xi(x)\sigma^2_{\tau V}(t)\\&+\sigma^2_\epsilon\sigma^2_{\tau V}(t)+2\sigma^2_\epsilon\sigma^2_\xi(x))-(\sigma^2_{\tau V}(t)+2\sigma^2_\xi(x))\\&(\sigma^2_\xi(x)\sigma^2_\tau(t)+\sigma^2_\epsilon\sigma^2_\tau(t)+2\sigma^2_\epsilon\sigma^2_\xi(x))]\end{aligned}$$

$$\frac{\partial E[b^{h*}_{NV}-b^{r*}_{RV}-(b^{h*}_{NV}-b^{r*}_{NV})|m,\ \mu]}{\partial\mu}=\frac{2\sigma^2_\epsilon\sigma^2_\xi(x)^2(\sigma^2_{\tau V}(t)-\sigma^2_\tau(t))}{Z^r_{NV}Z^r_{RV}}.$$

The above appears as equation 9 in text. Lemma 1 demonstrates that $\sigma^2_\tau(t)-\sigma^2_{\tau V}(t)>0$. All other terms are positive variances, implying that $\frac{\partial E[b^{h*}_{RV}-b^{r*}_{RV}-(b^{h*}_{NV}-b^{r*}_{NV})|m,\ \mu]}{\partial\mu}<0$, which in turn implies that the probability of transitions to uninformed principals increases with declines in teacher effectiveness (μ).

8.1.4 Comparative statics for out-of-district moves with respect to VA (V)

In determining the comparative statics with regard to the VA signal, I seek to sign $\frac{\partial E[b^{h*}_{NV} - b^{r*}_{RV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, V,\, \mu]}{\partial V}$.

$$
\begin{aligned}
E[b^{h*}_{NV} - b^{r*}_{RV} - &(b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu] = \\
&\frac{\sigma^2_\tau(0)\sigma^2_\xi(x)}{Z^h_{NV}} m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}} \mu + \frac{2\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^h_{NV}} \mu \\
&- \left(\frac{\sigma^2_{\tau V}(t)\sigma^2_\xi(x)}{Z^r_{RV}} m + \frac{\sigma^2_{\tau V}(t)\sigma^2_\epsilon}{Z^r_{RV}} \mu + \frac{2\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^r_{RV}} \frac{\sigma^2_\nu P^r_t + \sigma^2_\tau(t)V}{\sigma^2_\nu + \sigma^2_\tau(t)} \right) \\
&- \left(\frac{\sigma^2_\tau(0)\sigma^2_\xi(x)}{Z^h_{NV}} m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}} \mu + \frac{2\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^h_{NV}} \mu \right) \\
&+ \left(\frac{\sigma^2_\tau(t)\sigma^2_\xi(x)}{Z^r_{NV}} m + \frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{NV}} \mu + \frac{2\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^r_{NV}} \mu \right).
\end{aligned}
\tag{23}
$$

The derivative of equation 23 with respect to the VA signal (V) is presented below:

$$
\frac{\partial E\left[b^{h*}_{NV} - b^{r*}_{RV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ V,\ \mu\right]}{\partial V} = \frac{-2\sigma^2_\xi(x)\sigma^2_\epsilon\sigma^2_\tau(t)}{Z^r_{RV}(\sigma^2_\nu + \sigma^2_\tau(t))} < 0
$$

As equation 8.1.4 is the negative of a function of variances, it is less than zero. Thus after VA is released, as a teacher's VA decreases, the probability of moving to uniformed principals increases.

8.1.5 Informed out-of-district principals

It is important to note that good (or high-VA) teachers may choose to reveal their VA to out-of-district principals. Accordingly, the furthering of information asymmetries between employers may not universally apply to out-of-district moves. It may be truer to the setting to examine the expected difference in differences of bids between pre- and post-VA years, allowing for a mix between informed and uninformed out-of-district principals. In this context let δ_d be the home-district-specific probability that the outside principal is informed of the teacher's VA. Equation 24 gives the conditional expectation of this difference.

$$
\begin{aligned}
E[\delta_d(b^{h*}_{HV} - b^{r*}_{HV}) + &(1-\delta_d)(b^{h*}_{NV} - b^{r*}_{RV}) - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu] = \\
&\delta_d \left(\frac{\sigma^2_\tau(0)\sigma^2_{\xi V}(x)}{Z^h_{HV}} m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{HV}} \mu + \frac{2\sigma^2_\epsilon \sigma^2_{\xi V}(x)}{Z^h_{HV}} \mu \right) \\
&- \delta_d \left(\frac{\sigma^2_\tau(t)\sigma^2_{\xi V}(x)}{Z^r_{HV}} m + \frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{HV}} \mu + \frac{2\sigma^2_\epsilon \sigma^2_{\xi V}(x)}{Z^r_{HV}} \mu \right) \\
&- (1-\delta_d) \left(\frac{\sigma^2_{\tau V}(t)\sigma^2_{\xi}(x)}{Z^r_{RV}} m + \frac{\sigma^2_{\tau V}(t)\sigma^2_\epsilon}{Z^r_{RV}} \mu + \frac{2\sigma^2_\epsilon \sigma^2_{\xi}(x)}{Z^r_{RV}} \mu \right) \\
&- \left(\frac{\sigma^2_\tau(0)\sigma^2_{\xi}(x)}{Z^h_{NV}} m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}} \mu + \frac{2\sigma^2_\epsilon \sigma^2_{\xi}(x)}{Z^h_{NV}} \mu \right) \\
&+ \left(\frac{\sigma^2_\tau(t)\sigma^2_{\xi}(x)}{Z^r_{NV}} m + \frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{NV}} \mu + \frac{2\sigma^2_\epsilon \sigma^2_{\xi}(x)}{Z^r_{NV}} \mu \right).
\end{aligned} \tag{24}
$$

Taking the derivative of equation 24 with respect to μ gives the weighted average of symmetric and asymmetric introductions of VA.

$$
\begin{aligned}
&\frac{\partial E[\delta_d(b^{h*}_{HV} - b^{r*}_{HV}) + (1-\delta_d)(b^{h*}_{NV} - b^{r*}_{RV}) - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial \mu} = \\
&\delta_d \frac{2{\sigma^2_\epsilon}^2(\sigma^2_\tau(0) - \sigma^2_\tau(t))(\sigma^2_\xi(x) - \sigma^2_{\xi V}(x))}{Z^h_{NV} Z^r_{NV} Z^h_{HV} Z^r_{HV}} [\sigma^2_\xi(x)\sigma^2_{\xi V}(x)(2\sigma^2_\tau(t)\sigma^2_\tau(0) + \sigma^2_\epsilon\sigma^2_\tau(0) + \sigma^2_\tau(t)\sigma^2_\epsilon) \\
&+ 2(\sigma^2_{\xi V}(x) + \sigma^2_\xi(x))\sigma^2_\tau(t)\sigma^2_\epsilon\sigma^2_\tau(0))] + (1-\delta_d)\frac{\sigma^2_\epsilon {\sigma^2_\xi(x)}^2(\sigma^2_{\tau V}(t) - \sigma^2_\tau(t))}{Z^r_{NV} Z^r_{RV}}.
\end{aligned} \tag{25}
$$

Equation 26 shows that taking the derivative of equation 25 with respect to δ_d demonstrates that as the share of informed principals increases the probability that good teachers move increases as well.

$$
\begin{aligned}
&\frac{\partial^2 E[\delta_d(b^{h*}_{HV} - b^{r*}_{HV}) + (1-\delta_d)(b^{h*}_{NV} - b^{r*}_{RV}) - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial \mu \partial \delta_d} = \\
&\frac{2{\sigma^2_\epsilon}^2(\sigma^2_\tau(0) - \sigma^2_\tau(t))(\sigma^2_\xi(x) - \sigma^2_{\xi V}(x))}{Z^h_{NV} Z^r_{NV} Z^h_{HV} Z^r_{HV}} [\sigma^2_\xi(x)\sigma^2_{\xi V}(x)(2\sigma^2_\tau(t)\sigma^2_\tau(0) + \sigma^2_\epsilon\sigma^2_\tau(0) + \sigma^2_\tau(t)\sigma^2_\epsilon) \\
&+ 2(\sigma^2_{\xi V}(x) + \sigma^2_\xi(x))\sigma^2_\tau(t)\sigma^2_\epsilon\sigma^2_\tau(0))] - \frac{\sigma^2_\epsilon {\sigma^2_\xi(x)}^2(\sigma^2_{\tau V}(t) - \sigma^2_\tau(t))}{Z^r_{NV} Z^r_{RV}} > 0.
\end{aligned} \tag{26}
$$

As noted previously, VA was little known when Guilford adopted their usage in 2000. If principals place no value on the measure, it is the same being uninformed of its content.

Conversely, every out-of-district principal received an EVAAS VA of her school in 2008, when Winston-Salem began using EVAAS VA measures of teacher effectiveness. These different settings lead the share of out-of-district principals who are informed of VA to be higher for those leaving from Winston-Salem than for those moving from Guilford ($\delta_{WSF} > \delta_{GCS}$). Consequently, I expect the relationship between VA and the probability of moving from Winston-Salem to be more positive after Winston-Salem adopts VA than is the relationship between VA and the probability of moving from Guilford after Guilford adopts VA. Empirically, I expect $\gamma_{14OD_{GCS}} < \gamma_{14OD_{WSF}}$. The same logic can be applied to the fact that within Winston-Salem hiring principals did not directly receive teachers' VA whereas in Guilford they did. However, it is likely that principals still inferred something when a teacher chose not to reveal his VA. If the share of informed principals was lower within Winston-Salem than within Guilford ($\delta_{WSF} < \delta_{GCS}$), A safer prediction may be, $\gamma_{14WD_{GCS}} - \gamma_{14OD_{GCS}} > \gamma_{14WD_{WSF}} - \gamma_{14OD_{WSF}}$.

8.1.6 Comparative statics with respect to teacher effectiveness (μ) and school desirability (S)

In order to gain predictions regarding the probability of moving within-district in this framework, I take the cross partial of $E\left[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\, V,\, \mu\right]$ with respect to teacher effectiveness (μ) and both S^h and S^r below.

Taking the derivative of equation 19 with respect to μ gives the following:

$$\begin{aligned}
&\frac{\partial E[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\, \mu]}{\partial \mu} = \frac{E[\rho^h]\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{HV}} + \frac{2E[\rho^h]\sigma^2_\epsilon\sigma^2_{\xi V}(x)}{Z^h_{HV}} \\
&- E[\rho^r]\left(\frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{HV}} + \frac{2\sigma^2_\epsilon\sigma^2_{\xi V}(x)}{Z^r_{HV}}\right) - E[\rho^h]\left(\frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}} + \frac{2\sigma^2_\epsilon\sigma^2_{\xi}(x)}{Z^h_{NV}}\right) \\
&+ E[\rho^r]\left(\frac{\sigma^2_\tau(t)\sigma^2_\epsilon}{Z^r_{NV}} + \frac{2\sigma^2_\epsilon\sigma^2_{\xi}(x)}{Z^r_{NV}}\right). \\
&= \frac{2(\sigma^4_\xi(x) - \sigma^4_{\xi V}(x))\sigma^2_\epsilon\sigma^2_\tau(0)}{Z^h_{HV} Z^h_{NV}} E[\rho^h] - \frac{2(\sigma^4_\xi(x) - \sigma^4_{\xi V}(x))\sigma^2_\epsilon\sigma^2_\tau(t))}{Z^h_{HV} Z^r_{HV}} E[\rho^r].
\end{aligned}$$

$$\frac{\partial^2 E[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\, \mu]}{\partial \mu \partial S^h} = \frac{2(\sigma^4_\xi(x) - \sigma^4_{\xi V}(x))\sigma^2_\epsilon\sigma^2_\tau(0)}{Z^h_{HV} Z^h_{NV}} \frac{\partial E[\rho^h]}{\partial S^h}. \tag{27}$$

By Lemma 1 $\sigma^4_\xi(x) - \sigma^4_{\xi V}(x)$ is positive. Thus, $\frac{\partial E[\rho^h]}{\partial S^h} > 0$ implies that equation 27 is positive, meaning that all else equal, the release of VA increases the mobility of highly-effective teachers to high-performing schools.

$$\frac{\partial^2 E[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\, \mu]}{\partial \mu \partial S^r} = \frac{-2(\sigma^4_\xi(x) - \sigma^4_{\xi V}(x))\sigma^2_\epsilon\sigma^2_\tau(t)}{Z^h_{HV} Z^r_{HV}} \frac{\partial E[\rho^r]}{\partial S^r}. \tag{28}$$

By the same reasoning, equation 28 is negative, implying that the release of VA is predicted to increase the mobility of highly-effective teachers from low-performing schools. Taken together, the probability of a highly-performing teacher moving within-district increases as the hiring school desirability rises relative to the quality of the retaining school after the release of VA.

8.1.7 Comparative statics with respect to VA (V) and school desirability (S)

I take the cross partial of $E\left[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\, V,\, \mu\right]$ with respect to VA (V) and S^s. I present these cross partials below.

$$\begin{aligned}\frac{\partial E\left[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\, V,\, \mu\right]}{\partial V} =& E[\rho^h]\frac{\sigma^2_\tau(0)\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^h_{HV}(\sigma^2_v + \sigma^2_\xi(x))} \\ &- E[\rho^r]\frac{\sigma^2_\tau(0)\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^r_{HV}(\sigma^2_v + \sigma^2_\xi(x))}\end{aligned}$$

$$\frac{\partial^2 E\left[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\, V,\, \mu\right]}{\partial V \partial S^h} = \frac{\partial E[\rho^h]}{\partial S^h}\frac{2\sigma^2_\tau(0)\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^h_{HV}(\sigma^2_v + \sigma^2_\xi(x))} \tag{29}$$

As everything else is a function of variances, $\frac{\partial E[\rho^h]}{\partial S^h} > 0$ implies that equation 29 is positive.

$$\frac{\partial^2 E\left[\rho^h b^{h*}_{HV} - \rho^r b^{r*}_{HV} - (\rho^h b^{h*}_{NV} - \rho^r b^{r*}_{NV})|m,\, V,\, \mu\right]}{\partial V \partial S^r} = -\frac{\partial E[\rho^r]}{\partial S^r}\frac{2\sigma^2_\tau(0)\sigma^2_\epsilon\sigma^2_\xi(x)}{Z^h_{HV}(\sigma^2_v + \sigma^2_\xi(x))} \tag{30}$$

Conversely, $\frac{\partial E[\rho^r]}{\partial S^r} > 0$ implies that equation 30 is negative. Thus, the probability of a move within district increases as the hiring school desirability rises relative to the quality of the retaining school.

8.1.8 Comparative statics for within-district moves with respect to easily-observable teacher characteristics (m)

I derive the predicted change in the relationship between a teacher's easily-observable traits and the probability of moving within district with the introduction of VA, taking the derivative of $E\left[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu\right]$ shown in equation 19 with respect to (m).

$$\begin{aligned}\frac{\partial E\left[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu\right]}{\partial m} =& \frac{2\sigma^2_\epsilon(\sigma^2_\tau(0) - \sigma^2_\tau(t))(\sigma^2_{\xi V}(x) - \sigma^2_\xi(x))}{Z^r_{HV}Z^h_{HV}Z^r_{NV}Z^h_{NV}} \\ &[2\sigma^2_\tau(t)\sigma^2_\tau(0)\sigma^2_\xi(x)\sigma^2_{\xi V}(x) + 2\sigma^2_{\xi V}(x)\sigma^2_\epsilon\sigma^2_\xi(x)(\sigma^2_\tau(0) \\ &+ \sigma^2_\tau(t)) + (\sigma^2_{\xi V}(x) + \sigma^2_\xi(x))\sigma^2_\tau(t)\sigma^2_\epsilon\sigma^2_\tau(0)].\end{aligned} \tag{31}$$

Under the assumptions of prior private learning ($\sigma^2_\tau(0) - \sigma^2_\tau(t) > 0$), and informative VA ($\sigma^2_{\xi V}(x) - \sigma^2_\xi(x) < 0$), equation 31 implies that $\frac{\partial E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\, \mu]}{\partial m} < 0$. Thus, the model predicts the probability of moving after the introductions of VA decreases as a teacher's VA increases, or empirically, $\gamma_{24W} < 0$.

8.1.9 Comparative statics for out-of-district moves with respect to easily-observable teacher characteristics (m)

I derive the predicted change in the relationship between a teacher's easily-observable traits and the probability of moving out-of district with the introduction of VA, taking the derivative of $E\left[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu\right]$ with respect to (m).

$$\frac{\partial E\left[b^{h*}_{RV} - b^{r*}_{RV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu\right]}{\partial m} = \frac{2\sigma^2_{\xi}(x)^2\sigma^2_{\epsilon}(\sigma^2_{\tau}(t) - \sigma^2_{\tau V}(t))}{Z^r_{RV}Z^r_{NV}} \tag{32}$$

Under the assumption that VA is informative to current principals ($\sigma^2_{\tau}(t) - \sigma^2_{\tau V}(t) > 0$), $\frac{\partial E[b^{h*}_{RV} - b^{r*}_{RV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial m} > 0$. This implies that the probability of out-of-district transitions increases with declines in teacher effectiveness.

8.1.10 Comparative statics for within-district moves with respect to ability (μ) and tenure (t)

In order to examine whether there was prior private learning, I take the cross partial of $E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]$ with respect to μ and t. Below is the derivative of equation 19 with respect to μ.

$$\begin{aligned}\frac{\partial E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial \mu} &= \frac{\sigma^2_{\tau}(0)\sigma^2_{\epsilon}}{Z^h_{HV}} + \frac{2\sigma^2_{\xi V}(x)\sigma^2_{\epsilon}}{Z^h_{HV}} - \left(\frac{\sigma^2_{\tau}(t)\sigma^2_{\epsilon}}{Z^r_{HV}} + \frac{2\sigma^2_{\epsilon}\sigma^2_{\xi V}(x)}{Z^r_{HV}}\right) \\ &\quad - \left[\frac{\sigma^2_{\tau}(0)\sigma^2_{\epsilon}}{Z^h_{NV}} + \frac{2\sigma^2_{\xi}(x)\sigma^2_{\epsilon}}{Z^h_{NV}} - \left(\frac{\sigma^2_{\tau}(t)\sigma^2_{\epsilon}}{Z^r_{NV}} + \frac{2\sigma^2_{\epsilon}\sigma^2_{\xi}(x)}{Z^r_{NV}}\right)\right]\end{aligned} \tag{33}$$

Taking the derivative of equation 33 with respect to t gives the following:

$$\begin{aligned}\frac{\partial^2 E[b^{h*}_{HV} - b^{r*}_{HV} - (b^{h*}_{NV} - b^{r*}_{NV})|m,\ \mu]}{\partial \mu \partial t} &= \frac{\partial \sigma^2_{\tau}(t)}{\partial t}\frac{\sigma^2_{\epsilon}Z^r_{NV} - 2(\sigma^2_{\tau}(t)\sigma^2_{\epsilon} + \sigma^2_{\epsilon}\sigma^2_{\xi}(x))(\sigma^2_{\epsilon} + \sigma^2_{\xi}(x))}{{Z^r_{NV}}^2} \\ &\quad - \frac{\partial \sigma^2_{\tau}(t)}{\partial t}\frac{\sigma^2_{\epsilon}Z^r_{HV} - 2(\sigma^2_{\tau}(t)\sigma^2_{\epsilon} + \sigma^2_{\epsilon}\sigma^2_{\xi V}(x))(\sigma^2_{\epsilon} + \sigma^2_{\xi V}(x))}{{Z^r_{HV}}^2} \\ &= -2\frac{\partial \sigma^2_{\tau}(t)}{\partial t}\frac{\sigma^2_{\xi}(x)^2\sigma^2_{\epsilon}{Z^r_{HV}}^2 - \sigma^2_{\xi V}(x)^2\sigma^2_{\epsilon}{Z^r_{NV}}^2}{{Z^r_{HV}}^2{Z^r_{NV}}^2}\end{aligned}$$

$$\frac{\partial E[b_{HV}^{h*} - b_{HV}^{r*} - (b_{NV}^{h*} - b_{NV}^{r*})|m,\ \mu]}{\partial \mu} = \frac{\partial \sigma_\tau^2(t)}{\partial t} \frac{2\sigma_\epsilon^2 \sigma_\tau^2(t)(\sigma_{\xi V}^2(x) - \sigma_\xi^2(x))}{{Z_{HV}^r}^2 {Z_{NV}^r}^2}$$
$$2\sigma_\xi^2(x)\sigma_{\xi V}^2(x)(2\sigma_\epsilon^2 + \sigma_\tau^2(t)) + \sigma_\tau^2(t)\sigma_\epsilon^2(\sigma_\xi^2(x) + \sigma_{\xi V}^2(x)) \quad (34)$$

The assumptions of prior private learning $\left(\frac{\partial \sigma_\tau^2(t)}{\partial t} < 0\right)$ and informative VA $\left(\sigma_{\xi V}^2(x) < \sigma_\xi^2(x)\right)$, imply that equation 34 is positive. Thus, the growth in positive selection with the introduction of VA should be more pronounced for those with more tenure. Empirically, the model predicts the coefficient on the interaction between adopting VA, the VA measures, and tenure to be positive ($VA \times Ten \times TreatDist > 0$).

8.1.11 Comparative statics for within-district moves with respect to VA (V) and tenure (t)

In order to investigate the learning environment that prevailed in the absence of VA, I extend the model to provide differential predictions for workers who have been employed by the same school for a longer period of time or who are simply more experienced. In order to examine whether there was prior private learning, I take the cross partial of $E[b_{HV}^{h*} - b_{HV}^{r*} - (b_{NV}^{h*} - b_{NV}^{r*})|m,\ V,\ \mu]$ with respect to VA (V) and years of tenure (t).

$$\frac{\partial^2 E\left[b_{HV}^{h*} - b_{HV}^{r*} - (b_{NV}^{h*} - b_{NV}^{r*})|m,\ V,\ \mu\right]}{\partial V \partial t} = -\frac{\partial \sigma_\tau^2(t)}{\partial t} \frac{\sigma_{\xi V}^2(x) + \sigma_\epsilon^2}{Z_{HV}^h (Z_{HV}^r)^2} \frac{2\sigma_\xi^2(x)}{\sigma_\nu^2 + \sigma_\xi^2(x)} > 0 \quad (35)$$

The assumption of prior private learning provides ($\frac{\partial \sigma_\tau^2(t)}{\partial t} < 0$) leads equation 35 to be positive. This means that the model predicts larger positive effects of the introduction of VA on the probability that high-VA teachers move, when those teachers have more tenure, all else equal. Empirically, this means the model predicts that the coefficient on the triple interaction of $VA \times TreatDist \times tenure$ to be positive.

8.1.12 Comparative statics with respect to ability (μ) when the retaining principal is not one of the final two bidders

Relaxing the two principal assumption is mostly trivial in that the English auction will reduce to the final two bidders throughout the process, and we need only consider this final stage to make predictions for mobility. The one complication to this is the possibility that one of the final two bidders is not a retaining principal. In which case, were both remaining hiring principals from within the adopting district, the same predictions derived in appendix 8.1.1 would apply. Similarly, if both remaining principals were from outside the district the predictions from appendix 8.1.3 would apply. The remaining interesting case is if one of the final bidding principals is from within the district and the other is from outside the adopting district. In which case, the sign of $\frac{\partial E[b^{h*}_{HV}-b^{h*}_{NV}-(b^{h*}_{NV}-b^{h*}_{NV})|m,\,\mu]}{\partial \mu}$ implies how the the probability of a within-district move will change following VA adoption with respect to teacher effectiveness.

$$E[b^{h*}_{HV} - b^{h*}_{NV} - (b^{h*}_{NV} - b^{h*}_{NV})|m,\ \mu] = \frac{\sigma^2_\tau(0)\sigma^2_{\xi V}(x)}{Z^h_{HV}}m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{HV}}\mu + \frac{2\sigma^2_\epsilon\sigma^2_{\xi V}(x)}{Z^h_{HV}}\mu - \left(\frac{\sigma^2_\tau(0)\sigma^2_{\xi}(x)}{Z^h_{NV}}m + \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}}\mu + \frac{2\sigma^2_\epsilon\sigma^2_{\xi}(x)}{Z^h_{NV}}\mu\right) \tag{36}$$

Taking the derivative of equation 36 with respect μ gives the following:

$$\begin{aligned}\frac{\partial E[b^{h*}_{HV} - b^{h*}_{NV} - (b^{h*}_{NV} - b^{h*}_{NV})|m,\ \mu]}{\partial \mu} &= \frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{HV}} + \frac{2\sigma^2_\epsilon\sigma^2_{\xi V}(x)}{Z^h_{HV}} \\ &\quad - \left(\frac{\sigma^2_\tau(0)\sigma^2_\epsilon}{Z^h_{NV}} + \frac{2\sigma^2_\epsilon\sigma^2_{\xi}(x)}{Z^h_{NV}}\right) \\ &= \frac{\sigma^4_\tau(0)\sigma^2_\epsilon(\sigma^2_\xi(x) - \sigma^2_{\xi V}(x))}{Z^h_{HV}Z^h_{NV}} > 0.\end{aligned} \tag{37}$$

If VA is informative, by Lemma 2 $\sigma^2_\xi(x) - \sigma^2_{\xi V}(x) > 0$. Thus, equation 37 is positive, which implies that the probability of moving within-district increases with increases in μ. The comparative statics with respect to μ for out-of-district move is implied $\frac{\partial E[b^{h*}_{NV}-b^{h*}_{HV}-(b^{h*}_{NV}-b^{h*}_{NV})|m,\,\mu]}{\partial \mu}$, which is negative as it is the additive inverse of equation 37. Thus, the same predictions as are derived in appendix 8.1.1 and appendix 8.1.3 hold when allowing for multiple hiring principals.

8.1.13 Robustness of model predictions

Here, I use a general formulation of bids to illustrate the robustness of my predictions under a class of different bidding structures. I maintain that bids reflect principals' expectations of teacher effectiveness, and specifically that they be expressed as the weighted average of the signal(s) of teachers' true effectiveness (μ) and principals' common prior beliefs based on observable teacher characteristics (m). Thus, in expectation the optimal bid of a principal is given by the following:

$$E[b^{*p}_I] = w^p_I\mu + (1 - w^p_I)m, \tag{38}$$

where $1 \geq w^p_I \geq 0$ is the weight principal, p, with VA information, I, applies to the signals of true effectiveness and $1 - w^p_I$ is the weight she applies to the prior.[46]

For within-district moves, I examine the expected change in the difference of bids between

[46] A common, additively or multiplicatively separable constant can be added without loss of generality.

informed hiring principals and retaining principals before and after the VA release.

$$
\begin{aligned}
E[b_V^{h*} - b_V^{r*} - (b_N^{h*} - b_N^{r*})|m, \mu] = w_V^h \mu + (1 - w_V^h)m - w_V^r \mu + (1 - w_V^r)m \\
- [w_N^h \mu + (1 - w_N^h)m - w_N^r \mu + (1 - w_N^r)m)].
\end{aligned}
\tag{39}
$$

The superscript h indicates a hiring principal, r indicates a retaining principal, subscript V indicates having access to VA, and N denotes not having knowledge of teachers' VA. Again, the sign of $\frac{\partial E[b_V^{h*} - b_V^{r*} - (b_N^{h*} - b_N^{r*})|m, \mu]}{\partial \mu}$ provides the predicted effect of VA adoption on the selection of mobile teachers with respect to teacher effectiveness.

$$
\frac{\partial E[b_V^{h*} - b_V^{r*} - (b_N^{h*} - b_N^{r*})|m,\ \mu]}{\partial \mu} = w_V^h - w_V^r + w_N^r - w_N^h. \tag{40}
$$

There are naturally multiple ways in which equation 40 may be positive. An intuitive sufficient condition in keeping with private employer learning is in expectation, for VA to move retaining principals' expectations of teacher effectiveness less than it moves the expectations of informed hiring principals ($w_V^h - w_N^h > w_V^r - w_N^r$).

For out-of-district moves, I examine the expected change in the difference of bids between uninformed hiring principals and informed retaining principals before and after the VA release.

$$
\begin{aligned}
E[b_{NV}^{h*} - b_V^{r*} - (b_N^{h*} - b_N^{r*})|m, \mu] = w_{NV}^h \mu + (1 - w_{NV}^h)m - w_V^r \mu + (1 - w_V^r)m \\
- [w_N^h \mu + (1 - w_N^h)m - w_N^r \mu + (1 - w_N^r)m)],
\end{aligned}
\tag{41}
$$

where the subscript NV denotes not having knowledge of VA after the release of VA. I find $\frac{\partial E[b_{NV}^{h*} - b_V^{r*} - (b_N^{h*} - b_N^{r*})|m, \mu]}{\partial \mu}$ to predict the effect of VA adoption on the mobility of effective teachers to uninformed principals.

$$
\frac{\partial E[b_{NV}^{h*} - b_V^{r*} - (b_N^{h*} - b_N^{r*})|m,\ \mu]}{\partial \mu} = w_{NV}^h - w_V^r + w_N^r - w_N^h. \tag{42}
$$

Adverse selection to uninformed principals after the release of VA follows from larger shifts onto signals of effectiveness for retaining principals than occurs for uninformed hiring principals ($w_{NV}^h - w_N^h < w_V^r - w_N^r$). For this adverse selection result, VA must be informative to retaining principals, meaning that VA and retaining principals' private signals may not be perfectly correlated.

However, as discussed previously, even having significantly smaller effects of VA on the selection teachers moving out-of-district than on teachers moving within-district may provide evidence of prior private learning. For this weaker prediction, we need only $w_{NV}^h - w_N^h \leq$

$w_V^r - w_N^r$ in addition to $w_V^h - w_N^h > w_V^r - w_N^r$, allowing VA to be non-informative to either party for out-of-district moves.

The predictions with respect to easily observable characteristics summarized by m are trivial alterations of what is presented above. No new assumptions are required to generate these predictions. However, the remaining predictions regarding dynamics with respect to differences in school desirability and teacher tenure each requires additional structure. Sorting on the basis of school desirability requires some school-level constraint on bids that is correlated with observable characteristics of the school. In the text, these constraints take the form of multiplicative scalars to the bids that may differ between the retaining and hiring schools. In a previous version of the paper, these constraints were modeled as school-specific maximum bids. The prediction was consistent under either formulation. The prediction regarding dynamics with respect to tenure require weights on true effectiveness to be larger for teachers who have been in the same school for a longer time. The full model presented in text provides an example of one such structure, which is largely in keeping with the employer learning literature.

8.2 Standard errors

There are two distinct issues that complicate the estimation of standard errors in this study. First, the policy variation occurs at the district level, meaning the errors may be correlated for teachers moving from or within the same district. Clustering at the district level make the standard errors robust to this cross-sectional dependence. Secondly, the VA measures are estimated, and thus, inherently suffer from estimation error. Were this a singular issue, it would be appropriate to bootstrap the student data to account for this estimation error.

Accordingly, I adopt a sampling approach from DiCiccio and Romano (1988) that accounts for both the estimation error of VA measures and the clustered nature of the data. First, I sample districts randomly with replacement just as with the standard cluster-bootstrap. I then conduct stratified sampling at the teacher-level, such that for every teacher who was originally sampled, I randomly sample student/year observations with replacement.[47] In so doing, this provides generally more conservative standard errors across parameters. Table A1 presents all standard errors for Table 3 for comparison.

[47]Replications must include treatment districts in order to inform the analysis. As a result, approximately 13% of replication are discarded.

Table A1: Probability of moving schools using alternate standard errors

	Within-District Moves			Out-of-District Moves		
	Total	To higher performing schools	To lower performing schools	Total	To higher performing schools	To lower performing schools
VA	**0.0016**	**0.0032**	**-0.0016**	**0.0002**	**0.0014**	**-0.0012**
	[0.00139]	[0.00091]	[0.00083]	[0.00084]	[0.00057]	[0.00050)
	{0.00056}	{0.0004}	{0.00036}	{0.00039}	{0.00031}	{0.00022}
	(0.00129)	(0.00091)	(0.00074)	(0.00096)	(0.00072)	(0.00058)
VA 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)
	{0.00262}	{0.00204}	{0.00153}	{0.00192}	{0.00164}	{0.00106}
	(0.00265)	(0.00199)	(0.00151)	(0.00261)	(0.00195)	(0.00156)
VA x Treatment WSF	**0.0052**	**0.006**	**-0.0008**	**0.0009**	**0.0023**	**-0.0014**
	[0.00147]	[0.00094]	[0.00125]	[0.00084]	[0.00068]	[0.00051)
	{0.00323}	{0.00255}	{0.00204}	{0.00186}	{0.00167}	{0.00096}
	(0.00286)	(0.00229)	(0.00194)	(0.00241)	(0.00208)	(0.00129)
Treatment GCS	**-0.004**	**-0.005**	**0.001**	**-0.0162**	**-0.0232**	**0.007**
	[0.00829]	[0.00608]	[0.00537]	[0.00402]	[0.00319]	[0.00214)
	{0.00583}	{0.00436}	{0.00444}	{0.00261}	{0.00114}	{0.0024}
	(0.00851)	(0.00571)	(0.00679)	(0.00374)	(0.00233)	(0.00268)
Treatment WSF	**0.0555**	**0.0475**	**0.008**	**-0.002**	**0.0147**	**-0.0167**
	[0.00579]	[0.00417]	[0.00311]	[0.00258]	[0.00199]	[0.00184)
	{0.00314}	{0.00253}	{0.00215}	{0.0029}	{0.0022}	{0.00171}
	(0.00499)	(0.00372)	(0.00299)	(0.00274)	(0.00224)	(0.00178)
Observations	236,018	236,018	236,018	236,018	236,018	236,018

Clustered standard errors in brackets. Bootstrapped standard errors in braces. District-cluster-bootstrapped-teacher-stratified standard errors in parentheses.

8.3 District-level analysis

Due to the parameterization of the prior analysis to demonstrate the degree of informational asymmetry between employers, it is difficult to see the equilibrium effects of the VA policy. Table A2 presents the results from district-level analysis reporting the estimated effect of VA adoption on overall mobility, teacher effectiveness, and the across school variance of teacher effectiveness. In Table A2, I examine the effects of VA adoption on teacher mobility and the distribution of teacher VA within district. In the prior analysis, the magnitude of the information shock varies depending on teachers' effectiveness and observable characteristics, making the teacher-level microdata indispensable. In estimating equilibrium effects of the policy on the market, the teacher-level data adds no variation in treatment. Thus, I collapse the data to district-year observations. The analysis accordingly loses power when estimating the effect of VA adoption on the districts. Consequently, I pool both treatments together to afford the estimation greater precision. I estimate a simple differences-in-differences model at the district level including district fixed effects to capture time-invariant district heterogeneity and year indicators to capture general time trends. I perform the analysis both with and without district-level covariates.

Table A2: District-level analysis

VARIABLES	Leave NCPS	Move schools	Within-district move	Out-of-district move	Mean VA	Mean VA in lowest quartile 25 schools	Across-school variance in VA	Across-school share of VA variance
Parsimonious model								
Pooled Treatement	0.0006	0.0016	0.0008	0.0009	0.1049	-0.0023	0.0642***	0.0588***
	[0.028]	[0.02802]	[0.02325]	[0.01892]	[0.17973]	[0.12103]	[0.0154]	[0.02378]
Covariate adjusted								
Pooled Treatement	0.0026	0.0006	-0.0002	0.0009	0.0839	-0.0137	0.0480***	0.0506***
	[0.02866]	[0.02806]	[0.02317]	[0.01925]	[0.23646]	[0.10664]	[0.01425]	[0.01949]
Mean dep. var.	0.0585	0.0777	0.0508	0.0269	-0.0012	-0.1426	0.2358	0.2449
Observations	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158

CSB standard errors from 500 repetitions appear in brackets. All regressions use a linear functional form, year and district fixed effects, and are weighted by district size. Districts too small to estimate between school variances in teachers' VA or with fewer than 4 elementary schools are excluded from this analysis. The mean of dependent variables appear at the bottom. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Across mobility outcomes—leaving teaching in North Carolina Public Schools, within-district school transfers, and out-of-district school transfers—the point estimates are generally positive though very small in magnitude and not statistically significantly different from zero. While the estimates are noisy, I take these to suggest that the policy primarily affected the composition of movers rather than the overall rate of churn in the market. Though not statistically significant, the point estimates in column 5 of Table A2 imply the adoption of VA leads to an overall increase in average teacher VA by a 0.08-0.11 of a standard deviation. When examining the effect of the policy on average teacher VA in schools in the lowest quartile of performance prior to VA adoption, the estimated effect of the policy is negative though much closer to zero.[48] The only statistically significant results of this district-level analysis provide further evidence that the adoption of VA increased educational inequality. Column 7 shows that the policy increased the variance of teacher-VA across schools by 20 to 27 percent (p-values<0.001).[49] Column 8 shows that the adoption of teacher VA lead to a 5 - 6 percentage point increase in the share of total VA variance within-district that is due to across school differences in teacher effectiveness.[50] Both findings provide further evidence

[48] In designating schools' percentile ranks, I randomly use 1999 as the benchmark year for half the control districts, and the other half uses 2007 as the benchmark year. These years correspond to the years proceeding VA adoption in Guilford and Winston-Salem accordingly.

[49] Across-school variance in VA is defined as the variance within a district of school averages of teachers' VA.

[50] Across-school share of VA variance is defined as the share of total variance of teachers' VA within a

that the adoption of teacher VA increases the inequality in access to effective teachers.

8.4 Robustness: Mobility based on ABC Growth Policies

In the 1996/1997 school year the state of North Carolina began rewarding teachers who worked in schools in which the students made substantial growth. The state awarded bonuses of either $750 or $1,500 based on whether the school achieved growth in student test scores beyond predetermined tiered thresholds. These bonuses were given to all teachers in qualifying schools. For additional detail about the policy please see Vigdor (2008) and Ahn and Vigdor (2012).

Table A3: Probability of moving to higher or lower growth schools

VARIABLES	Within-District Moves: To a higher ABC growth school	Within-District Moves: To a lower ABC growth school	Out-Of-District Moves: To a higher ABC growth school	Out-Of-District Moves: To a lower ABC growth school
VA	0.0024***	-0.0006	0.0008	-0.0005
	[0.00073]	[0.00077]	[0.00056]	[0.0006]
VA x Treatment GCS	0.0031**	0.0013	-0.0048***	-0.0052***
	[0.00152]	[0.00153]	[0.00139]	[0.002]
VA x Treatment WSF	0.003**	0.0017	0	0.0014
	[0.0015]	[0.00155]	[0.00131]	[0.001]
Treatment GCS	0.0074*	-0.0023	0.0057***	-0.0129***
	[0.00385]	[0.00612]	[0.00187]	[0.00219]
Treatment WSF	0.0156***	0.0074**	-0.001	-0.0093***
	[0.00206]	[0.00297]	[0.00126]	[0.00209]
Observations	236,018	236,018	236,018	236,018

CSB standard errors from 500 repetitions appear in brackets. All regressions include teacher-level covariates and interactions with treatment indicators. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

As a result, teaching in high growth schools may be additionally attractive to teachers since the bonuses depended upon school performance. Table A3 is comparable to Table 3 except that the dependent variable here is whether the teacher moves to higher (lower) growth school as opposed to a higher (lower) performing school within and out of district. The total within and out-of districts mobility estimates in columns 1 and 4 of Table 3 are unaffected, and are omitted.

When examining this alternate school attribute on which teachers may sort, the primary findings remain intact. The within district mobility is driven by moves to more favorable schools for both districts. Though the results are attenuated here as a teacher with a full

district that is due to the variance of school-means of teacher-VA.

standard deviation higher VA is 0.3 percentage point more likely to move within district to a higher ABC growth school for teachers whose VA are released, the estimates remain statistically significantly positive for both districts. Though these estimates are not statistically different from the estimated effect on the probability of moving to higher performing schools, they suggest that school performance may be a stronger motivator for teacher mobility than student growth and the financial incentives.

The estimated effects for moves outside the district are remarkably close between Table 3 and Table A3. The adverse selection of movers out of Guilford County Schools holds for moves to both better and worse schools, while moves from Winston-Salem to better schools remain unrelated to teachers' VA after the policy takes effect.

8.5 Competing Risks Analysis

By performing separate regressions for each type of school transfer, the above analysis treats each type of move as independent of the others. However, it is possible that the propensity of a teacher to move within-district to a higher-performing school is related to the propensity of moving to a higher-performing school in another district. The same could be said with any combination of outcomes. To test the sensitivity of my earlier results to these possibilities, I adopt a competing risks approach, as proposed by Fine and Gray (1999).

Competing risks survival analysis models the subdistribution hazard ($\lambda_E(t)$) of a particular type of event, such as a move within a school district ($E = WD$), as a function of an unspecified baseline hazard ($\lambda_{E0}(t)$), as well as a vector of time-varying covariates ($\mathbf{Z}(t)$). [51]

$$\lambda_{WD}(t|\mathbf{Z}) = \lambda_{WD0}(t) exp\{\mathbf{Z}(t)\boldsymbol{\beta}_0\}, \tag{43}$$

In the context of this study, time at risk (t) is defined as the difference between the current year and the year at which the teacher first appears matched with the current school.[52] $\mathbf{Z}(t)$ is a vector including all covariates used in Table 3, with the exception of tenure, which is perfectly correlated with t. I additionally include district averages of all within-district-varying covariates to control for unobserved, district-wide effects, as in Mundlak (1978).[53]

[51] Gray (1988) defines the subdistribution hazard as, $\lambda_{WD}(t) = lim_{\Delta t \to 0} \frac{P(t<T\leq t+\Delta t, E=WD | t\leq T \bigcup t<T, E\neq WD)}{\Delta t}$, where T is the timing of the event occurrence of which there are different types.

[52] I use teacher to school matches as the basis of this survival analysis. Though this forces me to assume independence of matches, it allows me to retain the original sample making it easier to compare the results.

[53] Unreported regression results show little difference depending on whether or not district averages are included.

Table A4: Changes in the marginal probability of each type of transfer between schools

VARIABLES	Within-District Moves Total	Within-District Moves To a higher performing school	Within-District Moves To a lower performing school	Out-Of-District Moves Total	Out-Of-District Moves To a higher performing school	Out-Of-District Moves To a lower performing school
VA	0.03	0.09***	-0.07**	0.01	0.08**	-0.10**
	[0.021]	[0.024]	[0.030]	[0.028]	[0.035]	[0.042]
VA x Treatment GCS	0.09**	0.13**	0.10	-0.41***	-0.35***	-0.40**
	[0.045]	[0.051]	[0.076]	[0.104]	[0.111]	[0.164]
VA x Treatment WSF	0.04	0.11	-0.08	0.02	0.15	-0.21
	[0.050]	[0.068]	[0.095]	[0.116]	[0.141]	[0.238]
Treatment GCS	0.01	0.22**	-0.23**	0.24**	-0.12	0.49***
	[0.116]	[0.107]	[0.113]	[0.122]	[0.130]	[0.160]
Treatment WSF	0.56***	0.27*	0.87***	-0.87***	0.18	-7.22***
	[0.118]	[0.145]	[0.144]	[0.167]	[0.219]	[0.587]
Observations	236,018	236,018	236,018	236,018	236,018	236,018

CSB standard errors from 500 repetitions appear in brackets. All regressions include teacher-level covariates and interactions with treatment indicators. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4 reports the coefficient estimates for each type of transfer between schools. Accordingly, $\beta \times 100$ may be interpreted as the percent change in the marginal probability of a particular type of mobility due to a one unit change in the covariate. Columns 1 and 4, examine transfers within and out of the district respectively, with the other broad type of transfer serving as a competing risk. Columns 2, 3, 5, and 6, examine transfers to higher and lower-performing schools, within and out of the district, with the other types of transfers serving as competing risks.

In this framework, results remain largely consistent. From columns 1 and 2, the probability of moving within Guilford for a teacher with a one standard deviation higher VA score increases by 9 percent with the release of teacher VA, and for moves within-district to better schools, the probability increases by 13 percent. Both effects are significantly different from zero and are within a percentage point estimates shown in Table 3. For moves within Winston-Salem, the results are somewhat more sensitive. Using competing risks analysis drops the point estimate of the effect of the policy by teacher VA on within district moves by half and the estimate loses significance. The point estimate on moves to a higher-performing school is more stable staying between 10-15 percent, though the significance level drops with this specification to a p-value of 0.106. From columns 4 and 5, a teacher with a one standard deviation lower VA becomes 33.6 percent (29.5 percent) more likely to move out of Guilford (to a higher-performing school) after the policy takes effect. In Winston-Salem, there remain no statistically significant effects of the policy on which teachers move. In general, the public and private learning results are further verified in Guilford with this competing risks analysis, and while the point estimates in Winston-Salem are noisier, I believe they are sufficiently stable to avoid concern.

8.6 Normal Maximum Likelihood Estimation

The results in Table 3 are from a linear probability model, which are more straight forward both computationally and in interpretation. Taking the normality and orthogonality assumptions from Section 3 seriously would suggest normal Maximum Likelihood Estimation (probit estimation). As noted in Ai and Norton (2003), the functional form of probit estimation incorporates an interaction term, even when one is not specifically modeled. As a result, if the researcher is interested in estimating the average partial effect (APE) of an interaction additionally programming is necessary. Table A5 in Appendix 8.7 provides the APEs in accordance with Ai and Norton (2003). Comparison between Table 3 and Table A5 provides very similar results.

Table A5: Probability of moving schools using normal maximum likelihood estimation.

	Within-District Moves			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
VA	0.0022**	0.0030***	-0.0011	-0.0011	0.0005	-0.0018***
	[0.00114]	[0.00079]	[0.00068]	[0.00083]	[0.0006]	[0.0005]
VA x Treatment GCS	0.0046*	0.0040**	0.0021	-0.0117***	-0.0065***	-0.0053***
	[0.0025]	[0.00172]	[0.00185]	[0.00274]	[0.00203]	[0.0017]
VA x Treatment WSF	0.0029	0.0038*	-0.0010	0.0002	0.0026	-0.0020
	[0.00268]	[0.00193]	[0.00221]	[0.00313]	[0.00238]	[0.00324]
Treatment GCS	0.0110***	0.0112***	0.0001	-0.0009	-0.0036**	0.0027***
	[0.00268]	[0.0019]	[0.00177]	[0.0019]	[0.00161]	[0.00101]
Treatment WSF	-0.0149***	-0.0103***	-0.0080***	0.0022	-0.0011	-0.0226***
	[0.00441]	[0.00369]	[0.0031]	[0.00493]	[0.00342]	[0.00679]
Observations	236,018	236,018	236,018	236,018	236,018	236,018

CSB standard errors from 500 repetitions appear in brackets. All regressions include teacher-level covariates and interactions with treatment indicators. *** p<0.01, ** p<0.05, * p<0.1

8.7 Additional Appendices Tables

Table A6: Probability of moving schools within-district using restricted data VA

Panel	A: Within-District Moves			B: Out-Of-District Moves			C: School Quality Growth	
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
VA	0.0003	0.0011	-0.0008	-0.0013	-0.0006	-0.0007	0.0005	0.0004
	[0.00109]	[0.00097]	[0.00063]	[0.00079]	[0.00056]	[0.00043]	[0.00032]	[0.00033]
VA x Treatment GCS	0.0034	0.0030	0.0004	-0.0027	-0.0016	-0.0011	-0.0015	-0.0010
	[0.00249]	[0.002]	[0.00152]	[0.00201]	[0.00167]	[0.00102]	[0.00083]	[0.00076]
VA x Treatment WSF	0.0061*	0.0099***	-0.0038*	0.0019	0.0025	-0.0005	0.0025*	0.0037***
	[0.00312]	[0.00241]	[0.00216]	[0.00247]	[0.00224]	[0.00122]	[0.00131]	[0.00109]
Treatment GCS	-0.0034	-0.0042	0.0008	-0.0137***	-0.0220***	0.0082***	-0.0196***	-0.0156***
	[0.00848]	[0.00545]	[0.00717]	[0.00365]	[0.00243]	[0.00275]	[0.0022]	[0.00225]
Treatment WSF	0.0555***	0.0486***	0.0068**	-0.0017	0.0151***	-0.0168***	0.0299***	0.0241***
	[0.00533]	[0.00386]	[0.0033]	[0.00283]	[0.00217]	[0.0019]	[0.00165]	[0.00165]
Observations	236,018	236,018	236,018	236,018	236,018	236,018	209,424	202,943

CSB standard errors from 500 repetitions appear in brackets. All regressions include teacher-level covariates and interactions with treatment indicators. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Mobility between non-strategic-staffing schools with respect to students' race

	Within-District Moves			Out-Of-District Moves		
VARIABLES	Total	To lower percent black	To a higher percent black	Total	To lower percent black	To higher percent black
VA	-0.0015***	0.0000	-0.0015***	-0.0021***	-0.0011***	-0.0010***
	[0.00042]	[0.00032]	[0.00027]	[0.0003]	[0.00023]	[0.00019]
VA x Treatment GCS	0.0035*	0.0037**	-0.0001	-0.0063***	-0.0041***	-0.0023**
	[0.00206]	[0.00162]	[0.00121]	[0.00148]	[0.00111]	[0.00097]
VA x Treatment WSF	0.0090***	0.0129***	-0.0039**	0.002	0.0019	0.0001
	[0.00276]	[0.00216]	[0.00166]	[0.00166]	[0.00143]	[0.00084]
Treatment GCS	-0.0032	-0.0040***	0.0008	-0.0162***	-0.0239***	0.0077***
	[0.00408]	[0.00109]	[0.00409]	[0.00121]	[0.00098]	[0.00064]
Treatment WSF	0.0555***	0.0476***	0.0078***	-0.0021	0.0147***	-0.0167***
	[0.00232]	[0.00173]	[0.00162]	[0.00194]	[0.00193]	[0.00028]
Observations	236,018	236,018	236,018	236,018	236,018	236,018

CSB standard errors from 500 repetitions appear in brackets. All regressions include teacher-level covariates and interactions with treatment indicators. *** p<0.01, ** p<0.05, * p<0.1