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# School Location and Teacher Supply: Understanding the Distribution of Teacher Effects

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Abstract:
The U.S. Department of Education has recently called on all states to create plans to ensure equal access to excellent teachers. Although there are numerous limitations in using VAM in high-stakes contexts such as teacher evaluation, such techniques offer promise in helping states grapple with issues in equitable access. Research presented here expands our understanding of this topic, showing that disparities in access to high value-add teaching exist not only along lines of student poverty, but also across location. Furthermore, findings suggest that teacher supply may predict the relative disparities in access for a given location. The policy impacts of these findings are explored.

Keywords: teacher effectiveness, equity, value-added modeling, teacher supply, education policy

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Teachers perform critically important work, and are unquestionably a major influence on the achievement of students (Darling-Hammond, 1999; Rivkin, Hanushek, & Kain, 2005). Because there is meaningful variation in how well teachers perform, understanding the distribution of teacher effectiveness is a matter of great importance in the push for equality of opportunity. Schools serving students from disadvantaged communities face significantly greater challenges due to the countless out-of-school factors that impact learning (Berliner, 2009). Thus, it is critical that traditionally underserved students are not further disadvantaged because of the teachers assigned to them. Yet, research demonstrates that students in high-poverty schools receive instruction from teachers that are, on average, less qualified on a number of indicators such as experience, full licensure, and competitiveness of undergraduate education (Clotfelter, Ladd, Vigdor, & Wheeler, 2007). Another report found that schools with 55 percent or more of its students eligible for Free- or Reduced-Price Lunch (FRPL) have twice the rate of out-of-field teachers as do schools with a FRPL rate of 15 percent or less (Almy & Theokas, 2010). Furthermore, rural, high-poverty, and diverse schools exhibit considerably higher rates of beginning teachers than do more affluent schools (Gagnon & Mattingly, 2014). Overall, little doubt exists that teacher qualifications differ considerably across school characteristics, including the socioeconomic status of its students.

The conversation surrounding equal access to good teaching has recently turned its focus from teacher qualities to teacher effectiveness. Teacher effectiveness is a measure of how a teacher impacts student outcomes, whereas teacher quality speaks to the credentials that a teacher brings into a classroom (Hinchey, 2010). This distinction is an important one, as research has consistently shown that certain teacher qualities—most notably experience and advanced degrees—are poor predictors of teacher effectiveness (Harris & Sass, 2007; Nye, Konstantopoulos, & Hedges, 2004; Rivkin et al., 2005). Therefore, researchers are increasingly looking at how teachers influence student outcomes when analyzing teacher effectiveness, usually in the form of value-added to achievement on standardized assessments. Admittedly, this is a narrow way to operationalize a construct as complicated as teacher effectiveness, as it accesses a fraction of the impact of great teachers. Although one may get a more complete picture of teacher effectiveness by also taking into account other data such as those taken from structured classroom observations, such information is difficult to obtain and therefore not available when making comparisons across large numbers of schools from many different districts, and hence there is no conclusive evidence as to how teacher observations might differ across school type.

It is important to note that the use of value-added modeling (VAM) to identify trends in teacher effectiveness is much different from its use in high-stakes teacher evaluation, and considerably more caution is urged when VAM is used in cases of the latter than in those of the former (National Research Council, 2010). Two major criticisms of VAM being used for teacher evaluation are not applicable when aggregating teacher estimates to make research conclusions that are relatively low-stakes in nature.[1] The first major criticism of VAM is the lack of reliability when making individual estimates. However, if idiosyncratic teacher-level errors are indeed random, then aggregating teacher estimates to the school level will cancel out much of this error. Therefore, since the methodology here does not concern itself with individual estimates but rather only means, concerns of precision are less paramount. The second major criticism presented is that VAM creates unintended negative consequences on the learning environment when used in teacher evaluation. Since VAM in this context is not being used in personnel decisions nor are individual results being made public, teachers and administrators would have no incentive to resort to deleterious behavior: teaching to the test, narrowing the curriculum, or even outright gaming. Thus, the estimation of teacher value-added scores represents one of the most feasible and valid means to evaluate the distribution of teacher effectiveness in a context such as this.[2]

[1] By "relatively low-stakes" I mean, specifically, that such analytics do not inform teacher evaluations or personnel decisions.

[2] It is assumed that teacher effectiveness is context-specific. For example, some teachers may be effective in low-poverty environments, but not high-poverty ones—and vice versa. This clearly has policy implications. For instance, incentives to move high-performing teachers into needier schools might not be effective due to the context-specific nature of effectiveness. An exploration of this is beyond the scope of this paper. However, it is worth noting that context-specific teacher effectiveness would not diminish the findings of this paper, as in it I seek to explain, among other things, why some schools with challenging environments employ effective teachers, whereas similarly challenging—and contextually similar—schools do not. Importantly, a number of policy solutions exist which aim to improve the equitability of teacher access that do not require effective teachers to change contexts.

## Purpose

This study aims to extend the current literature on access to effective teaching. Recent studies suggest that lower-income students receive less effective instruction than their more affluent peers, but the degree to which this disparity exists is highly variable (Max & Glazerman, 2014). I hypothesize that levels of teacher supply may explain why a poor school in one area may have effective teachers, whereas an equally poor school in a different area may be seriously lacking. Literature which addresses the geographical distribution of teacher qualities is sparse, while no known study looks at teacher effectiveness in particular. However, it stands to reason that certain geographic locations may be especially attractive to teachers based upon an abundance of other work opportunities or other factors related to quality of life. This has the effect of benefitting all schools in that region—even those that would otherwise find it difficult to attract teachers due to a more challenging population of students. This trend is further compounded by the fact that the geographic scope of teacher markets tends to be rather small, as teachers generally express a preference for schools close to their home (Boyd, Lankford, Loeb, & Wyckoff, 2005). In short, certain regions attract more teachers from outside areas while simultaneous producing more teachers—teachers that are likely to stay in the area. Through this investigation I provide new evidence that furthers our understanding of these matters, and explore relevant policy implications.

## Area of Study

The sample used in this study comes from the State of New Hampshire, which provides an interesting context to examine trends in teacher effectiveness across poverty and place. Although New Hampshire is a relatively affluent, white, and rural state in comparison to others, the regions of the state vary considerably. The rate of childhood poverty in New Hampshire—once the lowest in nation—has been rising in recent years, and New Hampshire's child poverty rate is now lower than only 35 states (Mattingly, Carson, & Schaefer, 2013). Overall the state of New Hampshire offers a well-rounded sample in terms of urbanicity, with nearly equal numbers of children living in rural, suburban, and central city locations. Child poverty is nearly twice as common in rural areas as it is in suburbs, while central cities boast rates three times higher than suburbs (Mattingly et al., 2013).

The range of demographics found in New Hampshire is reflected in regional differences. With a long north-south axis, the state is marked by a short coastline in the more urban and suburban southeast corner, while it is flanked by more sparsely populated mountainous regions in the north and west. Three counties in New Hampshire are considered metropolitan areas—Stratford, Rockingham, and Hillsborough—which together account for 62 percent of the state's population (Johnson, 2012). Figure 1 shows a map of New Hampshire with its ten counties labeled. Hillsborough county, which contains the Manchester-Nashua urban corridor, is the most populous and diverse county in the state, in terms of race as well as income. Demographer Ken Johnson (2012) reports that nearly a quarter of children in the city of Manchester live in poverty, compared to less than 5 percent in suburban Hillsborough county. Adjacent to this metropolitan area are the counties of Carroll, Belknap, Merrimack, and Cheshire. Johnson (2012) reports that Carroll County is representative of one of 300 rural growth nodes in the country, buoyed by recreational activities that are in relative proximity to metropolitan areas. This contrasts with Coos County in the far north, a region that has experienced a population decline for three generations. The state as a whole exhibits very different of forms of rurality—from affluent and growing to relatively poor and economically stagnant.


*Figure 1.* A County Map of the State of New Hampshire.

Overall, there is a broad trend in New Hampshire where the state becomes poorer, less-diverse, more rural, and less populous as one looks north and west across the state. I use data from this study to construct Figure 2, which consists of a pair of maps that show the proportion of students who are in town or rural schools,[3] and the proportion of students eligible for FRPL, at the county level across the state. The map on the left shows that the state is composed of predominantly rural or town designations, with only the southeastern counties of Hillsborough, Rockingham, and Strafford serving more urban and suburban students than town and rural students. The map on the right shows a slightly more complicated trend in FRPL rates, with more affluent Rockingham and Merrimack Counties in the south central part of the state contrasting with the poorer counties of Coos and Sullivan in the north, and west, respectively.

## Data

All student-level data and teacher linkages are obtained from the New Hampshire Department of Education. These data include a number of student-level covariates: free- or reduced-price lunch status, English language learner status, disability status, race, gender, attendance, and suspensions. The achievement data used here come from the 2011-2012 New England Common Assessment Program (NECAP), a criterion-referenced assessment which was administered in 3rd through 8th and 11th grade for mathematics and ELA. The mathematics and

[3] Town/Rural and Suburban/Urban designations roughly coincide with Metro and non-metro assignments, another common classification of urbanicity. Therefore, town and rural were combined in this graphic in order to represent urbanicity as a binary variable.

ELA NECAP assessments were administered in the states of New Hampshire, Vermont, Rhode Island, and Maine. Much of the school-level information used in this study was taken from the New Hampshire Department of Education website. Data on the percentage of students within a school who are registered for FRPL is readily available. The county within which each school resides was obtained using the "NH School and District Profile" page of the Department's website, which was then hand-entered. Information on the urbanicity of each school was taken from the National Center for Education Statistics. Data sets were merged using NCES school identification codes.

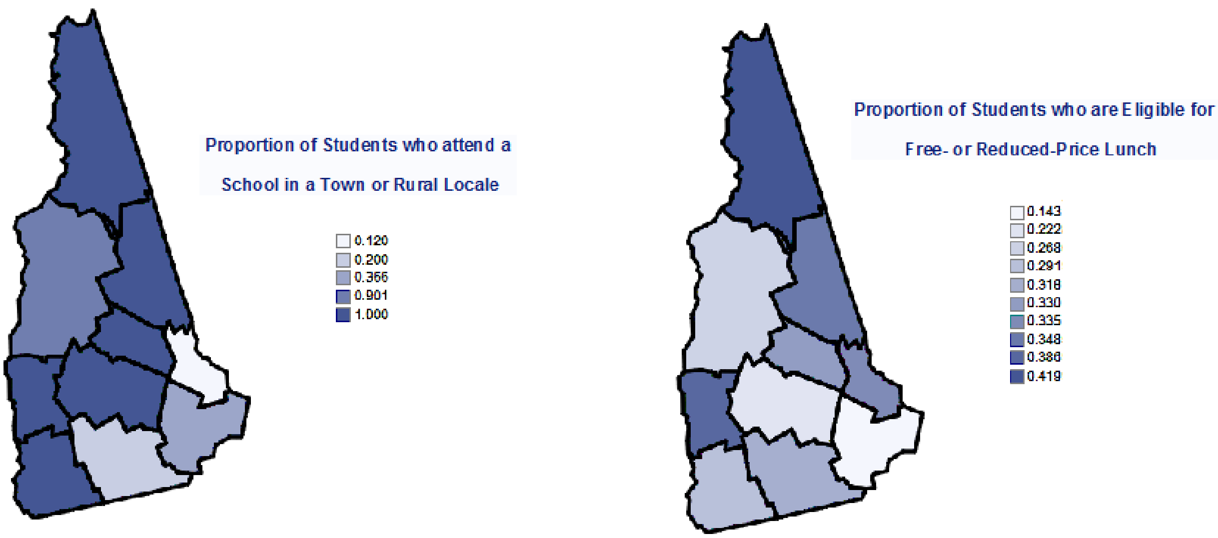


*Figure 2*. Proportions of Students who attend Rural or Town Schools, and who are eligible for Free-or Reduce-Priced Lunch, by County.

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## Methods

There are three primary analysis steps in this study. First, I create a value-added model which estimates teacher contributions to student achievement. Then, a second-stage regression methodology is employed, fitting a taxonomy of regressions that use teacher effectiveness estimates from the value-added model as the outcome variable and school characteristics as predicting variables. Finally, I conduct a correlational analyses to understand how findings from the second-stage regressions may be explained using proxies for teacher supply, examining relationships at the county level. Each of these three primary analysis steps is now discussed in detail.

### Creating a Value-Added Model

A value-added model is constructed using high-dimensional fixed effects to estimate a teacher's contribution to student achievement, which is used here to operationalize teacher effectiveness. This value-added model is typical in its structure, estimating a teacher's individual contribution to student learning after controlling for prior achievement as well as the following student-level covariates: free- or reduced-price lunch status, English language learner status, disability status, race, gender, attendance, and suspensions. A formula for i students and j teachers, with one level of high-dimensional teacher fixed effects, may be parsimoniously written as:

$$\mathbf{A} = \boldsymbol{\beta}_1\mathbf{A}_{\mathbf{prior}}+\boldsymbol{\beta}_2\mathbf{X} + \mathbf{F}\boldsymbol{\Psi} + \boldsymbol{\varepsilon}.$$

**A** is a i x 1 vector of current year test scores; $\mathbf{A_{prior}}$ is a i x 6 matrix of prior student achievement; **X** is a matrix of student demographic information. **Ψ** is a j x 1 vector of teacher identifiers, and **ε** is a vector of error terms. This is accomplished using a Stata command called fese, which is a user-developed command developed to deal with high-dimensional fixed effects when the value of the fixed effects are of interest (Nichols, 2008). Computationally speaking, fese uses least squares approximation to estimate unit effects, in this case the teacher, and reports coefficients and heteroscedasticity- and cluster-robust standard errors. The difference between an individual teacher effect and the mean of all teacher effects represents that teacher's estimated contribution to achievement. The sample of teachers for which value-added estimates are created is limited to teachers in the $4^{th}$ and $7^{th}$ grades. Assessments which cover the content in these grades are actually administered in the start of $5^{th}$ and $8^{th}$ grades, respectively. These cohorts will be identified as $5^{th}$ and $8^{th}$ grade throughout this paper, with the understanding that this refers to the year of the assessment, not the groups of teachers for which the value-added estimates refer to. The resulting subsamples include 603 teacher estimates in $5^{th}$ grade mathematics, 603 in $5^{th}$ grade ELA, 190 in $8^{th}$ grade mathematics, and 201 in $8^{th}$ grade ELA.

**Second-stage Regression**

Once teacher effects are estimated, they are then used as the outcome measure in the second-stage regressions which use school characteristics as predictors. A taxonomy of fitted regression models is constructed, adding predictors one group at a time: FRPL rates and urbanicity, then county indicators, and finally FRPL-county interaction terms.[4] Outcome and predictor variables in the second-stage regression are listed below.

*Teacher Effectiveness:* value-added estimates of teacher effectiveness. This is the estimate of the average contribution a teacher makes to student learning, presented in standard deviation units. This serves as the outcome variable in the second-stage regression.

*School Lower-Income (School_FRPL):* The percentage of students qualifying for FRPL within a school is used as an indicator of the proportion of students in lower-income families, and a rough proxy for the level of poverty within a school.

*Urbanicity (URB):* A vector of urbanicity dummy variables as defined according to the urban-centric codes developed by the U.S. Census Bureau and supported by the National Center for Education Statistics (NCES). These urban-centric codes of urban, suburban, town, and rural also have three subcategories: population gradations of large, medium, and small for city and suburb; distance from urbanized area gradations of fringe, distant, and remote for towns and rural areas. However, due to the very small number of schools in some subcategories—and research questions which do not require such granular divisions of urbanicity—only the four main categories were used.

Urban: 1 if the school is in a territory inside an urbanized area and inside a principal city; 0 otherwise.

Suburban: 1 if the school is located outside a principal city and inside of an urbanized area then all other urbanicity dummy variables=0. Otherwise this serves as the excluded variable.

Town: 1 if the school is located outside an urbanized area and inside of an urban cluster; 0 otherwise.

Rural: 1 if the school is located outside an urban cluster; 0 otherwise.

[4] These interaction terms estimate the unique impact of county-level FRPL rate on teacher effectiveness estimates in each of the ten counties in the state, as this yields a distinct slope for each county.

Since the suburban variable is excluded, all other urbanicity variables are interpreted with respect to suburban schools.

*County (COU):* A vector of county dummy variables.
The Cheshire county binary variable is excluded,[5] and all other urbanicity variables are interpreted with respect to it.

**Correlational Analyses**

Finally, I conduct descriptive, correlational analyses for county-level aggregate variables of interest. To address questions related to teacher supply, two county-level variables are examined: FRPL rates, and normalized NECAP achievement levels. Teacher supply is used in a general sense in this study, as one cannot simply measure the overall quality and quantity of teachers in a given geographic area. However, both student achievement and student income are highly correlated to levels of adult education. Therefore, it is a reasonable assumption that areas with a more educated adult populace will also have more teachers, and hence overall academic performance and lower rates of student poverty serve as useful proxies for the level of teacher supply in a given county. Both proxy variables are calculated by taking the average of the all students from the sample who reside in that county, for each respective variable.

**Research Questions**

1. Do teacher effectiveness estimates exhibit meaningful variability?
2. Can school characteristics such as FRPL rates, urbanicity, and county predict teacher effectiveness?
3. Do county-level proxies for teacher supply explain disparities in access to effective teaching?

## Results

Establishing meaningful variability in teacher effectiveness estimates is a necessary precursor to addressing research questions 2 and 3 in this study, as a lack of variability precludes any examination of such. In related literature, the size of teacher effects are most commonly reported as the estimated impact that a teacher 1 standard deviation (s.d.) above the mean has on standardized student achievement. I find that the estimated impact of having a teacher 1 s.d. above the mean is a 0.2 s.d. difference in student achievement**.** Effects are slightly larger in 5$^{th}$ (0.22 s.d.) than in 8$^{th}$ grade (0.18 s.d.), and slightly larger for ELA (0.22 s.d.) than for mathematics (0.18 s.d.). This represents a somewhat surprising finding as prior research has shown teacher effects to be greater in mathematics than in ELA (Hanushek & Rivkin, 2010). Overall, however, the magnitudes of these estimates are meaningfully large, and relatively similar to those found in past research (Aaronson, Barrow, & Sander, 2007; Nye, Konstantopoulos, & Hedges, 2004; Rockoff, 2004), and as such, allow for further investigation into teacher effectiveness across poverty and place.

To answer the second research question, a series of regression models is fitted using school characteristics to predict teacher effectiveness estimates. Table 1 presents the coefficient estimates for these fitted regression models. Models 1 through 6 suggest that the relationship between school FRPL rates and teacher value-added is robust to the inclusion of controls, while urbanicity is sensitive to other covariates. That is to say, the relationship between the income level of a school and the estimated effectiveness of its teachers remained relatively consistent whether or not one accounts for the urbanicity or county of a school; the same cannot be said of the relationship between urbanicity and teacher effects vis a vis the other school factors that are

[5]As the following analyses illustrate, Cheshire County exhibited the lowest average teacher value-added estimates and therefore is offers the most clarity to use as the excluded variable.

Table 1

*OLS Estimates, Teacher Value-Added (Contribution to Student Achievement, in Standardized Units)*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Intercept | 0.056 *** | 0.023 *** | -0.075 ** | 0.067 *** | 0.010 | 0.017 | -0.029 |
| | (0.010) | (0.009) | (0.028) | (0.012) | (0.030) | (0.035) | (0.089) |
| Percentage of Students eligible for FRPL | -0.0018 *** | | | -0.0022 *** | -0.0019 *** | -0.0024 *** | -0.0012 |
| | (0.0003) | | | (0.0003 | (0.0003) | (0.0004 | (0.0024) |
| **Urbanicity (Suburban Excluded)** | | | | | | | |
| Urban | | -0.030 † | | 0.031 | | 0.037 | 0.059 * |
| | | (0.017) | | (0.019) | | (0.025) | (0.028) |
| Town | | -0.031 † | | 0.006 | | 0.002 | 0.005 |
| | | (0.017) | | (0.017) | | (0.024) | (0.026) |
| Rural | | -0.025 † | | -0.016 | | -0.025 | -0.017 |
| | | (0.013) | | (0.013) | | (0.016) | (0.017) |
| **County (Cheshire County Excluded)** | | | | | | | |
| Belknap | | | 0.025 | | 0.030 | 0.035 | 0.210 † |
| | | | (0.038) | | (0.038) | (0.037) | (0.124) |
| Carroll | | | 0.059 | | 0.064 | 0.080 † | -0.062 |
| | | | (0.040) | | (0.039) | (0.041) | (0.113) |
| Coos | | | 0.144 *** | | 0.166 *** | 0.176 *** | 0.046 |
| | | | (0.041) | | (0.041) | (0.041) | (0.158) |
| Grafton | | | 0.075 * | | 0.068 † | 0.076 * | 0.113 |
| | | | (0.037) | | (0.036) | (0.038) | (0.101) |
| Hillsborough | | | 0.083 ** | | 0.079 ** | 0.056 † | 0.106 |
| | | | (0.029) | | (0.029) | (0.034) | (0.089) |
| Merrimack | | | 0.083 ** | | 0.066 * | 0.062 † | 0.020 |
| | | | (0.032) | | (0.032) | (0.032) | (0.094) |
| Rockingham | | | 0.102 *** | | 0.068 * | 0.059 * | 0.066 |
| | | | (0.030) | | (0.030) | (0.033) | (0.033) |
| Strafford | | | 0.052 | | 0.047 | 0.042 | 0.161 † |
| | | | (0.033) | | (0.033) | (0.037) | (0.098) |
| Sullivan | | | 0.056 | | 0.076 † | 0.084 * | 0.271 † |
| | | | (0.040) | | (0.040) | (0.040) | (0.146) |
| **Interaction Terms (Cheshire County Excluded)** | | | | | | | |
| Belknap * FRPL rate | | | | | | | -.0048 |
| | | | | | | | (0.003) |
| Carroll * FRPL rate | | | | | | | 0.0037 |
| | | | | | | | (0.0035) |
| Coos * FRPL rate | | | | | | | 0.0025 |
| | | | | | | | (0.0037) |
| Grafton * FRPL rate | | | | | | | -0.0011 |
| | | | | | | | (0.0028) |
| Hillsborough * FRPL rate | | | | | | | -0.0017 |
| | | | | | | | (0.025) |
| Merrimack * FRPL rate | | | | | | | 0.0020 |
| | | | | | | | (0.0027) |
| Rockingham * FRPL rate | | | | | | | 0.0009 |
| | | | | | | | (0.0027) |
| Strafford * FRPL rate | | | | | | | -0.0035 |
| | | | | | | | (0.0027) |
| Sullivan * FRPL rate | | | | | | | -0.0044 |
| | | | | | | | (0.0035) |

*Note.* Standard errors in parentheses. †p<.10,*p<.05, **p<.01, ***p<.001

controlled for. Ultimately, this adds validity to establishing a connection between school poverty and teacher effectiveness. Furthermore, the magnitude of the FRPL coefficient is meaningfully large, as high-poverty schools (FRPL=76%), for example, are associated with teacher effects 0.12 s.d. lower than those of low poverty schools (FRPL=25%). The impact of school county on estimated teacher effects is also meaningful: half (five) of the counties in New Hampshire have significantly higher coefficients than that of the lowest county.

Next, county-level FRPL slopes are analyzed and interpreted (model 7), as these coefficients speak to within-county relationships between school poverty and teacher effectiveness. Because these coefficients are interaction terms, they must be interpreted with respect to the FRPL coefficient; by adding these two terms, one can determined the estimated relationship between school FRPL rates and teacher effectiveness estimates within a county. The FRPL term alone represents the relationship between FRPL rate and estimated teacher effects when all other county dummy variables are zero, which occurs when the county is the excluded category (Cheshire). The findings presented here again reveal interesting trends. In the county with the most negative slope,[6] a 20 percentage point difference in FRPL rates is negatively associated with a 0.12 difference in teacher value-added. This contrasts to the three counties (Carroll, Coos, and Merrimack) where the estimated effect of FRPL rates is actually positive, although not significantly different from no effect.[7] Rockingham and Cheshire counties exhibit small negative coefficients that are also not statistically different from zero. Thus, findings here suggests that affluent schools in Carrol, Cheshire, Coos, Merrimack, and Rockingham Counties employ teachers no more effective, on average, than lower-income schools in each respective county, while significant disparities in other counties do exist.

Table 2

*The Relationship between School FRPL Rate and Teacher Value-Added, by County (First Column), and its Corresponding State Rank (Second Column). State Rank in Absolute Achievement (Third Column) and FRPL Rates (Fourth Column) Are also Presented.*

| County | FRPL Coefficienct (from Model 7) | Rank, FRPL Coefficient (10=most negative) | Rank, Absolute Achievement (10= lowest achievement) | Rank, FRPL Rates (10= highest rate of students on FRPL) |
|---|---|---|---|---|
| Belknap | -0.0060 | 10th | 6th | 6th |
| Carroll | 0.0025 | 1st | 1st | 8th |
| Cheshire | -0.0012 | 5th | 5th | 5th |
| Coos | 0.0012 | 2nd | 8th | 10th |
| Grafton | -0.0023 | 6th | 4th | 3rd |
| Hillsborough | -0.0030 | 7th | 9th | 4th |
| Merrimack | 0.0008 | 3rd | 2nd | 2nd |
| Rockingham | -0.0003 | 4th | 3rd | 1st |
| Strafford | -0.0047 | 8th | 7th | 7th |
| Sullivan | -0.0057 | 9th | 10th | 9th |

[6] Belknap had the most negative slope, which equals the Belknap*FRPL coefficient (-0.0048) plus the FRPL coefficient (-0.0012), or -0.006.

[7] T-tests reveal that the interaction terms of Belknap, Strafford, and Sullivan Counties (the most negative effects of FRPL rates) are significantly different (alpha=.05) from Carroll, Coos, and Merrimack Counties.

To answer research question 3, the relationship between within-county FRPL effects and proxies for teacher supply are examined. The county-level FRPL coefficients exhibit a modest, negative relationship ($\rho = -0.21$) with the percentage of students in that county eligible for FRPL, and a strong, positive correlation ($\rho = 0.65$) between the overall level of achievement in a county and its FRPL coefficient. Both of these correlations support the primary hypothesis of this study, namely that areas of high teacher supply should exhibit a more equitable distribution of effective teachers across school poverty. Table 2 further illustrates this point: counties with lower income and achievement levels generally have more negative FRPL slopes, and vice versa.

Figure 3 graphically represents how disparities in access vary according to a teacher supply proxy. On this graph is plotted the estimated teacher effectiveness versus the FRPL rate of a school, with separate best fit lines for schools in the five higher-, and five lower-, achieving counties in the state. In the higher-achieving counties, this difference is not statistically significant. In lower-achieving counties, however, the difference is noteworthy: a teacher at a school with 30 percent FRL students (moderately-low poverty) adds an additional 0.1 standard deviations to student achievement compared to a teacher at a school with a 70 percent FRL rate (moderately-high poverty). Overall, it appears that disparities in access to effective teaching are greatest in areas that have lower levels of teacher supply.

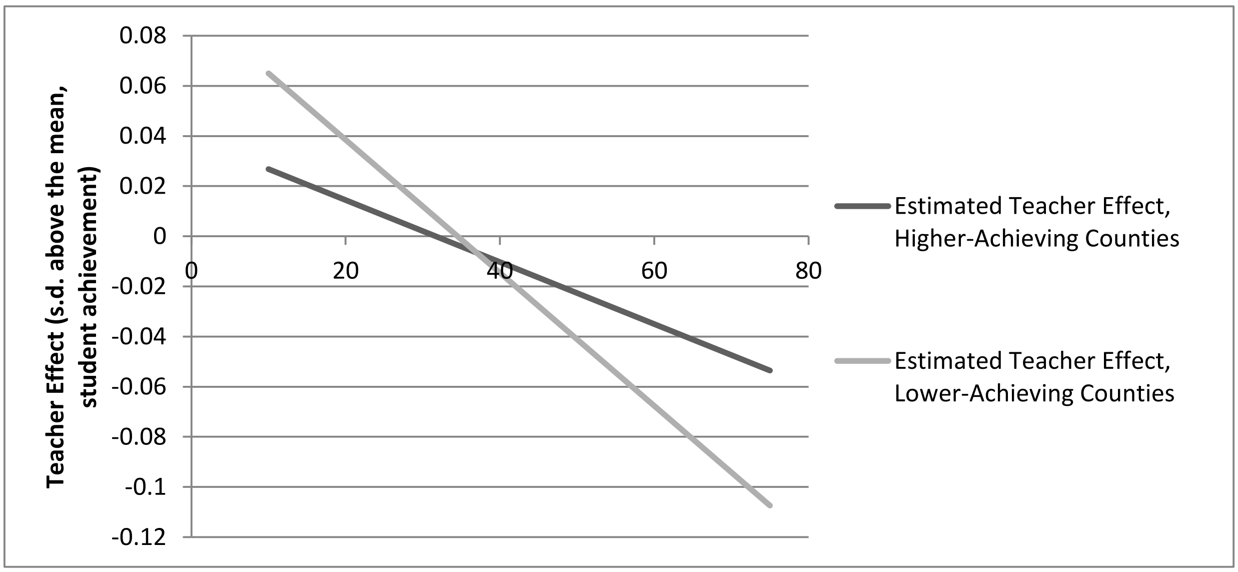


*Figure 3.* Estimated teacher effect across school FRPL rate, higher- and lower-achieving counties.

## Conclusions

This study's primary contribution to related literature is its incorporation of geographical location to our understanding of the distribution of teacher effectiveness. Meaningful differences were found in the average effectiveness ratings across counties in the State of New Hampshire, with differences between high and low value-added counties on the order of 0.1 standard deviation. Such variation might be expected; more interesting findings emerge when such variation is explored in greater detail—specifically that the level of disparity in access to effective teaching may be predicted by the overall levels of achievement and poverty in a county. This finding speaks directly to the conclusion by Max and Glazerman (2014) that, although high-poverty schools are more likely to employ teachers with lower effectiveness ratings, there exists considerable variation and in fact some districts do not exhibit such an inequality. I argue that this equity-inequity spectrum may be caused in part by differences in factors related to teacher supply. Specifically, one would suspect that geographic regions which can better attract teachers due to any number of quality of life factors—a more educated populace, recreational activities, employment opportunities, or higher pay—would be better able to staff all of its schools with effective teachers. Proximity to teacher training programs is yet another factor which may be related to the supply of effective teachers. Conversely, those regions that find it difficult to attract professionals in general likely find it especially difficult to staff its poorest schools.

Indeed, the counties in New Hampshire where this relationship is the strongest are the very places where one would expect inequities to be sharpest. In the New Hampshire counties that exhibit lower rates of student achievement and affluence, there is considerably more inequality in teacher effectiveness ratings across schools of higher and lower compositions of students on free- or reduced-price lunch. One may take a supply-side view of teacher staffing to understand this finding. If regional factors exist which differentially attract talented teachers, poorer schools in high-supply counties may benefit considerably more than similarly poor schools in low-supply counties. In order to illustrate an example of high-supply region, I offer the case of Rockingham County, which is located on the New Hampshire coast and boasts an affluent and well-educated population. Although the overall rate of lower-income students in Rockingham County in this sample is quite low at 14 percent, there are also a number of schools with one-third or more of its student eligible for FRPL. It stands to reason that these schools with moderate levels of lower-income students benefit from being situated in such an affluent area. Indeed, Rockingham County shows no difference in effectiveness ratings across lines of school FRPL rates. Merrimack and Carroll Counties present similar examples, as both regions likely have little difficulty attracting and retaining a well-educated populace when compared to other counties in the state. Furthermore, these counties are located closer to many of the state's major teacher preparation programs, which are by-in-large located in the southern and eastern parts of the state, providing another explanation for these results.

## Policy Implications

Policy and politics must address unequal opportunity, as most Americans find the growing disparities between rich and poor to be alarming (Putnam, 2015; Reardon, 2013). Clearly the factors at play are complex, as numerous issues ranging from parenting and values, to educational access, to the social capital of one's neighborhood—all viewed through a historical tapestry of systematic disadvantage for immigrants and minorities—each seem to explain away a piece of the puzzle. One thing is certain: no panacea exists through which the disparities in achievement may be quickly closed. Despite this, students, educators, and policy makers understand the classroom teacher to be the single-greatest school factor in diminishing or perpetuating disparities in achievement. No other entity outside of the home works as intimately with students, and research has consistently shown the outsized effect that teachers can have on students (Nye et al., 2004; Rivkin et al., 2005). Perhaps just as importantly, and unlike many other family and community factors, the qualifications and performance expectations of teachers may to a significant degree be determined through policy decisions.

In November, 2014, the U.S. Department of Education asked each state to submit a plan describing the steps it will take to ensure that poor and minority children are not taught at higher rates by inexperienced, unqualified, or out-of-field teachers. These plans required states to identify gaps in access to "excellent" teaching, and to propose strategies aimed at closing identified gaps. Plans, first submitted in June, 2015, vary considerably in the metrics used to identify excellence, driven in part by the teacher personnel and evaluation data available. Some states that lack sophisticated data systems and analytic capacity had to rely on trends in novice teachers and Highly Qualified Teacher rates, alone, to serve as proxies for unqualified and/or out-of-field teachers. Given that roughly 99% of teachers in the US are "highly qualified," this measure offers very limited insight into disparities in teacher quality across schools. However, some states that have constructed more robust data systems may be able to assemble a dashboard of metrics that will allow for a more complete examination of access to excellent teaching. Imazeki and Goe (2009) argue that many states looking to improve the distribution of teachers use too few indicators to identify the schools and districts most in need of assistance, and should use additional teacher quality data. I argue that states should do this and more, taking into account regional trends and teacher value-added estimates. Improved data systems link student test scores to individual teachers, thus paving the way for VAM to be used to estimate teacher effectiveness within states. Indeed, there are many states that do not currently use VAM in teacher evaluation but do have the data links necessary to create a value-added metric for the purposes of understanding equity.

Although many criticisms of VAM are entirely compelling, we should not cast aside these techniques in appropriate low-stakes applications. States can create a dashboard of important metrics such as the most meaningful quality indicators, value-added scores, teacher turnover and retention data, and other school and regional demographic information. Ultimately this allows for a more efficient and targeted use of incentives and supports by states, as VAM may help to identify particular districts and regions that suffer from low teacher supply. However, often times such schools are identified with incomplete and sometimes anecdotal evidence; clearly more information, including VAM results, would improve such identification. If VAM is not an option for states, this study suggests that states may want to pay special attention to poor, low-achieving schools that are also located in a broader region of poverty. Many states are already instituting "grow-your-own" policies, financial incentives, and providing support for communities of practice in order to help schools that struggle to find effective teachers. Clearly solutions will vary depending on the contexts of schools; successful rural solutions will likely look very different than urban ones, for example. But regardless of the policy initiative, it is important that a full complement of evidence is used to support implementation strategy as well as in evaluating the effectiveness of programs that attempt to promote equal access to excellent teachers.

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