

Examining the Maldistribution in Teacher Quality: A Spatial Analysis of the Distribution of Credentialed Educators in California Schools

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Abstract

Teacher quality is a primary factor influencing student achievement, which subsequently affects future earnings. Studies show that quality teachers are not distributed equally across the U.S., resulting in a maldistribution of quality teachers that disfavors minority groups. However, despite analyzing an outcome that involves distribution across geographical space, these studies do not employ the spatial econometric techniques needed to ensure accurate results. Exploratory Spatial Data Analysis (ESDA) and spatial regression analysis are used to test for spatial autocorrelation in the distribution of credentialed teachers throughout California's unified school districts. Those results are compared with a non-spatial regression analysis to uncover the implications of eschewing spatial modeling on these types of data. Spatial econometrics reveal that credentialed teachers are not distributed equally—non-random clustering of teachers exists—to the disadvantage of areas with higher populations of traditionally disadvantaged minorities. However, non-spatial techniques overestimate the significance of race and fail to uncover the significance of other important variables affecting the distribution of teacher quality: the distribution of neighboring districts and pre-established student achievement. This reaffirms claims that utilizing non-spatial techniques on spatial data can lead to bias and incorrect estimates. *Key Words:* spatial econometrics, ESDA, spatial regression, spatial autocorrelation, teacher quality

I. Educational Egalitarianism

EDUCATIONAL EGALITARIANISM—the notion that the public education sector should provide equal opportunities for students to succeed by ensuring a parity of education resources—should be a priority for any government seeking to create a stable and productive society. Educational attainment is a crucial variable affecting one's future socioeconomic status, job mobility, and salary attainment (Breen and Jonsson 2005). Providing equal educa-

tion opportunities to everyone can help mitigate the disadvantages that hinder the ability of those in some underprivileged groups to move up the socioeconomic ladder (Babones, Felmet, and Hwang 2007). Thus, because education equality reduces income inequality (Lin 2007), policy makers should strive to create egalitarian education systems by more equitably distributing resources that affect student achievement.

Education scholars have long debated the impact of education resources on student achievement. Some have argued that schools have little independent impact compared to social context and student background (Coleman et al. 1966), while others contend that schools do have an impact on student learning (Darling-Hammond 2000; Ferguson 1991; Mosteller 1995), a sizeable portion of which is attributable to teachers (Ferguson 1991; Sanders and Rivers 1996). Although a range of background factors, such as race and socioeconomic status, are related to student performance, research has shown that school-level factors also have considerable impact, and that, of these education resources, teacher quality is the most reliable predictor of student achievement (Darling-Hammond 1997, 1999, 2000).

As important as teacher quality is to student success (Seebruck 2015), quality teachers are not distributed equally across U.S. school districts (Prince 2002). Several studies have revealed a maldistribution of quality teachers across the U.S. that disadvantages lower-class and minority youth (Borman and Kimball 2005; Peske and Haycock 2006). However, extant studies do not utilize spatial analysis techniques to examine the spatial relationship between variables in their data, using instead non-spatial statistical techniques that do not account for geography. In a regression analysis, failure to consider the potential existence of spatial autocorrelation across neighboring units of analysis causes omitted variable bias and can lead to incorrect standard errors and inconsistent parameter estimates (Greenbaum 2002).

Accordingly, spatial econometrics can be used to determine whether teachers are non-randomly distributed across California's school districts. In line with the literature, the results reveal that credentialed teachers are not fairly distributed across California and that this maldistribution disadvantages traditionally disadvantaged racial minorities such as blacks and Latinos. However, in comparing the spatial regression model with the non-spatial regression model commonly found in the literature, it becomes clear that it is not race alone that is driving this maldistribution. Other significant variables influencing the distribution of credentialed teachers include the distribution of teacher quality in neighboring districts as well as the pre-existing capabil-

ities of the student body—effects not captured by the non-spatial regression model. Of course, race has been shown to affect student achievement in the U.S., with racially based gaps beginning as early as elementary school (Bali and Alvarez 2004), making the causal relationship between these variables difficult to unpack. But, it is important to note that, even after controlling for the racial composition of schools, pre-existing student achievement still significantly affects the distribution of teacher quality across school districts. That non-spatial regression techniques fail to uncover these relationships reaffirms the need to consider proper research methods when analyzing the geographic distribution of inequality.

Teacher Quality and Student Achievement

Numerous studies have argued that factors such as teacher quality are so important to student achievement that they can explain away the performance gap that currently disfavors poor and minority students (Prince 2002). Coleman et al. (1966) long ago argued that teacher characteristics tended to explain more variance in student achievement than any other school resource. This claim was substantiated by a study of New York City schools in which differences in teacher qualifications (educational attainment, certification status, and experience) accounted for approximately ninety percent of the total variation in school-level student achievement in reading and mathematics at all grade levels tested, holding constant student characteristics (Armour-Thomas et al. 1989). In their study on teacher quality and educational equality in Washoe County, Nevada, Borman and Kimball (2005) used multilevel models, nesting students within classrooms, to show that classes taught by higher-quality teachers produced higher mean achievement than those taught by lower-quality teachers. Teacher quality was measured by teacher evaluation ratings and teacher experience. Their sample included nearly five thousand elementary students in urban, suburban, and rural schools and controlled for minority and poverty status and student pre- and post-test scores.

These studies are in line with numerous others demonstrating that teacher quality is one of the predominant predictors of student achievement (Darling-Hammond 1997, 1999, 2000), even more so than student background characteristics such as poverty, language background, and minority status (Rowan, Correnti, and Miller 2002). Prince (2002:13) asserts that “teacher quality is the single most important school variable affecting student achievement.” Certainly student background characteristics affect achievement, but these are factors that schools cannot control. In order to promote educational

egalitarianism, schools and districts need to focus on providing a parity of education resources, by far the most important of which is teacher quality.

Given the impact of teacher quality on student achievement, and its subsequent impact on future earnings, the cumulative economic effects of teacher quality for a society are noteworthy. Hanushek (2011) estimates that, for a class size of thirty students, an effective teacher (ninety-third percentile) can produce annual macroeconomic gains of more than \$963,000 over a less effective teacher (sixtieth percentile), based on total collective increases to those students' lifetime incomes due to higher student achievement. Thus, given the economic link between teacher quality and student achievement, it is in a society's best interest to distribute teacher quality more equitably, so as to avoid the detrimental effects of social inequality (Wilkinson and Pickett 2009).

Operationalizing Teacher Quality

While the literature agrees that teacher quality is important to student achievement, there remains to be a standard measure of teacher quality. Darling-Hammond (2000) lists several common measures of teacher quality cited in the sociology of education literature: intelligence and academic ability, knowledge of subject matter and having received education training, years of teaching experience, and certification status. While each of the aforementioned measures have been shown to contribute to the distinction between a high-quality teacher and a low-quality teacher, certification status—that is, teacher credentialization—is often considered one of the best predictors of teacher competence (Goldhaber and Anthony 2007; Goldhaber and Brewer 2000).

Some argue that such credentialization programs are unreliable estimators of teacher efficacy and should be replaced by systems designed around teachers' cognitive abilities or classroom competency. For instance, Walsh (2001) questions the reported causal relationship between teacher credentialization and student achievement, citing a lack of evidence that it is truly credentialization that positively affects student achievement and not a lurking variable such as subject matter knowledge. In the years since, there has been a volume of research demonstrating teacher credentialization as a significant predictor of teacher quality (Monk 1994; Seebruck 2015)—one that affects student performance at all grade levels (Goldhaber and Anthony 2007; Rockoff 2004). Furthermore, the subject-matter knowledge that Walsh (2001) puts forth is almost always a component of teacher certification programs, reaffirming its robustness as a measure of teacher quality.

For instance, teacher credentialization varies by state and school level, but for the most part requires a significant amount of formal education training, which has been shown to be positively associated with teacher performance (Evertson, Hawley, and Zlotnik 1985; Ferguson and Womack 1993; Guyton and Farokhi 1987). In the state of California, a multiple-subject, elementary-level teaching credential has several requirements (CTC 2014). First, one must complete a baccalaureate degree from an accredited university. Second, one must satisfy a basic skills requirement, usually done by passing the California Basic Educational Skills Test (CBEST)—a standardized test for basic proficiency in reading, writing, and mathematics—but can also be accomplished via other means, such as passing a similar exam in another state. Third, one must complete a professional teacher preparation program, which includes student teaching at the elementary level, from an accredited institution. Fourth, one must demonstrate subject matter competence by passing either a subject matter examination or an approved subject-matter program, if eligible. Following that, depending on the rigor of the teacher-preparation program one graduated from, some applicants may have to demonstrate additional competencies in reading, language skills, civics, or computer technology. The requirements for teaching secondary education are similar.

Admittedly, it is not possible to identify and measure all the characteristics of a quality teacher. As Ferguson (1998:351) writes, “No one characteristic is a reliable predictor of a teacher's performance. Nor are most teachers uniformly good or bad in every subject or with all types of students.” This is true and it is also precisely why credentialization is the most robust predictor of teacher quality, for credentialization in most states requires formal education training in state-sanctioned education programs, including majoring in the subject field in which one will teach, in addition to student teaching (Darling-Hammond 2000). Because of the rigidity and robustness of credentialization requirements, credentialization is seen by both educational administrators and researchers as one of the strongest indicators of teacher quality.

In short, there are several reasons to examine the causes of the persistent maldistribution of credentialed teachers across schools in the U.S. First, credentialization is an important outcome variable because it is highly correlated with student performance across all grade levels (Clotfelter, Ladd, and Vigdor 2010; Seebruck 2015). Second, studies have found a maldistribution of credentialed teachers in the U.S. (Clotfelter, Ladd, and Vigdor 2006, 2007, 2010). Third, such studies did not employ the spatial econometrics

techniques necessary to test for variable distribution over geographic space, intimating the need to check the robustness of extant studies by examining these spatial data using the proper spatial analysis methods. Following that, the spatial distribution of credentialed teachers across California school districts is examined to determine whether students in California have an equal opportunity to be taught by quality teachers.

II. Methods and Data

Spatial Econometrics

Spatial econometrics consists of statistical tests and models used to address potential issues in regression analysis caused by the presence of spatial effects such as spatial dependence (Anselin 1988). Spatial dependence—that is, spatial autocorrelation, or a “lack of independence...among observations” (Anselin 1988:8)—is the geographic clustering of similar outcomes among neighboring observations (Darmofal 2006). The “auto” in spatial autocorrelation means that correlation occurs among a given variable, as opposed to cross-correlation between multiple variables (Anselin, Syabri, and Smirnov 2002). Positive spatial autocorrelation exists if neighboring units share similar values on the given variable; negative spatial autocorrelation indicates that neighboring units have dissimilar values on said variable (Darmofal 2006:4). If there is spatial autocorrelation in these data—that is, if there is non-random clustering of credentialed teachers among neighboring districts—then such findings could make clearer the role that geography plays in the distribution of teachers.

I use spatial econometrics techniques to examine California’s school districts for spatial autocorrelation in teacher quality, operationalized as *teaching credentialization* (the percentage of teachers in a district who are credentialed), since credentialization has been shown to be strongly correlated with student achievement (Goldhaber and Anthony 2007; Goldhaber and Brewer 2000), including in California public schools (Seebruck 2015). There are two primary types of spatial econometrics techniques: preliminary analyses known as Exploratory Spatial Data Analysis (ESDA), which offer insight into the presence of spatial autocorrelation in the data, and complementary spatial regression analysis, which models the effects of independent variables on an outcome of interest, factoring in the characteristics of a unit’s geographic neighbors. Both methods require the use of a spatial weight matrix.

Spatial Weight Matrix

Tobler’s (1970:236) First Law of Geography states, “Everything is related to everything else, but near things are more related than distant things.” This

notion of spatial dependence—that is, that distance has effects on observations—implies the need to determine which other spatial units influence a particular unit, which is usually expressed via a spatial contiguity matrix or a spatial weight matrix of a unit’s nearest neighbors (Anselin 1988). The spatial contiguity matrix defines as neighbors those spatial units that share a border. In this approach, the concept of neighbor is symmetrical, meaning that if A is B’s neighbor, then B is also A’s neighbor. In contrast, a spatial weight matrix considers both the distance between spatial units and the length of the common border between units, in order to determine a particular unit’s nearest neighbors. Thus, the spatial weight matrix is asymmetrical: Even if A is one of B’s nearest neighbors, B may not necessarily be one of A’s nearest neighbors. This is preferable to the contiguity-based approach because imposing symmetrical relationships often makes little sense in the real world, particularly for units such as islands that technically have no shared borders. Thus, in accordance with Anselin’s (1988:21) argument against the contiguity-based approach, the analyses in this paper use a spatial weight matrix to examine spatial autocorrelation, since it does not impose symmetric assumptions on the model.

Spatial weight matrices are further divided into two types: one based on distance that does not limit the number of neighbors a unit can have, and another based on nearness that does limit the number of neighbors. Choosing between the two is an important methodological issue, since different specifications can lead to different results (Anselin 1988:20). The first, based purely on distance, defines as neighbors those spatial units that are within a certain distance threshold. The second, while still based on distance, imposes a cutoff based on the k-nearest neighbors. One benefit of the latter approach is that it removes the problem of islands—spatial units that have no neighbors because they are outside the minimum threshold distance. However, in doing so, it often artificially constricts neighbors in nonsensical ways. For example, a k5-nearest neighbors matrix would, in dense areas such as New England where states are small, result in a constricted analysis, omitting influential neighboring states. In contrast, in the sparser West Coast, the nearest five states may span great distances that unrealistically overestimate a neighbor’s impact. Distance-based matrices avoid this problem but bring about a new one: the concept of “islands,” or units that lack neighbors if the distance cutoff is too large. One way to mitigate concern of islands in the distance-based approach is to set the threshold to eliminate islands (Repkine 2008). However, one must be cautious when doing so, as expanding the threshold to unrealistic distances can result in too many neighbors, which could decrease the theoretical relevance of the results (Repkine 2008). To

address this, many spatial researchers employ a minimum-distance threshold that ensures all units have at least one neighbor, while minimizing the overloading of neighbors on units in more-dense areas.

While there is no standard for choosing the right type of matrix, several scholars recommend analyzing different matrices and selecting the one that achieves a high coefficient of spatial autocorrelation with a high level of statistical significance for the response variable (Anselin 2002; Chi and Zhu 2008; Voss and Chi 2006). Accordingly, spatial weight matrices were tested ranging from $k-1$ to $k-12$ nearest neighbors, as well as those based on arc distance from a minimum threshold of 53.7 miles up to 100 miles. The minimum threshold, distance-based spatial weight matrix of 53.7 miles, yielded the highest Moran's I statistic for the dependent variable, making it the preferred matrix. Once the spatial weight matrix has been determined, spatial data analyses can be conducted.

Data

If teacher credentialization is one of the predominant predictor variables affecting student performance, then presumably a more egalitarian education system would more equally distribute its teachers. To determine whether California's education policies have produced an egalitarian education system, spatial econometrics can be used to examine California's school districts for spatial autocorrelation in the distribution of credentialed teachers.

Data come from the California Department of Education's online statistics database, DataQuest (2008), and the Alameda County Office of Education's online statistics database, Ed-Data for the 2007–08 academic year. The California public education system—the largest in the U.S. (Ed-Data 2008)—is divided into 977 school districts, which comprise 560 elementary school districts, 87 secondary school districts, and 330 unified school districts. Elementary school districts typically include elementary schools and middle schools ranging from kindergarten through sixth grade, but sometimes include schools up to eighth grade. Secondary school districts typically include high schools ranging from ninth to twelfth grade, but sometimes include middle school grades as well. The lack of uniformity makes it difficult to compare these districts statistically. In contrast, unified school districts unvaryingly include elementary, middle, and high schools in the same geographic area. Thus, to avoid comparison issues between different types of school districts, the analytic sample is restricted to unified school districts. Two unified districts are listwise deleted due to missing data, resulting in a final sample of 328 districts.

III. Exploratory Spatial Data Analysis (ESDA)

The first step in spatial econometrics is to explore the data for spatial autocorrelation—the spatial clustering of similar outcomes among neighboring observations (Darmofal 2006). Exploratory Spatial Data Analysis (ESDA) techniques can be used to determine the presence of spatial autocorrelation in the data and reject, or fail to reject, the null hypothesis. The null hypothesis on a test of spatial autocorrelation is that the values of a given variable are distributed randomly in relation to space (2006:4). A true null hypothesis implies that knowledge of an observation's spatial location does not aid in predicting that observation's values on the given variable.

Moran's I and LISA Statistics

Spatial autocorrelation can be measured at the global or local level. Analyses of spatial autocorrelation at the global level examine whether the data as a whole exhibit spatial autocorrelation, whereas analyses at the local level identify specific observations that exhibit spatial autocorrelation with their neighbors (Darmofal 2006). To measure spatial autocorrelation for continuous variables, Moran's I is used at the global level, and local indicators of spatial association (LISA) statistics are used at the local level. The global Moran's I defines value similarity as deviations from the mean (Darmofal 2006:12); LISA statistics measure the extent of significant spatial clustering around similar values among that unit's neighbors in proportion to the global indicator, Moran's I (Anselin 1995:94).

The value of Moran's I usually varies from -1.0 to $+1.0$ —although it is not technically bound by these numbers (Darmofal 2006:12)—and measures whether the pattern expressed is clustered, dispersed, or random (Anselin 2003). A value closer to $+1$ indicates clustering (i.e., positive autocorrelation—the clustering of similar values on the random variable among neighboring observations), a value closer to -1 indicates dispersion (i.e., negative autocorrelation—the clustering of dissimilar values on the random variable among neighboring observations), and a value closer to 0 indicates random spatial distribution (Anselin 2003). Under the null hypothesis of no spatial autocorrelation, the expected value of Moran's I is 0 (Darmofal 2006).

Exploratory Spatial Data Analysis can help determine whether there is spatial autocorrelation in the distribution of teacher credentialization—an important predictor of student achievement, and therefore a crucial factor influencing educational egalitarianism. As previous studies on the distribution of teacher quality do not employ spatial econometrics techniques, the

following analyses will be beneficial in testing the robustness of previous studies that have argued of a maldistribution of teacher quality in the U.S.

ESDA Results

LISA statistics aid in identifying clustering of similar or dissimilar values of a given variable through the use of both the Moran scatterplot, which plots the values of an observation for a given variable against another variable, and the LISA cluster map, which plots the significant values of the Moran scatterplot on a map by type of association.

Figure 1A is a univariate Moran scatterplot of the dependent variable: the percentage of credentialed teachers in a school district. A univariate Moran scatterplot displays observed values of the given variable as standardized values (z-scores) on the horizontal axis against the weighted average of the values among each spatial unit's group of neighbors on the vertical axis (known as a spatially lagged variable) (Darmofal 2006:14). That is, the same variable is plotted for each observation and its neighbors. The Moran scatterplot shows spatial clustering in the upper-right and lower-left quadrants, and spatial outliers in the upper-left and lower-right quadrants (Anselin 2003). Significant values in the upper-right quadrant indicate positive local spatial autocorrelation above the mean of a variable (known as high-high correlation, because a given spatial unit and its neighbors have a high value on the given variable); significant values in the lower-left quadrant denote positive local spatial autocorrelation below the mean (known as low-low correlation, because a given spatial unit and its neighbors have a low value on the given variable); significant values in the upper-left quadrant indicate negative local spatial autocorrelation in which observations have lower values than their neighbors (known as low-high correlation); and significant values in the lower-right quadrant indicate negative local spatial autocorrelation in which observations have higher values than their neighbors (known as high-low correlation) (Darmofal 2006:14).

In a Moran scatterplot, Moran's I is visualized as the slope (solid line). The Moran's I statistic of 0.137 indicates the presence of positive spatial autocorrelation, as it is highly significant with a p-value of 0.0001. The scatterplot shows a fair number of observations distant from the slope in both the high-high (upper-right) and low-low (lower-left) quadrants, suggesting the presence of spatial autocorrelation. That is, the distribution of credentialed teachers across California's unified school districts is not random: Many districts have a significant overlap with their neighbors regarding the mean level of teacher credentialization.

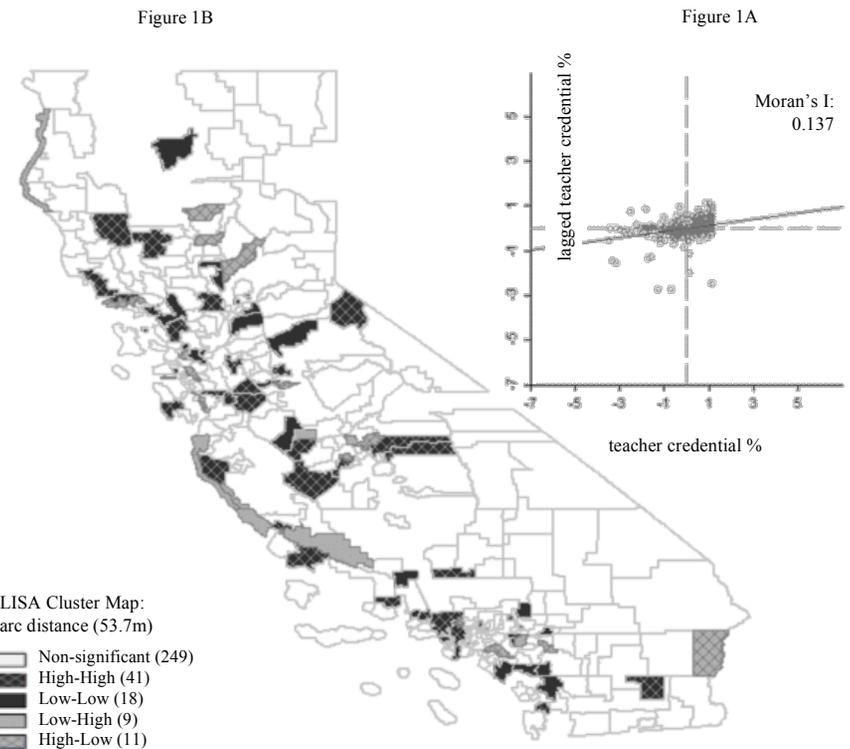


Figure 1.—Univariate Moran scatterplot (Figure 1A) and LISA cluster map (Figure 1B) of the percentage of credentialed teachers in California's unified school districts (N=328).

Complementing Figure 1A, Figure 1B is a univariate LISA cluster map which shows, by type of association (high-high, low-low, low-high, high-low), those observations in Figure 1A having significant local measures of spatial autocorrelation (Anselin 2003). Figure 1B shows several areas of California that have spatial autocorrelation with regard to teacher credentialization. The northwestern coastal region and Sacramento Valley is pocked with high-high autocorrelation (i.e., school districts with high levels of credentialed teachers neighboring other districts with high levels of credentialed teachers) among school districts in Mendocino, Lake, Glenn, and Napa counties. South of the Sacramento Valley, the San Joaquin Valley and southeastern interior regions see low-low autocorrelation among districts in El Dorado, Amador, Calaveras, San Joaquin, and Stanislaus Counties. Further south are several low-high districts acting as buffers for high-high districts, notably low-high districts in Monterey, San Luis Obispo, and Fresno sitting adjacent to high-high districts in those same counties. There is also a pocket of high-high spatial autocorrelation in Ventura and Los Angeles Counties, as well as a

pocket of low-low spatial autocorrelation in northern San Diego County. These findings are relevant to policy makers trying to create equal educational opportunities for all youth: There is a disparity in the distribution of credentialed teachers, meaning that where a child lives largely influences his or her opportunity to be taught by qualified teachers.

While the univariate analyses above are useful in revealing whether the outcome variable is randomly distributed across geographic space, bivariate analyses further illuminate the relationship between the dependent variable and influential independent variables. For instance, as race has been found in the sociology of education literature to be a crucial variable affecting a plethora of education outcomes (Darling-Hammond 2000; Peske and Haycock 2006; Prince 2002), examining the racial distribution of students may inform the maldistribution of teacher quality found above.

Accordingly, Figures 2A and 2B examine the bivariate relationship between the distribution of teacher quality and the racial distribution of students—in this case, the percentage of white, Asian, and Pacific Islander students in a district, as these groups consistently outperform other racial groups such as blacks, Latinos, and Native Americans on student achievement in California (Tucker 2009). Although it has been successfully established that Asians and Pacific Islanders are a diverse group and that the model minority stereotype is an unfair classification (Education Trust-West 2010), it remains that the Asian and Pacific Islander students, overall, significantly outperform other minority groups in California (Tucker 2009). My own supplementary analyses (not shown) on these data indicate that Asians and Pacific Islanders perform more closely to whites than other racial groups, and because they represent such a significant portion of the California student population, lumping them in with other minorities or leaving them out of the analyses altogether would be inappropriate. Thus, they are included with whites so as to shed light on how these groups compare to traditionally more disadvantaged groups: blacks, Latinos, Native Americans, and other minorities.

Following that, Figure 2A is a bivariate Moran scatter plot of the percentage of credentialed teachers in California's unified school districts (horizontal axis) on the percentage of students who are white, Asian, or Pacific Islander (vertical axis). A bivariate measure of spatial autocorrelation relates the value of a variable at a location to that of a different variable at neighboring locations (Anselin 2003). Correspondingly, in a bivariate Moran scatterplot, the vertical axis pertains to neighboring values for a different variable than the one listed on the horizontal axis—here, it plots the percentage of

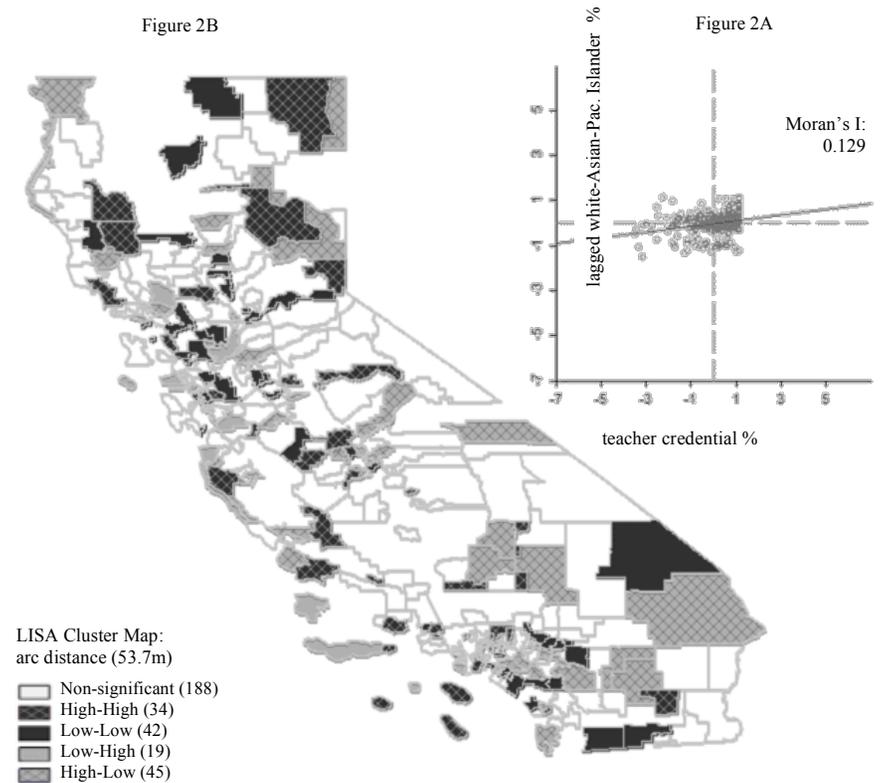


Figure 2.—Bivariate Moran scatterplot (Figure 2A) and LISA cluster map (Figure 2B) of the percentage of credentialed teachers by student race in California's unified school districts (N=328).

credentialed teachers in a district against the percentage of white, Asian, or Pacific Islander students in nearby districts. In Figure 2A, the Moran's I statistic of 0.1289 indicates the presence of positive spatial autocorrelation, as it is highly significant with a p-value of 0.0001. Values in the high-high (upper right) quadrant have high levels of teacher credentialization, while their neighbors have a high percentage of white, Asian, or Pacific Islander students. Values in the low-low (lower left) quadrant also indicate positive spatial autocorrelation in that they have low levels of teacher credentialization while their neighbors have a low percentage of white, Asian, or Pacific Islander students. These results indicate a link between the racial distribution of students and the distribution of credentialed teachers.

Further examining the link between the distribution of race and teacher quality, Figure 2B is a bivariate LISA cluster map which shows that several areas of California have spatial autocorrelation with regard to teacher cre-

dentialization and the racial distribution of students. In the north there is widespread high-high autocorrelation (i.e., school districts with high levels of credentialed teachers and neighboring districts with high levels of white, Asian or Pacific Islander students), particularly in the northwestern coastal and Sacramento Valley regions, among school districts in Mendocino, Trinity, and Colusa Counties. This pairs up well with the univariate analysis of Figure 1B, which found high-high spatial autocorrelation for districts in nearby counties. Furthermore, as with the univariate analysis in Figure 1A, in Figure 1B there are pockets of low-low spatial autocorrelation in the Sacramento and San Joaquin Valley regions, particularly in Napa, Yolo, and Solano Counties as well as Contra Costa, Alameda, San Joaquin, and Fresno Counties. Likewise, as with the univariate findings, there are notable low-low pockets in San Diego County. Therefore, one explanation for the clustering of teacher quality in California appears to be the racial composition of a region: The racial demographics of a school district and its neighbors are significantly correlated with the type of teachers who are clustered there.

The ESDA results show a great deal of inequality in the distribution of teacher quality throughout California. The univariate analyses of Figure 1B indicate that teacher quality is not randomly distributed throughout the state, but rather is spatially autocorrelated with neighboring districts. The bivariate analyses of Figure 2B indicate that this maldistribution may be linked to other factors such as the racial distribution of students in nearby districts. The next section features spatial regression analyses to explore further the maldistribution of teacher quality found in these ESDA tests.

IV. Spatial Regression Analysis

Because the dependent variable, *teacher credentialization percentage*, is a continuous variable, a non-spatial regression analysis would call for Ordinary Least Squares (OLS) regression. However, the appropriateness of OLS regression is dependent on several assumptions requiring that the parameter estimates be unbiased, consistent, and efficient (Allison 1999). The appropriateness of OLS regression assumes that the covariates are independent of the error term and that the error term is independently, randomly, and normally distributed—that is, uncorrelated with the error terms of any of the other covariates (Allison 1999). If these assumptions are violated, then OLS regression analysis could provide biased, inconsistent, or inefficient estimates, and thus should not be used. Instead, a spatial regression analysis is needed, as suggested by the exploratory analyses in the previous section.

Model Selection

Exploratory Spatial Data Analysis (ESDA) demonstrated that there are spatial components to these data, suggesting the need to eschew OLS regression in favor of a spatial regression analysis. Additional diagnostic tools can be used to reaffirm the need for a spatial regression model and to select the proper model by determining which type of spatial regression model best fits the data. Thus, the first step in spatial regression analysis is to reaffirm the results of the ESDA (i.e., that spatial regression analysis is needed). A Jarque-Bera test on the normality of errors is significant beyond the .000 level, meaning that the errors are not normally distributed. This confirms the inappropriateness of using OLS regression.

The second step is to determine the proper type of spatial regression analysis. There are two ways in which spatial interaction is incorporated into model specifications for spatial analysis: the spatial error model or the spatial lag model (Anselin 2002). Selecting the appropriate model is important because the different models induce different spatial correlation patterns (2002:248). In the spatial error model, neighboring units impact the dependent variable in the unit of interest through interrelated error terms (Beck, Gleditsch, and Beardsley 2005:6). In the spatial lag model, both the error term and the covariates in neighboring units impact the dependent variable in the unit of interest (2005:7).

A Lagrange Multiplier (LM) test examines spatial dependence in the residuals of the spatial lag and spatial error models as an indicator of which model is more appropriate (Beck et al. 2005:8). In line with Anselin et al.'s (1996) finding that the robust LM test is more suitable than the standard LM test as identifying the source of dependence—that is, lag or error—I rely on the robust version. Results indicate strong support in favor of the spatial lag model, with a statistically significant p-value of 0.02 for the lag model in comparison to a non-statistically significant p-value of 0.92 for the error model. To complement the statistical justification for selecting the spatial lag model, Beck et al. (2005) provide theoretical justification, arguing that the spatial lag model is usually preferred because in the error model, the effects of space matter only in the error portion of the regression model but not in the substantive portion of the model (2005:5). The error term represents unexplained variation in the dependent variable and can be thought of as the collective effects of omitted or unmeasured variables. Following that, adding a new independent variable to the model effectively moves its effects from the error to the substantive portion of the model. The spatial error model then assumes that this new variable no longer has

a spatial impact on nearby observations since, in a spatial error model, the only way that neighboring units have an impact on a particular unit is through interrelated error terms. Thus, because the error term is simply the disturbance left over from the variables that were not measures, Beck et al. argue in favor of the spatial lag model, unless there is strong theoretical and statistical justification otherwise.

Having selected the spatial lag model as the appropriate model, goodness-of-fit tests can reaffirm the proper weight matrix specification. For the ESDA above, goodness-of-fit tests preferred a distance-based spatial weight matrix set at the minimum threshold needed to prevent “islands.” Though it is not always the case, as multivariate analysis is different from the univariate and bivariate analyses of ESDA, Lagrange Multiplier model fitness tests here reaffirm selection of that same spatial weight matrix. Subsequent tests confirm this as well, with that matrix having lower log likelihood, Akaike Information Criterion, and Bayesian Information Criterion values than other matrices. Thus, the same spatial weight matrix used in the ESDA analyses is also justified for use in the spatial regression analysis.

Spatial Regression Variables

The spatial regression model analyzes the effects of covariates on a continuous dependent variable, the percentage of credentialed teachers in a district. Independent variables affecting the distribution of this outcome come from Hanushek, Kain, and Rivkin’s (1999) analysis of variables that affect teacher labor supply, such as salary, poverty, racial composition, and proficiency levels of students. Other education-related control variables that may influence a teacher’s decision on where to live and work include student enrollment, average class size, the percentage of students who are English learners, the charter status of a school (Prince 2002), as well as the socio-demographics of the area, such as the median household income and population density of the area. Thus, predictor variables include measures of student enrollment, student poverty, student demographics including race and English language skills, average class size, student proficiency, teacher salary, the percentage of charter schools in a district, the median household income and the population density of the county in which a school district is located.¹

Because teacher salary schedules are based on experience level and certification status, using average teacher salary would produce biased results (Greenbaum 2002). Consequently, the analyses in this paper use the average salary for those teachers on step ten of the certificated teacher salary sched-

ule: teachers with a bachelor’s degree and sixty continuing education credits.² Continuing education units refer to compulsory participation in continuing education or professional development programs. Rather than comparing the average salaries for all teachers in the district, which would be skewed by the number of senior and certified teachers in a district, comparing the average salaries for teachers who are at the same career and experience level provides a standardized comparison across districts.

Student poverty is measured as the percentage of students in a district who are eligible to receive free or reduced school lunch. Student demographics are measured as the percentage of students in a district who are white, Asian, or Pacific Islanders. Enrollment is measured as the district’s total student enrollment, which measures the size of the school district. Average class size is measured as a district’s average class size per school and will serve as a proxy for a teacher’s working conditions, since higher class sizes typically result in an increased work load without increased remuneration. Population is the total number of residents in the county in which a school district is located. Finally, median household income is a three-year moving average of the average household income for the district’s county. Data for these final two variables come from the U.S. Census Bureau (2007).

Student achievement is operationalized as the percentage of students in a district who achieve proficiency on the state-issued math exam. Other available data include the ability to test for proficiency on the state-issued English exam, but because of collinearity concerns with student demographics (namely, race and those whose native language is not English, a sizeable number in diverse California), math is used as a less-biased predictor. However, because the response variable has been shown to affect student achievement (Fetler 1999), to mitigate endogeneity—the problem of reverse causality—I adopt Rupasingha and Goetz’s (2007) recommendation to measure the predictor variable at a point in time that precedes the measurement of the dependent variable. In this case, teacher credentialization for a given year cannot affect student achievement for the preceding year. Thus, to combat endogeneity, the student achievement measure comes from the 2006–07 school year, whereas the response variable is from the 2007–08 school year. While this technique mitigates endogeneity, it does not wholly eliminate such concerns, as these two variables are likely entwined in a long-standing, self-fulfilling prophecy. Nevertheless, given the autonomy of employment decisions in the U.S., particularly in the education realm where the academic calendar allows teachers the opportunity to change jobs more easily, controlling for students’ capabilities in the year prior is a

fair indicator of teachers' employment decisions, as it indicates to them the types of students they would be teaching if they choose to work in a given district. Furthermore, the state-issued exams occur after the school year has begun, highlighting endogeneity concerns. In contrast, the other covariates' values are set at the beginning of the year, meaning that teacher traits for that year have no effect on them.

Regression Results

Model fitness tests and Exploratory Spatial Data Analysis (ESDA) above concluded that there are spatial components to these data and that spatial regression should be used to analyze them. However, to examine how results compare to non-spatial regression techniques, two models—an Ordinary Least Squares (OLS) regression and a spatial lag regression—are run on *teacher credentialization percentage* with ten independent variables. Table 1 displays results of both models.

The OLS model sees two variables with significant coefficients: charter schools and race. The coefficient for *charter schools* is significant (p-value < .002) and negative, indicating that for every one-percent increase in charter schools in a district there is a 0.09-percent decrease in credentialed teachers in the district. The coefficient for *race* is significant (p-value < .003) and positive: for every one-percent increase in white, Asian, or Pacific Islander students in a district, there is a 0.06-percent increase in credentialed teachers. These results suggest that districts with higher percentages of charter schools and black, Latino, and Native Americans are less able to procure credentialed teachers.

However, the spatial regression results indicate that the OLS regression results are flawed. Most importantly, because it is a spatially lagged regression analysis, the spatial lag term (*_lagged DV_*) of the dependent variable is included in the output and indicates that there is spatial autocorrelation in the variable of interest: Credentialed teachers in California are not randomly distributed across districts. The spatial lag term's coefficient parameter (ρ , rho) reflects the spatial dependence inherent in the data, measuring the average influence on a district by its neighbors. The coefficient for the spatial lag term is significant at the .0002 level and indicates that for every one-percent increase in credentialed teachers for a district's nearest neighbors, there is a 0.41-percent increase in credentialed teachers for that district. In fact, the coefficient for the spatial lag term is larger in magnitude and significance than any other variable in both the OLS and spatial regression models, re-

Table 1.—OLS and Spatial Regression on Teacher Credentialization (Maximum Likelihood)

[raw beta coefficients (β), standard errors (se), p-values (p)]							N=328
IVs ↓	Models →	OLS Regression			Spatial Lag Regression		
		β	(se)	p	β	(se)	p
<i>_lagged DV_</i>					0.41***	(0.11)	0.000
average class size		-0.04	(0.07)	0.576	-0.03	(0.07)	0.610
population density		-0.00	(0.00)	0.690	-0.00	(.000)	0.473
salary		-0.00	(0.00)	0.428	-0.00	(0.00)	0.697
median household income		0.00	(0.00)	0.863	0.00	(0.00)	0.868
enrollment		-0.00	(0.00)	0.204	-0.00	(0.00)	0.122
charter school %		-0.09**	(0.03)	0.002	-0.10***	(0.03)	0.000
English learners %		-0.00	(0.03)	0.935	-0.00	(0.03)	0.918
free lunch %		-0.01	(0.02)	0.784	-0.01	(0.02)	0.792
math proficiency %		0.05	(0.03)	0.053	0.06*	(0.03)	0.014
race % (white, Asian, Pac. Isl.)		0.05**	(0.03)	0.003	0.05*	(0.02)	0.012
<i>_constant_</i>		92.39	(4.56)	0.000	52.17	(11.5)	0.000
				Adj. R ² = .208	Spat. Pseudo-R ² = .242		
				BIC=1961.42	BIC=1950.76		
n.b., two-tailed t-tests are reported for all models							
		* p < .05	** p < .01	*** p < .001			

affirming the importance of employing proper statistical techniques when analyzing variables with spatial components like teacher quality distribution.

As further evidence that the OLS regression is not suitable, the spatial regression model identifies another independent variable with a significant coefficient that was not found to be significant in the non-spatial model: the pre-established math proficiency of the students in the district. The coefficient for this variable is positive and highly significant (p-value < .014): For every one-percent increase in students who achieved proficiency on the state-issued mathematics examination in the year prior, there is a 0.06-percent increase in credentialed teachers who work in that school district the following year. This intimates that high-quality teachers prefer teaching more-proficient students—something that is not surprising but

clearly needs to be considered by policy makers seeking to create a more egalitarian distribution of teachers.

Not only did the OLS model fail to identify the significance of the proficiency level of students in affecting the distribution of quality teachers, it also overestimated the significance of race. In the spatial regression model, the racial composition of the student body was also found to significantly affect the distribution of teacher quality, but, compared to the OLS model, the coefficient and the p-value are both slightly smaller in magnitude. This suggests that the OLS model's inability to capture the spatial effects of the outcome (`_lagged DV_`) resulted in error that affected the estimation of other variables in the model. These results reaffirm Greenbaum's (2002) proclamation that failing to account for potential spatial autocorrelation in the data and subsequently running non-spatial regression analyses when spatial regression is required results in bias and incorrect estimates.

Nevertheless, race is still highly significant in the spatial model ($p < .012$), indicating that most minority students do not have the same opportunities to be taught by high-quality teachers as traditionally more-advantaged white, Asian, or Pacific Islander students. This is in line with Peske and Haycock's (2006) meta-analysis of studies that demonstrated that minority students are shortchanged when it comes to having access to more experienced teachers. Given the strong relationship between teacher credentialization and student achievement, this is an important finding: Minorities are disadvantaged when it comes to opportunities to be taught by credentialed teachers, which can have long-lasting effects on students' ability to excel in life and school (Hanushek 1992).

Other seemingly surprising findings are that neither salary nor student poverty have significant coefficients. Sensitivity analyses (not shown) explain the latter finding: Race is an intervening variable between poverty and the distribution of credentialed teachers. If race is removed from the model, a significant negative effect of poverty appears. Therefore, it is important that race is included. That salary is non-significant is explained by the fact that public school teaching salaries are fairly uniform across the state when cost-of-living differences are factored in. This suggests that salary incentives could be used to correct the maldistribution of teachers by encouraging quality teachers to migrate to disadvantaged districts by offering higher salaries there.

Collectively, the spatial regression model reveals a maldistribution of teachers throughout California, to the disadvantage of both underperforming

students and minority groups such as blacks, Latinos, and Native Americans. That the clustering of quality teachers in certain school districts correlates highly with the percentage of proficient students suggests a self-fulfilling prophesy where quality teachers seek job placements in districts with a higher number of intellectually proficient students, who then enjoy the added benefits of being taught by better teachers, further exacerbating the achievement gap between districts. Correspondingly, that districts with higher percentages of black, Latino, and Native American students have lower levels of credentialed teachers exacerbates the cycle of disadvantage that minority students face when it comes to equal educational opportunities.

V. Conclusion

Results from spatial econometrics analyses reveal that there is spatial autocorrelation in the distribution of credentialed teachers, an important measure of teacher quality, across California's public schools. Neighboring school districts have similar levels of credentialed teachers, and this phenomenon is not a random occurrence. The racial composition of the students, a variable that is itself correlated with poverty, is highly correlated with the clustering of teacher quality. This finding of a non-random distribution of teacher credentialization is in line with extant studies that also reveal an unequal distribution of quality teachers in the U.S. that disfavors minority students (Borman and Kimball 2005).

However, extant studies on teacher quality distribution do not use spatial econometrics techniques, bringing into question the validity of those results. Indeed, comparing the spatial regression model with an Ordinary Least Squares regression model indicates that the non-spatial OLS model failed to identify two highly significant variables affecting the distribution of teacher quality: 1. the spatially lagged dependent variable, which reveals that the teacher quality levels of a district's geographic neighbors significantly affects the teacher quality level of that district; and 2. that the pre-existing capabilities of students also affect the distribution of quality teachers, with credentialed teachers significantly more likely to work in regions that have higher levels of proficient students.

The first finding should be of interest to policy makers interested in racial inequality in educational opportunities. The spatial econometrics analyses here have shown that a maldistribution in teacher quality permeates California's unified school districts and is highly correlated with the racial composition of the student population: Districts with higher percentages

of white, Asian, or Pacific Islander students, or that neighbor such districts, tend to employ a higher percentage of credentialed teachers.

The second finding suggests that credentialed teachers, usually having human-capital advantages in choosing where they work, tend to choose employment at schools with more-proficient students. This is likely a self-fulfilling cycle where schools with higher-quality teachers produce higher-achieving students, which in turn encourages the clustering of higher-quality teachers, thereby exacerbating the disadvantage that students who live outside of these districts face. When paired with the first finding, this is a troubling reality that likely traps minority students in a cycle of disadvantage. Consequently, both findings are germane to public policy makers interested in promoting educational equality, because teacher quality has been shown to be the prominent factor affecting student achievement, even more so than race, ethnicity, socioeconomic status, school spending, or class size (Darling-Hammond 2000).

Creating equal educational opportunities is important because educational attainment is one of the primary factors influencing socioeconomic status and salary attainment (Breen and Jonsson 2005). In their review of the literature on social inequality, Babones et al. (2007) found that educational attainment matters most and can usually overcome the negative effects of other demographic variables in achieving higher socioeconomic status. Thus, promoting educational egalitarianism should be a goal of any society, as education equality has been found to reduce income inequality: A lower educational inequality, as measured by an education Gini coefficient, will also cause a lower income inequality (Lin 2007). Given that inequality has a plethora of detrimental effects on a society (Wilkinson and Pickett 2009), engineering more equal societies should be a primary goal of any government.

VI. Discussion

The distribution of teacher quality in a district is spatially correlated with the distribution of its neighbors. Future research could examine the causes for such clustering and posit structural solutions to mitigating it. One explanation for the widespread maldistribution of teacher quality in U.S. school districts is because the U.S. has a more laissez-faire education labor market, in which teachers largely have autonomy over where they work (Prince 2002). This locally controlled system has led to numerous policies that inhibit educational egalitarianism, such as funding laws that enable schools in wealthy cities to attract teachers with higher salaries, teacher transfer restrictions that make it difficult to transfer to low-achieving dis-

tricts, or seniority clauses that allow experienced teachers to choose their placements (Prince 2002).

A possible solution to mitigating this maldistribution in teacher quality is to adopt a mandatory teacher rotation system similar to the one employed in Japan (Letendre 2000; White 1987; Wray 1999). That system involves the systematic rotation of teachers to other schools within a prefecture every few years, throughout their entire careers. This system has been lauded by several qualitative scholars, who argue that it creates a more equal distribution of quality teachers by preventing the clustering of quality teachers at certain schools (Letendre 2000; White 1987; Wray 1999). These qualitative studies suggest that teacher rotation creates a more equal distribution of teacher quality, which should create more equal educational opportunities for students.

Implementing a more centrally controlled teacher education labor market such as Japan's may be one way to stanch the growing problem of educational inequality in the U.S., where reports have shown a trend in wealthy neighborhoods seeking to secede from large school districts in order to create new, separate districts with fuller coffers (Newkirk 2014). Because school districts in the U.S. are largely funded by local property taxes, larger districts that lose wealthy neighborhoods will suffer significant decreases in revenue, making it more difficult to lure in quality teachers and provide students with resources equal to those of their peers in the newly created, wealthier districts. Further fragmenting an already localized education system will only exacerbate the education inequalities discussed in this paper. However, such a rotation system, if implemented in the U.S., would need to be adapted to U.S. cultural expectations. For instance, instead of rotating teachers across all districts within a state, a smaller rotation zone such as counties would be more feasible in the U.S.

Although this study demonstrated that there is a maldistribution in teacher quality in California, it is limited in that it was restricted to one measure of teacher quality: credentialization. There are many other ways to operationalize teacher quality, such as the percentage of full-time teachers at a school, years of experience, the percentage of beginning teachers, teaching within one's field, having an advanced degree, and the prestige of one's university alma mater (Darling-Hammond 2000). Further research on this issue could examine the spatial distributions of other measures of teacher quality to determine whether there is spatial autocorrelation among them as well. Determining whether the maldistribution in teacher quality only

affects certain types of teacher quality could aid in combating the problem by enabling policy makers to allocate resources more efficiently.

Endnotes

1. Population was also tested as a variable. Results were nearly identical; there were no statistically significant differences between the two models. Population density was chosen for the final model so as to mitigate the modifiable areal unit problem (MAUP), where correlation coefficients increase for variables when area units are aggregated, providing a false correlation (Fotheringham and Wong 1991).

2. Alternative measures of salary were also analyzed, such as the ratio of the standardized teacher salary to the mean household income of the county, but never were they significant, and model-fitness tests always preferred the base standardized teacher salary used in the final models.

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