Adjusting for Geographic Differences in the Cost of Educational Provision in Maryland

Report Prepared for the State of Maryland

December 31, 2003

William Duncombe
Syracuse University

&

Dan Goldhaber
University of Washington

Acknowledgements

We are greatly indebted to Dan Player, of the University of Washington, for his research assistance in completing this project, and Howard Nelson, of the American Federation of Teachers, for assistance in researching cost adjustment methods used by states, and advice on earlier drafts of the report. We also greatly appreciate the assistance of Donna Gunning of MSDE. This report could not have been completed without her help.

Any and all errors are solely the responsibility of the authors. The views expressed here are those of the authors and thus do not necessarily reflect those of Syracuse University, the University of Washington, or the State of Maryland.

Biographies of the Authors

William Duncombe is Professor of Public Administration, and Senior Research Associate, Center for Policy Research, The Maxwell School, Syracuse University. He is also the Associate Director of the Education Finance and Accountability Program at Syracuse University. His research specialties include estimating the cost of educational adequacy, school aid design, educational costs and efficiency, demand and costs of state and local government services, budgeting and financial condition assessment. His work has appeared in numerous journals in public administration and economics. He has also published several reports for the New York State Board of Regents on school finance issues in New York, and several papers on school finance reform in Kansas.

Dan Goldhaber is a Research Associate Professor at the Evans School of Public Affairs at the University of Washington. He is also an Affiliated Scholar of the Urban Institute's Education Policy Center, and he served as an elected member of the Alexandria City School Board from 1997-2002. Dr. Goldhaber's research focuses on issues of educational productivity and reform at the K-12 level and the relationship between teacher labor markets and teacher quality. His work has appeared in numerous economics and education journals, such as *Journal of Human Resources, Journal of Urban Economics, Economics of Education Review, Journal of Education Finance*, *Education Economics, Education Matters/Next, Industrial and Labor Relations Review, Educational Evaluation and Policy Analysis, Education Researcher,* and *Phi Delta Kappan*.

Table of Contents

Chapter 1

Introduction to the GCEI Concept

The creation of a Geographic Cost-of-Education Index (GCEI) is central to the effort in Maryland to ensure that school systems in Maryland are able to meet the challenge of providing an adequate education for all students in the state.[1] The purpose of the GCEI project is to identify the factors leading to cost differences associated with providing comparable education services in different Maryland counties. The GCEI can be integrated into Maryland's school finance formula to adjust funding to account for geographic differences in the cost of educational provision.

The GCEI will be composed of two components: a personnel cost index (PCI) and a non-wage index (NWI). The PCI is designed to take account of factors that influence the level of wages that must be offered to attract comparable personnel to each locality. The NWI is designed to account for differences in the costs of procuring non-personnel supplies, other than capital expenditures, such as paper products and energy.

Personnel costs including employee benefits typically account for over 80 percent of current expenditures of school districts (U.S. Census Bureau, 2003). Instructional salaries alone are not only the largest single expenditure category but also typically account for over 50 percent of overall expenditures (Goldhaber, 1999). In Maryland, personnel costs are very near to the national average, accounting for 83 percent of total current expenditures, and instructional

[1] The passage of the Bridge to Excellence Act in 2002 significantly changed the education funding system in the state to focus on adequacy (Department of Legislative Services, 2002, Volume I). The guiding principles of the school finance proposal of "The Commission on Education Finance, Equity, and Excellence" ("Thornton Commission," 2002) include adequacy, equity, simplicity, and flexibility. The Commission defines adequacy as the "projected costs associated with meeting state performance standards, including the additional costs associated with providing necessary services to students with special needs." (pp. 51-52) For more detail on the concept of adequacy in education, see Clune (1994) and Minorini and Sugarman (1999).

compensation accounting for 57 percent of current expenditures in 2001 (U.S. Census Bureau, 2003). Thus, the GCEI is weighted heavily by the PCI, which itself is primarily influenced by teachers' salaries.

The methodology used here for creating the PCI is hedonic modeling, which is a statistical methodology that assigns dollar "weights" to the factors (both teacher specific and location specific) that determine individual teacher's salaries. The theory behind the hedonic model is that salaries will reflect not only compensation paid for specific human capital characteristics (e.g., the specific skills and training an individual brings to the job), but also other characteristics of the job that influence the *attractiveness* of living and working in a particular geographic locale. The theory behind hedonic wage models holds that it will be more expensive to hire personnel into less attractive jobs than it would be to hire personnel of comparable quality into jobs that are more attractive.[2] We might think of many different factors besides salary and benefits that influence the relative attractiveness of a job. For example, all else equal, teachers are likely to favor jobs in schools with fewer difficult-to-educate students, and in areas that have a low cost of living and greater amenities.

School districts have direct control over some factors affecting personnel costs. For example, they may choose to hire more senior, highly credentialed teachers. They also have control over some aspects of what makes a particular teaching job attractive. For instance, the class size influences a teacher's work load, and the number or type of professional development opportunities may also affect the attractiveness of a teaching position. However, many of the non-pecuniary characteristics of a job that influence its attractiveness are outside of a district's control. For example, school districts have little or no influence on regional housing costs, crime rates, weather patterns, and demographics of the local community. Prospective teachers might

[2] For more on the hedonic theory, see Chambers (1981, 1997), Goldhaber (1999), or Hanushek (1999).

consider all of these factors when making decisions about in which districts to seek employment. Thus, the various factors that influence teachers' salaries may be divided into those that are within the control of districts, referred to here as "discretionary factors", and those that are outside of district's control, referred to here as "cost factors."

Many of the cost factors are related to the attractiveness of particular jobs, but others are a function of non-personnel costs that are outside of a district's control. For example, there may be regional differences in the cost of supplies, and/or differences in the cost (or required use of) energy. Non-wage expenditures can also be affected by factors within district control (e.g., energy management), and factors outside district control, such as district size and the weather. The GCEI must therefore account for non-wage related costs to districts, which are outside district control. Cost categories considered for inclusion in the non-wage index (NWI) for Maryland include materials, supplies, equipment, energy costs, and other contractual services. These categories represent approximately 15 percent of current expenditures.[3]

The GCEI is designed to provide the state of Maryland a way to adjust the allocation of state resources so that they reflect differences between localities in the cost of providing educational services. One of the tasks in developing a school finance system to support an adequacy standard is to determine the cost of providing an adequate education. Thus, the GCEI contributes to this endeavor by allowing for adjustments to the so-called "cost of adequacy" for differences between districts in the relative costs of purchasing educational resources.[4]

In this report, we describe the construction of a GCEI for the state of Maryland, and explain how it may be used with the state's existing school finance formula. The report is laid

[3] Expenditure categories that are not within the scope of the GCEI include transportation and facility construction and renovation.

[4] Adequacy costs should also be adjusted for the greater resources needed to support some students with special needs. The "Thornton Commission" (2002) made recommendations on the extra weight that should be given to special needs students in the funding formula.

out as follows. Chapter 2 details the methodology used in the analysis for constructing the GCEI. Chapter 3 provides a discussion of the data sources used for the analyses as well as the various checks for data quality that were completed. Chapter 4 describes the results of our data analyses. This includes the analyses of the factors affecting personnel and non-personnel costs along with tests of how sensitive the model is to using different variables to capture the attractiveness of a particular job, and tests of the stability of the model over time. In Chapter 5 we discuss the results of several tests of the external validity of components of the GCEI. We describe some options for integrating the GCEI into Maryland's existing school funding formula in Chapter 6, and in Chapter 7 we offer some concluding thoughts.

Chapter 2

Models and Methodology Used in the Construction of the CGEI

The fact that prices of goods and services can vary across geographic areas, and that this can affect the purchasing power of school districts has been recognized for decades (Brazer and Anderson, 1974; Chambers, 1978). Several methods for estimating cost of education differences have been developed, and a few states have incorporated these measures into their school funding formulas. In this chapter, we will explain the methods we use to calculate a geographic cost of education index (GCEI) for the state of Maryland. Our approach has drawn heavily from past research on cost-of-living adjustments, and we begin this chapter with a comparison of approaches for accounting for geographic cost differences (Fowler and Monk, 2001).

1. Methods for Adjusting for Geographic Cost Differences

There is widespread agreement on both the need for geographic cost adjustment, and on the basic principles used for such adjustments. As summarized by McMahon (1996),

> Conceptually, what is needed for determining the regional cost differences, either within states or among states, is a measure of price differences that determine the unit costs of purchasing a standardized market basket of inputs of fixed quality. The inputs purchased are specific to those needed to produce education by the district…These prices *should not be subject to the control of the school district or the state...* (p. 95)

While there is consensus on the broad objectives, several different approaches have been developed for estimating geographic cost differences. Specifically, these approaches differ in whether they focus on prices for good or services, or wages, and whether they identify cost differences across districts or broader regions.

A. Cost-of-Living Index

The cost-of-living approach estimates the price differences for a "market-basket" of goods and services purchased by a typical consumer. The market basket is usually defined as broad consumption categories (food, transportation, utilities, etc.), and budget shares are often estimated using information from the U.S. Bureau of Labor Statistics (BLS).[5] A set of commodities and/or services is identified within each budget category, and data are collected on their prices across geographic areas. Based on these data, a statewide price index is calculated for each commodity (local price/average state price). The final price index represents a weighted average of the individual price indices using statewide average budget shares as weights.

While there are a few estimates of cost-of-living at the national level, they are either for a selected set of metropolitan areas or at the state level.[6] States such as Colorado, Florida, and Wyoming have developed and used this type of cost-of-living index in their school aid calculations (Rothstein and Smith, 1997; Florida Department of Education, 2002; Wyoming Division of Economic Analysis, 1999; Colorado Legislative Council Staff, 2002).[7] The geographic unit for construction of the index is counties for Florida and Wyoming, and counties and their neighbors for Colorado. In Maryland, the cost-of-living index developed by the Department of Business and Economic Development (DBED) is similar in design.

---

[5] Budget shares can either be calculated using the *Consumer Expenditure Survey* produced by the BLS or using the market basket and weights used to construct the *Consumer Price Index* (CPI).

[6] Presently, the only widespread cost-of-living index available nationally is produced by the nonprofit organization, ACCRA (formerly affiliated with the Chamber of Commerce). ACCRA utilizes local communities to voluntarily submit price information to ACCRA, and the sample of communities in the index varies across time. Nelson (1991) and McMahon (1996) have developed cost-of-living indices using simple supply and demand models. They estimate cost of living (as measured by ACCRA) as a function of income, housing prices, and population change. Based on this simple model, they have predicted the cost of living for geographic areas not in the sample. Because both income and housing prices have a positive coefficient in the model, this method leads to higher cost of living in high income and high wealth communities, which works against the wealth equalizing objectives of most school aid formulas.

[7] A description of geographic cost adjustments used in other states is presented in Appendix A.

The principal strengths of the cost-of-living approach are its conceptual simplicity and that it measures prices differences outside district control. To apply this consumer oriented cost-of-living measure to education, it is necessary to assume that the cost of resources in education is going to reflect underlying price differences for a market basket of consumer goods. However, on a conceptual level there are several problems using this type of index to adjust education costs. First, the commodities in a consumer basket and their associated budget shares may not reflect very closely the budget of a school district. Second, even if we assume that this bundle reflects the spending patterns of a typical school employee, school personnel do not necessarily shop or live where they work.[8] Third, cost of living for consumer products does not necessarily reflect the pay differentials that a district will have to offer to attract teachers, because they do not consider working conditions in a district. Two districts with the same cost-of-living for consumers may have to pay different salaries to attract the same teacher, because of differences in working conditions.

B. Competitive Wage Index

Another approach for determining geographic education cost differences is to focus on the principal resource used in providing education services—personnel. With personnel costs commonly representing 80 percent or more of district budgets, measuring underlying costs in hiring personnel will capture most of the variation in costs. There are several approaches to measuring wage differentials across districts. In his comprehensive review of cost adjustments, Barro (1994) constructs a simple comparison across states of the salary of a teacher (or other professional staff) with a specified level of experience and education, which is used to construct a personnel cost index. The cost of education index would be composed of a weighted average

[8] Colorado has recognized this fact by calculating cost of living for "labor pool areas." Labor pool areas are designed to reflect where teachers in the district live, rather than where they work.

of personnel cost indices by type of personnel. While this approach may be acceptable for state-level comparisons, at the district level it will reward districts that *choose* to pay above market wages by identifying them as having high personnel costs.

In an attempt to avoid this type of inappropriate incentive, wage indices can be based on salaries in similar private-sector occupations. The competitive wage approach is based on the assumption that private sector wage levels affect public sector salaries, but not visa versa. The validity of this assumption depends on the labor market that is being considered. For instance, in small rural labor markets, where public schools represent one of the major employers in the area, the salary scales for teachers may well affect what private employers must pay.

Using data on average payroll by either industrial sector or occupation, it is possible to construct an average private sector wage in similar occupations (Rothstein and Smith, 1997). The competitive wage index could conceivably be disaggregated into different types of occupations, which are more closely linked with specific personnel categories in education (e.g., teachers, administrators, and non-professional staff).   States such as Ohio, Massachusetts and Tennessee have used measures of average private wages as cost adjustments in their foundation programs (Rothstein and Smith, 1997; Massachusetts Department of Education, 1999).[9]

The strength of the competitive labor market approach is the direct link of the cost index to personnel costs, which represent the large majority of a school district's budget. Assuming the private labor market is large enough, private salaries should not be influenced by school district salary decisions. Private wages should reflect differences in cost of living in an area, and availability of amenities, both of which should affect teacher salaries as well, but there is no reason to expect that factors affecting working conditions in education (at-risk children, old buildings) will necessarily affect working conditions for private employees. Thus, the drawback

[9] See Appendix A for details.

to this methodology is that private wages are not likely to reflect differences in working conditions for teachers across districts, and such conditions have been shown to have a significant influence on teacher employment conditions (Hanushek et al., 2004).

C. Hedonic Wage Models

Hedonic wage models incorporate elements of both the cost-of-living approach and the competitive labor market methods. The conceptual basis of this approach is summarized by Chambers (1981), "The intuitive notion underlying this theoretical structure is that individuals care both about the quality of their work environment as well as the monetary rewards associated with particular employment alternatives, and that they will seek to attain the greatest possible personal satisfaction by selecting a job with the appropriate combination of monetary and non-monetary rewards."(p. 51).

As discussed more fully in the following section, hedonic wage models for teachers (and other personnel) attempt to measure the value teachers place on various community factors (e.g. crime rates, housing costs) and job characteristics (e.g. student demographics) by including these factors in wage equations. Similar to competitive wage market methods, hedonic models attempt to capture factors affecting the local labor market. One of the factors affecting relative wages is local cost-of-living differences such as housing prices. What sets this approach apart from the other two methods is that it also tries to capture the impact of working conditions in education on the required salaries for professional staff. Though the hedonic approach, in our view, represents the most appropriate and sophisticated method for making geographic adjustments in the cost of education, we are aware of only one state, Texas, that uses this approach to determine cost of education differences.[10] The complexity of using this methodology to develop a GCEI, which is discussed below, is the most likely reason that it is not more widely adopted.

The key assumption behind the development of hedonic wage models is competitive labor markets. Under the competitive labor market theory, any firm overpaying for employees will be driven out of business by lower-cost competitors. Thus, competitive labor markets imply that wages reflect the *minimum* required to attract a particular employee into a particular job.

Public sector wages are likely to be directly influenced by competitive pressures, but in the public sector pressure to maintain efficiency will be more indirect since it must occur either through the pressure of taxpayers on elected officials, or through the loss of population as households sort across communities to find the best package of taxes and public services. If teacher labor markets are not competitive, and teachers in some districts are paid more than necessary to recruit them for a particular position, adjustments in the basic hedonic model may be necessary.

2. Construction of the GCEI

In developing a geographic cost of education index (GCEI) for the state of Maryland, we adhere to the following principles. First, cost differences should reflect the cost of doing business for a typical school district. In other words, cost differences need to be determined for the major resources used by school districts, and the resulting cost indices for each resource should be weighted by their share of the budget. Second, cost differences should reflect only those factors outside district control. Efficient districts should not be penalized because they have lower spending. Finally, personnel cost indices should capture what it would take to recruit an employee of a given quality into a particular school district. Consequently, regional personnel

[10] See Appendix A for details.

cost indices are not appropriate, because they do not reflect the specific working conditions in a particular school district.

The construction of the GCEI can be represented simply as a weighted average of personnel costs and non-wage items – that is, the GCEI is weighted by the personnel cost index (PCI) and a non-wage index (NWI):

$$GECI = \lambda_1 PCI + \lambda_2 NWI \tag{1}$$

The weights assigned to the PCI, λ_1, and the NWI, λ_2, are defined by the relative spending at the aggregate state-level spending on personnel and non-personnel items. The budget share for non-personnel spending should reflect only those items where prices are expected to vary across districts. In Maryland, for instance, personnel costs (salary and benefits) accounted for about 85 percent of total current expenditures with the remainder of expenses made up by non-personnel items (MSDE, 2003a).[11]

A. Hedonic Salary Models and the PCI

Basic model: The PCI is constructed based on a hedonic salary model, which is designed to predict what a school district will have to pay an equally qualified teacher to work in this district based on district characteristics. The assumption behind this model is that less attractive school districts will have to pay teachers more to work in their district. The attractiveness of a district is affected by both factors that are within control of the district (discretionary factors), such as class size and number of teacher assignments, and factors outside district control (cost

[11] The personnel expenditures weight is based on expenditure figures that include spending on both salaries and benefits. The construction of the PCI, described below, does not account for variation between districts in benefit levels, since there are typically few differences in benefit packages within Maryland (see Appendix Table B-1 for a review of information on benefits). Thus, the implicit assumption is that the cost of benefits varies in proportion to salary costs.

factors), such as the underlying cost of living and working conditions. Specifically, the model we estimate takes the following form:

$$\log(salary) = \alpha_0 + \alpha_1 D + \alpha_2 C + \alpha_3 YEAR + \alpha_4 FC + \varepsilon \ . \qquad (2)$$

D represents a set of discretionary factors, and C represents a set of cost factors. Discretionary variables include personnel characteristics for which districts are willing to pay higher salaries, such as education and experience. They also include the results of decisions made by the district that affect the working environment for the staff. For example, teachers may find a district more attractive that has smaller class sizes, newer facilities, and better staff development opportunities.

Cost factors (C) include a set of characteristics of the school, district, and community, which are outside school district control but affect the attractiveness of a position to a teacher. For example, teachers may find a job more attractive where students come to school ready to learn, where discipline problems and school violence are minimal, and where the cost of living in the community is low. Cost factors can fall into several broad categories including variables that are designed to capture working conditions, cost of living, and quality of life. (Specific variables that we considered for the model are discussed in the following chapter.)

The YEAR variables are a set of dichotomous variables identifying the year of the data, and it is included to measure general price changes across years affecting all districts in Maryland (i.e., inflation). FC is a set of variables designed to control for the preferences and fiscal capacities of each district. We are attempting in this hedonic model to account for the extent to which districts must offer differential salaries to reflect the preferences of teachers over community and job characteristics -- that is, the factors that influence the willingness of teachers to accept employment in a particular locality. Consequently, we do not want our results to be confounded by factors that influence the amount school districts are willing to pay beyond what is required for teachers to accept offers (Alexander, et al., 2000). We therefore include measures of fiscal capacity to attempt to account for school district preferences. The portion of the variation in salaries that is not explained by the model is represented by the error term, ε. If the model is successful in explaining most of the salary differences across districts, then the error term should be randomly distributed.[12]

The coefficients calculated in this model can be viewed as the financial weights that either the district or employee puts on this factor. Specifically, α_1 represents the set of coefficients that define the impact of the discretionary variables on salary, α_2 represents the set of coefficients that define the impact of the cost variables on salary, α_3 is a set of coefficients that define the impact of the year on salary (α_3 is essentially a measure of inflation in personnel salaries), and α_4 is a set of coefficients that define the influence of fiscal capacity and preferences on salary. Because the model is specified in a log-linear form (we take the natural log of salary), the estimated coefficients represent the percentage change in the salary that result from a unit change in any of the variables in our model.[13]

Types of personnel: The factors influencing the attractiveness of a position may differ depending on the type of personnel. We may, for example, think of three distinct classes of employees: teachers, non-teaching professionals (NTP) who have close contact with students

---

[12] Technically, the error term is assumed to have a normal distribution, with a mean of zero.
[13] The log-linear function used for the hedonic salary equation is the one most commonly used in the literature, because it tends to fit the data better than a linear function. This functional form implies that a given change in one of the dependent variables will have the same effect on the *percentage* change in the required salary. The change in the *level* of the required salary, however, increases with the salary. For example, for the working condition variables, it implies that the harsher the working conditions get, the greater the impact they have on required salaries. For example, a change in the poverty rate from 80 percent to 90 percent has a larger impact on required salaries than a change from a poverty rate from 10 percent to 20 percent. This makes sense when one considers that marginal costs (in this case the costs of poor working conditions) are generally increasing, implying that districts must offer larger and larger amounts to compensate teachers for more difficult working conditions as those conditions worsen.

throughout the day, and other non-professional personnel (NPP). It would not be surprising, for instance, if variables defining characteristics of a district's student body (e.g. the percentage of students on free or reduced price lunch) had a more significant impact on the salaries of teachers than non-professional personnel. Teachers have direct contact with students throughout the day and, depending on the nature of the job, non-teaching personnel may have little or no direct contact with students. Furthermore, we might imagine that these employees have quite different labor market opportunities, which would affect their ability to be selective in the jobs they take or pass over.

We test the above hypotheses by dividing up our personnel sample into these three classes of employees, then estimating separate hedonic models for each group, and finally testing whether the coefficients differ significantly between groups. This allows us to determine whether or not it is appropriate, from a statistical standpoint, to estimate the models for different classes of employees grouped together, or whether it is more appropriate to estimate the models for one or more groups separately. Thus we might think that the PCI will actually be comprised of up to three separate indices: a teacher cost index (TCI), a non-teacher professional cost index (NTPCI) and a non-professional cost index (NPCI)[14]

Methodological considerations: While the above model can be estimated with standard statistical techniques, we need to evaluate the methodology used in the analysis to assure its accuracy. Essentially, we are concerned about two types of problems. First, we want to assure to the greatest extent possible that the estimated coefficients represent the underlying relationship between salaries and each factor. The accuracy of the coefficients is particularly important,

[14] If we conclude that these groups should be estimated separately, then the PCI will be a weighted index of the PCIs for each employee class, where the weights are defined by the overall state share of educational expenditures on each class of employee: PCI = γ_1(TCI) + γ_2(NTPCI) + γ_3(NPCI).

because it can directly affect the calculation of the personnel cost index. In chapter 3, we evaluate the validity and reliability of the factors used in the hedonic model.

Second, the best insurance against biased coefficients is to include in the model all the important factors affecting salaries. Since it is difficult to assure that all the important variables are included in a model, we can employ methods that control for unobservable factors. The most common of these methods, "fixed effects", includes dichotomous variables (0-1) in a model for all school districts and time periods. The variables for school districts control for all factors that are unique to a school district and do not vary across time. The variables for years control for factors that are unique to a particular year, but which affect all school districts, such as changes in state (or federal) policy.[15]

Besides estimating accurate weights for each salary factor, we also want to be confident that these estimates are made with precision. If we find, for example, that the effect of an additional year of experience for teachers is associated with a 1 percent increase in salaries plus or minus 1.5 percent then we do not have much confidence in our estimates. In this case, we could not assert that teacher experience affects teacher salary. In order to make judgments about the precision of our estimates, it is important that the measures of precision we use are accurate (commonly called a standard error). The data used in this analysis is at the teacher level (teacher characteristics), school level (class size, school enrollment, student characteristics), and at the county level (student characteristics, crime rate, cost of living). Standard regression techniques assume that all data is at the same level. If data is at multiple levels, then the measures of

[15] Another problem that can affect the accuracy of the coefficients is when the dependent variable can cause the independent variables, and not visa versa (commonly called an endogeneity problem). One example is if test scores for a particular grade and school are included as explanatory variables in the salary model. Clearly, teachers may be attracted to a school with high test scores as a measure of working conditions, and would accept lower wages. However, lower wages may be related to the quality of the teacher, which can directly affect the test scores. In this case, it is difficult to identify which factor is at work without more information. We have attempted to avoid inclusion of endogenous variables in the model.

precision will be estimated inaccurately. We explore several methodological options for correcting the standard errors to make sure they are accurate.[16]

Calculating the PCI: As a step toward calculating the PCI for each district in a particular year, it is first necessary to calculate an *adjusted* predicted salary for each district in that particular year. This adjusted predicted salary describes what a district would be predicted to have to offer to get a teacher (or other school official) of a quality (defined by the personnel variables in the model) comparable to any other district in the state. Specifically, this calculation is done by holding constant the discretionary factors that influence salaries, setting the cost factors to the district mean for each district, and setting the year variable to one in the year for which we are calculating the PCI:

$$\text{Adjusted } (salary)_{jt} = \exp\,(\alpha_0 + \alpha_1 \overline{D}_t + \alpha_2 \overline{C_{jt}} + \alpha_3 YEAR_t\,)\,, \tag{3}$$

where the subscript j denotes the district, the subscript t denotes the year. The “exp” function is used to convert the logarithm of salaries used in the regression models to predicted salaries expressed in dollars. Note that the vector D does not have a j subscript because the variables in D are not allowed to vary by district.[17] (The above calculation is actually slightly more complicated because some of our cost variables are potentially defined at the school level. This does not present a problem, however, as we can simply calculate a school-level adjusted salary

---

[16] Several methods exist for relaxing the assumption of independence between error terms for all observations. One approach involves estimating “robust standard errors”, which correct the heteroscedasticity problems associated with standard errors in OLS (White, 1980). Robust standard errors can be calculated to explicitly account for clusters of observations (e.g., all teachers in one school). Another option is to estimate the model using a “random effects” specification that explicitly accounts for the possibility that the error terms are correlated within each cluster. Random effects models can be estimated with generalized least square (GLS) method or maximum likelihood method (Greene, 2000).

[17] The variables in D may be set at the state mean or any other value. Numerically it makes no difference in the calculation of the PCI so long as they are held constant for all districts in the state.

and aggregate to the district level by weighting each school level adjusted salary by the number of students in the school.)

Once the adjusted salary for each district j is calculated, the PCI for each district is simply the ratio of the adjusted salary in district j relative to the adjusted salary for the state as a whole. Thus, the PCI for a particular district J in year T is calculated in the following manner:

$$PCI_{jt} = \frac{\exp(\alpha_0 + \alpha_1 \overline{D}_t + \alpha_2 \overline{C_{jt}} + \alpha_3 YEAR_t)}{\exp(\alpha_0 + \alpha_1 \overline{D}_t + \alpha_2 \overline{C_t} + \alpha_3 YEAR_t)}. \tag{4}$$

Note here that the vector C has the subscript j in the numerator, but not in the denominator. This signifies that the cost factors are varying for each district, but are held constant for the state as a whole.

There are many different variables that we might employ to capture underlying cost factors (e.g. working conditions, cost of living, etc.) that are thought to influence salaries. We are, however, limited in our use of variables by the number of districts in the state (this is true because many of these variables are specified at the district level). We describe these in greater detail in the next chapter.

3. Construction of the NWI

The non-wage index is intended to capture the variation in non-wage expenditures across districts, which is outside the control of district personnel. For example, larger districts may be able to negotiate more favorable prices on energy and supplies than smaller districts, because of volume discounts. Included among non-wage expenditures are supplies and materials, energy and other utilities, contracted services, and other charges (MSDE, 2003a).[18] These objects of expenditures represent approximately 15 percent of current expenditures in Maryland.

Constructing a non-wage index involves three stages. First, each type of cost needs to be analyzed to determine whether costs are likely to vary due to factors outside district control. Second, for those expenditure categories where external factors affect costs, a model needs to be constructed to separate the effects of discretionary factors from cost factors. Finally, the results of the cost model need to be used to construct cost indices.

A. Analysis of expenditure categories

To assess whether variation in non-personnel expenditures is due in part to external factors, we consulted with school business professionals in the state of Maryland about what they felt affected expenditure differences across districts. With regard to energy costs, the consensus was that the determinants of these prices are a complicated combination of district management decisions, condition and age of facilities, the size of the district, and weather conditions. Because district size and weather are outside district control, an energy cost index should be included in the GCEI.

Prices for supplies and materials can also vary by size of the district, as larger districts can take advantage of volume purchases. However, small school systems in Maryland have several opportunities to participate in purchasing cooperatives when making decisions regarding supplies and materials purchases. In addition to "eMaryland M@rketplace", an electronic purchasing and procurement portal for the State, local schools systems are members of buying consortiums like the Baltimore Regional Cooperative Purchasing Committee (BRCPC), the Southern Maryland Consortium and the Eastern Shore Consortium. The General Assembly

[18] Excluded from consideration in constructing the GCEI is transportation, community service, capital, and debt service.

passed legislation several years ago allowing local school systems to "piggyback" onto existing purchasing contracts negotiated by other public entities, including national buying consortiums.[19] These initiatives allow local school systems the opportunity to reap the pricing benefits of the economies of large scale purchasing.

"Contracted services" is a composite of various types of services provided to school districts, including professional/technical services, repair and maintenance services, cleaning services, construction services, advertising, printing, publishing, and food services (MSDE, 1996). The "other charges" object includes employee benefits, energy services and "other purchased services," such as travel, insurance, communications, and non-energy utility services. Contracted services and other purchased services are either services that could potentially be provided by district personnel, or services supporting district personnel. If the district chose to provide these services in-house, then most of their costs would have been recorded as salary expenditures. We have disaggregated these services into those related to instruction, those related to administration and student and health services, and those related to maintenance, operations and food service. To maintain consistency across districts, we will apply the appropriate PCI to each of these categories.

B. Energy Cost Model and Index

Energy costs are the one non-wage object of expenditure where developing a separate cost index appears justified. In discussions with school business officials about the determinants of energy costs, they identified several factors that are under district control, and several that districts cannot affect directly. The energy cost model can be represented as:

$$\log EC = \alpha_0 + \alpha_1 D + \alpha_2 C + \varepsilon \quad , \tag{5}$$

[19] Education Article §5-112, Annotated Code of Maryland

where EC represents energy costs per pupil, D represents a set of discretionary factors, and C represents a set of cost factors.[20] Discretionary variables include energy sources used, overall capacity of facilities, age of buildings, and physical size of buildings. Data is not available on the existence of air conditioning, or whether the district aggressively attempts to apply energy conservation measures. While outside the control of the district, district wealth was included as a rough proxy for the existence of air conditioning (under the assumption that this is a relative luxury that poorer districts cannot afford). Cost variables can include measures of district size, and number of cold or hot days.

To calculate an energy cost index (ECI), we first calculate an adjusted energy cost per student, which describes the predicted energy cost if the district had average values for the discretionary factors and average wealth. Specifically, the discretionary factors are held constant at the state average for each year, and the cost factors are allowed to vary:

$$\text{Adjusted EC}_{jt} = \exp(\alpha_0 + \alpha_1 \overline{D}_t + \alpha_2 C_{jt}), \tag{6}$$

where the subscript j denotes the district, the subscript t denotes the year. The "exp" function is used to convert the logarithm of energy expenditures used in the regression models to predicted energy expenditures expressed in dollars. Note that the vector D does not have a j subscript because the variables in D are not allowed to vary by district. Once the adjusted energy cost for each district j is calculated, the ECI for each district is simply the ratio of the adjusted ECI in district j relative to the adjusted ECI for the state as a whole in a particular year.

[20] The functional form of the model used to construct the index is actually a double-log model. Both energy costs are expressed as a natural log, and most of the independent variables are expressed as natural logs. The only variables that were not logged are dichotomous (0-1) variables.

4. Constructing Comparable Housing Prices

One of the key factors affecting an area's cost-of-living is housing prices. Not surprisingly, estimates of cost-of-living commonly make housing prices a key variable (McMahon, 1996). Typically, measures of the median housing price in an area (often based on information in the *Census of Housing*) are used as the measure of housing costs. While housing prices are undoubtedly one of the key sources of local price variation, simply using median housing prices in a school district as the measure of housing costs may be inadequate for several reasons.

A. Housing Price Model

First, median housing prices do not control for differences in the quantity and quality of housing in an area. The median house in one area may be substantially larger and of better quality than in another. If areas with higher property wealth and income also have larger and higher quality housing, then comparisons of unadjusted housing prices will overstate the housing costs in the wealthy area. To control for this we estimate a housing price model that includes measures of house size (S), and house quality (Q). The dependent variable is unadjusted house sales price (HP):[21]

$$HP = \alpha_0 + \alpha_1 S + \alpha_2 Q + \alpha_3 DIST + \varepsilon , \tag{7}$$

where DIST is a dichotomous (0-1) variable for all but one district, and ε is a random error term.

[21] In contrast to the hedonic wage model, which is a log-linear specification, we use a linear specification for the housing price model. This linear model fits the data slightly better, and conceptually makes more intuitive sense. In a linear model, for example, an additional square foot of house size will have the same effect on house price when the house is small as when it is large. Were we to employ a log-linear specification, by contrast, an additional square foot of house size would be have a larger impact on housing prices for a larger house than for a smaller house, which is somewhat counterintuitive.

Housing size can include both the size of the land and size of the house itself, number of floors, or number of rooms. Housing quality measures can include the overall condition of the house, the type of building materials (e.g., brick versus frame construction), and whether it is a detached house or townhouse. The results of the housing price model can be used to construct comparable housing price by holding the housing size and quality constant (at the state average), and using the coefficients on the district variables (α_3) to measure housing price differences:

$$\text{Adjusted HP}_j = \alpha_0 + \alpha_1 \overline{S} + \alpha_2 \overline{Q} + \alpha_3 \, DIST_j \,, \qquad (8)$$

where the subscript j denotes the district.

B. Regional Housing Prices

A second potential concern with using adjusted housing prices for each district as the measure of the cost of living is the implicit assumption made about the residence of teachers. Simply using housing prices as the measure of cost-of-living in a school district assumes that personnel working in a school district live in the same district. There is no reason to expect that substantial inter-county and even in some cases interstate commuting by teachers and other school personnel does not occur. Unfortunately, information on the residence of teachers is not available in the Staff Reporting System maintained by MSDE. Examining commuting travel time information from the Census Bureau indicates which counties appear to have high commuting times, however, these are commuting patterns for residents of the county, not commuters into the county. We will explore the use of regional housing prices (county and its neighbors) as well as alternative measures of commuting and traffic congestion in the hedonic wage models.

5. Conclusions

Three methods have principally been used for calculating geographic cost differences across local areas: cost-of-living indices based on a bundle of private consumer goods; competitive private sector wages, and hedonic wage models. In developing the PCI we have selected the hedonic wage model, because it incorporates cost-of-living measures, differences in local labor markets, and variation in working conditions across districts (and schools). The resulting index should reflect more closely the differences in salaries required to recruit teachers with a given set of characteristics into different school districts.

The general methodological approach we use for constructing the GCEI is to estimate price or cost models using multiple regression. Price models measure the determinants of price differences, such as teacher salaries or housing prices, across districts. We also estimated an energy cost model that captures factors affecting both the energy price the district pays and quantity of energy consumed. The factors included in these hedonic models include discretionary variables, which are under the control of the district, and cost variables that are outside the control of the district. To construct a PCI, we predict the teacher salaries in each district if they had average values for the discretionary factors (held at state average), and then divide this by the state average salary. The resulting PCI (or adjusted housing or energy prices) varies only as a result of the cost factors outside district control. Thus, we can use these indices to adjust the allocation of Maryland's educational resources so that districts with unusually high (or low) costs, not resulting from the choices they make, are not unduly penalized (or *subsidized* or *rewarded*).

Chapter 3

Measures and Data Sources Used in Developing the Maryland GCEI

In developing the personnel cost index (PCI) and non-wage index (NWI), a number of choices need to be made about the measures (and data sources) used in the analysis. The objectives of this chapter are threefold: 1) to present a number of measures that will be tested in the development of the PCI and NWI; 2) to describe the data sources used to construct these measures; and 3) to evaluate different measures in the same category. Strengths and limitations of different measures will be presented. Chapter 3 is organized into seven sections. We begin with a brief review of the different data sources considered in the analysis. Next, we discuss key criteria that should be considered in selecting among different measures. We then turn to presenting a review of measures for teacher characteristics, student needs, cost-of-living, cost and amenity factors, and district data used in constructing the NWI.

1. Data Sources

In selecting data sources to be used in developing the GCEI, we followed several criteria. First, whenever possible we collected data from the organization that produced the data, rather than from secondary sources. This hopefully minimized errors in our dataset by allowing us to verify how the data were collected, and to directly address any questions about the data elements. It also provided us with more flexibility in terms of the types of measures that could be used. For example, the Maryland Department of Business and Economic Development (DBED) has a detailed county-level database that provides a number of relevant variables. Instead of using the DBED database, we collected data directly from the source producing this data, when available.

Second, whenever possible we attempted to use data produced by state agencies in Maryland. We viewed this to be important, in order to allow MSDE, working cooperatively with other state agencies, to easily update the GCEI using consistent measures. Finally, we tried if at all possible to identify data sources that produce information on a regular (ideally annual) basis to permit the GCEI to be updated on a regular schedule.

Table 3-1 summarizes data sources for teacher-level, school-level and district-level variables that will be evaluated for use in the PCI and NWI. Staff salaries and a range of staff characteristics are available in the Staff Data File available from MSDE. The information that is available on staff characteristics depends on the type of staff. For teachers, information is available on age, experience, education, gender, and race/ethnicity. In addition, information on teacher certification status and test score performance is available in the Certification Data File and Certification Testing File also available from MSDE.

For student need variables, there are two primary data sources. As part of the Maryland School Performance Program, MSDE assembles an annual "Maryland Report Card" with information on student characteristics available from 1992 to 2002 (MSDE, 2003b). Additional student information is available from the U.S. Census Bureau in the *2000 Census of Population and Housing*. While some Census data is available for intercensal years (child poverty rates), most socio-economic variables are not.

Cost-of-living and labor market variables are available from several sources. DBED has produced a cost-of-living index (COL) for 1998 and 2000. Housing prices can serve as an alternative measure of cost-of-living, because they typically represent the largest source of variation in cost-of-living (McMahon, 1996). Presently, housing prices are available from three sources: the State Department of Assessment and Taxation (SDAT), Maryland Association of Realtors, and the Bureau of the Census (*2000 Census of Housing*). The SDAT data is available at both the county level and at the individual house sales level as part of the "Sales History File". The latter file will be the principal source used to estimate the housing price model. Labor market information is obtained from the U.S. Bureau of Labor Statistics and the Maryland Department of Labor; both organizations regularly collect information on employment, unemployment and payrolls.

Table 3-1 Description of Availability, Level and Source for Major District-Level Variables to be Evaluated in the Construction of GCEI

Variables	Years Available	Level[1]	Source
Staff Data:			
Salaries	1999-2002	T	MSDE (SDF)
Characteristics	1999-2003	T	MSDE (SDF)
Teacher Certification	1999-2004	T	MSDE (CERT)
Student Need Variables:			
Students Getting Subsidized Lunch	1992-2002	D, S	MSDE
Child Poverty Rate	1990, 2000	D	CENSUS1
	1995,97,99		CENSUS2
At-Risk Students	1990, 2000	D	CENSUS1
Title 1 Students	1992-2002	D, S	MSDE
Limited English Proficiency	1992-2002	D, S	MSDE
English at Home Spoken "not well"	1990, 2000	D	CENSUS1
Female-Headed Household with Children	1990, 2000	D	CENSUS1
Special Education Students	1992-2002	D, S	MSDE
Student Mobility--Share New Students	1992-2002	D, S	MSDE
Economic Variables:			
DBED Cost-of-Living	1998, 2000	D	DBED
Average Home Price	1997-2002	D	REALTOR
Median Home Price	1997-2002	D	REALTOR
Median Home Price	1994-2002	D	SDAT
Median House Value (Census)	1990, 2000	D	CENSUS1
Per Capita Income	1991-2001	D	BEA
Wealth	1992-2002	D	MSDE
Unemployment Rate	1993-2002	D	BLS/MDL

Table 3-1 Description of Availability, Level and Source for Major (Cont.) District-Level Variables to be Evaluated in the Construction of GCEI

Amenity Variables:			
Total Crime Rate	1991-2001	D	MSP
Violent Crime Rate	1991-2002	D	MSP
Miles of Shoreline	2001	D	DBED
Precipitation	1994-2002	D	NOAA/MSC
Heating (and Cooling) Degree Days	1994-2003	D	NOAA/MSC
Vehicle Miles per Lane Mile	1998-2002	D	MDOT
Average Travel Time to Work	1990, 2000	D	CENSUS1
Distance to Nearest Major (Hub) Airport	2001	D	DBED
Population Density	1990, 2000	D	CENSUS1
Enrollment	1992-2002	D, S	MSDE
Number of 4-Year Colleges	2001	D	DBED
% College Graduates	1990, 2000	D	CENSUS1
Energy/Expenditure Variables:			
Expenditures by object	1999-2001	D	MSDE
Energy Expenditures	1999-2002	D	From Districts
Adjusted Building Age	1999-2002	D, S	PSCP
Building Capacity (square feet)	2002	D, S	PSCP

[1]T=teacher, S=school, D=district.

Sources: BEA = U.S. Bureau of Economic Analysis
BLS = U.S. Bureau of Labor Statistics
Census1 = Decennial Census of Population and Housing
Census2 = Inter-Census Estimates of child poverty rates
DBED = Dept. of Business and Econ. Development County Comparison
MDL = Maryland Department of Labor
MDOT = Maryland Department of Transportation
MSDE = Maryland State Department of Education Teacher File
MSDE (SDF) = MSDE Staff Data File
MSDE (CERT) = MSDE Certification Data File and Certification Testing File
MSC = Maryland State Climatologist Office
MSP = Maryland State Police Uniform Crime Rate database
NOAA = National Oceanagraphic and Atmospherice Administration
PSCP = Public School Construction Program
REALTOR = Maryland Association of Realtors housing sales information
SDAT = State Department of Assessment and Taxation

We have evaluated a range of factors related to amenities associated with living in a particular county for use in the teacher wage model. Crime rates are developed as part of the Uniform Crime Reporting (UCR) system, which is administered by the FBI in cooperation with state agencies such as the Maryland State Police. Climate data is collected in a series of weather stations reporting to the National Oceanographic and Atmospheric Administration (NOAA).

This data is available from NOAA and the Maryland State Climatologist Office. Information on population density, travel time to work, and education level of the adult population is produced every ten years as part of the decennial census. DBED has collected information on physical characteristics of Maryland (e.g., miles of shoreline), distance to major airports, and number of colleges by type in each county. Information on traffic volume (vehicle miles per lane mile) is available form the Maryland Department of Transportation.

Several sources of data are used for the energy cost model. Expenditure information by object of expenditure is available from MSDE, and is used to construct budget shares for weighting the different indices. Energy expenditures, however, are not readily available in the MSDE expenditure reports. Instead, districts were contacted directly to provide energy expenditures by energy source. Weather information used in this model was from NOAA and MSC. Building age and capacity information was collected from the Public School Construction Program in Maryland.

2. Criteria Used to Evaluate District Variables

As indicated by Table 3-1, a number of different variables are available under each of the broad categories of factors to be included in the staff salary models and energy cost model. It is important to note that, at most, only a few variables can be selected from each category because there are only 24 school systems in the state. As a result, there is relatively little variation in any of the district/county level variables, therefore selection criteria must be identified for choosing alternative measures. We identify three criteria that may be used in variable selection: validity, reliability and "updatability".

In many respects the fundamental criteria for evaluating any measure is its ***validity*** in capturing the underlying phenomenon to be measured. Therefore, careful development of the conceptual models is crucially important in guiding selection of valid measures. Each variable must be evaluated logically to see how closely it relates to the underling factor in the model (face validity). Variables also should be evaluated empirically to see if they have the expected relationships with other similar and dissimilar variables (construct validity).

If the conceptually strongest measures are only available on an infrequent basis, they can still be used as a benchmark for evaluating other measures. For example, the most direct measure of child poverty is produced by the Census Bureau as part of the decennial Census of Population. Alternative measures, such as the share of students receiving a subsidized lunch, will be compared to census child poverty rates. We examine the correlation between these various measures both at a point in time and over time to assess the degree to which they are measuring the same underlying concept.

It is also important that the measures be reliable. ***Reliability*** implies consistency in measurement of the phenomenon. A reliable measure is one that yields similar results when measured at several points in time or by different people. Several steps are taken to examine reliability. First, we evaluate the reasonableness of extreme observations for each variable. Unusually high or low measures may suggest measurement error problems. Second, for those variables with multiple years of data, we examine the stability of these variables. Variables that fluctuate significantly in value may be susceptible to measurement problems or changes in how the variable is defined or how data is collected. Variable stability is of particular concern in the development of the GCEI, because of the impacts on the volatility of the GCEI. We experiment using various measures in the calculation of the GCEI to determine the degree to which the volatility of a particular variable may cause the overall GCEI to be more volatile.

Another criterion is whether the variable is produced on a regular basis allowing for MSDE to update the GCEI. Ideally, each measure would be produced annually using a consistent definition and data collection process. The Census of Population and Housing is an excellent source of demographic and socio-economic information on school districts. However, most of this information is available only once every decade. Annual data is preferred as long as the variables meet reasonable standards of validity and reliability.

3. Personnel Data

Personnel data come directly from the MSDE in two data files. The first is a comprehensive set of variables on all faculty, administrators and support staff. These data contain such measures as years of experience, current assignment and salary as well as some teacher demographics including race and gender. These data are for years 1999-2002 and include approximately 105,000 observations per year resulting in a complete dataset comprised of slightly more than 420,000 observations.

We divided our sample into three categories: teachers, non-teaching professionals (NTP), including principals, assistant principals, library and media specialists, and counselors, and non-professional personnel (NPP). For each of these groups we restricted our analysis to only those who were reported by the state to have a full-time equivalency equal to 1.[22]

The State of Maryland also provided us with certification test scores of personnel. These data were not for a particular year, but contained one observation per individual. The file contained a total of 108,099 observations, most of these were for teachers or former teachers.

To create the full dataset we merged test scores to the personnel data using a unique identifier created by using the first five letters of the individual's last name, first initial of first name, and date of birth. Table 3-2 summarizes the number of teacher observations (since we are

[22] This restriction was made in order to avoid the problem of having to adjust salaries for those who were working part-time. The one exception was non-professional staff positions, where a large share of some occupations are part-time. In this case we divided salary by FTE to get a full time equivalent salary, which is used in the hedonic salary model for non-professional staff.

primarily concerned about the certification scores for teachers) that properly merged from both files for teachers. The merge rate was quite high, with about a 93 percent successful merge rate overall.

Table 3-2 Description of Testing Merge Quality

	1999	2000	2001	2002
Total Teachers	52,026	53,507	55,031	56,608
Teachers who Merged with Testing Data	49,051	49,272	51,539	50,853

We eliminated observations where it appeared that the reported salary was outside the proper range (i.e. it was unreasonably high or low) according to state documents detailing high and low salaries for professionals in the state of Maryland.[23] There were some reported coding problems with the experience variable prior to 2002, thus we used the information provided in 2002 to backdate experience for those in our sample who were in the sample in earlier years.[24] Since not all personnel in the sample in earlier years were in the sample in 2002, we used mean value replacement for experience for those not in the sample whose experience values appear to be outside of the proper range.[25]

In describing our sample we focus primarily on teachers, since there are, in some cases, public figures for the state that can be used as benchmarks against which we judge the quality of our dataset. Furthermore, many of the readers of this document are likely to be more familiar

[23] We relied on figures from MSDE on maximum and minimum salaries on the salary schedule for all counties (MSDE, 1999, 2002). For teachers, aides, counselors and library/media specialists we used the minimum salary in 1999 ($25,174) and the maximum in 2002 ($85,000). For principals, we eliminated all above the maximum salary for principals in 2002 ($119,000). For non-professional staff we eliminated staff with salaries in the bottom 1 percent and top 1 percent, to avoid the effects of extreme outliers on the results.
[24] For example, if a teacher was reported to have 14 years of teaching experience in 2002, we credited that teacher with 13 years of experience in 2001, 12 years in 2000, and 11 years in 1999 (the first year of our data).
[25] Mean value replacement, which is a standard method for accounting for missing or incorrect data, simply replaces the variable for some observations with the sample mean for those variables.

with the characteristics of the Maryland teacher workforce than the non-teaching professionals or the non-professional personnel.

Table 3-3 shows salary and experience data for the teacher sample. The state of Maryland reports the mean teacher salary in 2002 was $49,679, similar to our sample mean of $49,276. However, the median teacher salary reported by Maryland is $47,800, compared to $45,375 in our sample. We are unaware of any data currently published by the state of Maryland on the experience level of teachers.

Table 3-3 Descriptive Statistics of Teacher Characteristics

Assigned Salary	Mean	Std. Dev.	Minimum	10th Percentile	Median	90th Percentile	Maximum
1999	43403.63	11242.04	25174	23237	41256	59001	81606
2000	45671.74	11926.79	25199	23555	42386	62137	81192
2001	47874.89	12462.11	25235	24406	44159	65380	84887
2002	49276.11	12969.64	25201	26339	45375	67409	85000

Years Experience	Mean	Std. Dev.	Minimum	10th Percentile	Median	90th Percentile	Maximum
1999	13.50	107.91	0	0	10	29	50
2000	13.08	109.03	0	1	11	29.4	50
2001	12.58	108.45	0	1.2	10	22.9	50
2002	12.24	107.98	0	1	9	29.9	50
NTE: Communications	663	10	270	651	664	676	710
NTE: General Knowledge	661	11	447	647	661	676	695
NTE: Professional Knowledge	663	9	618	651	664	675	687

Table 3-4 shows the demographic breakdown of teachers in the sample. In 2002, 75 percent of teachers reported their race as white, and about 77 percent self-reported as female. All of the figures reported in this table are close to the national norms of race, ethnicity, and gender of the teacher workforce (U.S. Department of Education, 2003).

Table 3-4. Teacher Demographics.

	1999	2000	2001	2002
Teacher Demographics				
Black	0.210	0.220	0.220	0.220
White	0.760	0.760	0.750	0.750
Native American	0.002	0.002	0.002	0.002
Hispanic	0.010	0.010	0.010	0.010
Asian	0.010	0.010	0.010	0.010
Male	0.240	0.240	0.230	0.230
Female	0.760	0.760	0.770	0.770
Teacher Credentials				
BA	0.336	0.355	0.366	0.371
MA (and BA+30)	0.528	0.512	0.499	0.494
MA30	0.125	0.123	0.124	0.124
Phd	0.006	0.006	0.006	0.006
professional	0.897	0.879	0.859	0.824
alternative	0.003	0.002	0.001	0.000
provisional	0.079	0.084	0.101	0.098

4. Measures of Student Characteristics

As indicated in Chapter 2, student characteristics play a crucial role in the development of the PCI, because they measure the underlying working conditions facing teachers. Research on teacher labor supply indicates that teachers generally prefer to teach in classrooms where students are ready to learn, and where discipline problems are minimal (Hanushek et al, 2003; Hanushek et al, 2001; Murnane et al., 1989; Greenberg and McCall, 1974; Theobold, 1990). In addition, a high share of students with limited proficiency in English or with special needs may complicate both classroom management and instructional strategies. Thus, three different categories of student need factors are considered: at-risk students, students with limited English proficiency, and special needs students.

A. Measures

At-risk students: The term "at-risk" implies that a student is at a higher risk of falling behind grade level, because of characteristics of the student, family or peers. The significant research on factors affecting student performance indicates that poverty status, stressful family situations and lack of parental education and ability to speak English affect a child's success in school (Haveman and Wolf, 1994; Pollack and Ginther, 2003; Ferguson and Ladd, 1996; Jensen and Seltzer, 2000). In addition, students that are highly mobile are at a disadvantage because of differences in curricula across school districts.

The most common measure of at-riskness is poverty. The Census Bureau, as part of the decennial census, produces a range of poverty measures for individuals, families and households. To capture poverty among the school-age population, we use the share of children between the ages of 5 and 17 living in poverty. Another advantage of this particular measure is that the Census Bureau makes intercensal estimates of child poverty using a regression model and data from the Current Population Survey.[26] Other measures of at-risk students available in the decennial census include the share of children living in a single-parent (female-headed) household, and composite measures of "at-risk" children. One definition of an "at-risk" child used by the Census Bureau includes children living with a single mother who has an income below the poverty line and is not a high school graduate.

An alternative measure of at-riskness is the share of students that qualify for free or reduced price lunch in a school. This measure is produced as a function of the National School Lunch Program administered by the U.S. Department of Agriculture. Children with incomes at or below 130 percent of the federal poverty line are eligible for free lunch, and students between 130 and 185 percent of the poverty line are eligible for reduced price lunch. In addition, households receiving Food Stamps, Aid to Dependent Children (ADC), Temporary Assistance to

[26] One comparison of intercensal estimates of child poverty and the decennial census in 1989 found that these measures at the county level varied by 17 percent on average. Information on estimation methodology, and predictive accuracy for the intercensal estimates of poverty are available from the Census Bureau at the following website: http://www.census.gov/hhes/www/saipe/schooltoc.html

Needy Families (TANF), or the Food Distribution Program on Indian Reservations (FDPIR) are also eligible for free lunch.[27] Free or reduced price lunch has an advantage over the census poverty measure in that it is updated on a more regular basis. However, this measure is based in part on the decision by families to apply to participate in the program, which may affect its validity and reliability.

Other at-risk measures available through administrative records in Maryland include "Title 1" students and measures of student mobility. Title 1 students are those receiving Title 1 services either through targeted assistance programs, or through a school-wide program. Student mobility measures available in the Maryland Report Card are the number (and share) of new entrants to and withdrawals from a school.[28]

LEP students: Several measures are available for students with limited English language proficiency. MSDE collects information on the number and percentage of students assessed as eligible for Limited English Proficient (LEP) services. As defined by MSDE, "LEP students have a primary or home language other than English and have been assessed as having limited or no ability to understand, speak, read, or write English".[29] An alternative measure is available from the Census Bureau, which collects information as part of the decennial census on children (5 to 17 years), who live in households where English is spoken "not well" or "not at all". The Census measure is less direct than that available from MSDE, but can serve to validate the MSDE measure.

Special needs students: One measure of the share of special education students is presently available from MSDE in the Maryland Report Card. Special education students are

---

[27] A description of the program and eligibility requirements is available on the Food and Nutrition Service website: http://www.fns.usda.gov/cnd/Lunch/AboutLunch/faqs.htm.
[28] Definitions of student measures provided by MSDE are available on the website: http://msp.msde.state.md.us/supporting/index.asp
[29] From the website: http://msp.msde.state.md.us/supporting/special_srvs_LEP.asp

those "students with disabilities who have current Individualized Education Plans (IEPs)". Given that only one measure of special needs status is available, we question whether this variable should be included in the model. Without a detailed analysis of classification patterns for special needs students, a definitive answer to this question cannot be easily reached. However, there are conceptual grounds for being cautious about including this variable in the model. It should be included if it is related to the classroom environment. However, different choices by districts on whether to use inclusive vs. separate special education programs will clearly affect the impact these students will have on the classroom environment. Without information on the types of programs used by districts, this variable may be a poor measure of the impact of special needs students on the working conditions for teachers.

B. Reliability Evaluation

Reliability of student need variables is assessed in several ways. First, descriptive statistics are presented to examine the likelihood of measure error for each variable. Table 3-5 provides several measures of the center (average, median) and tails of the distribution (minimum and maximum, and 10^{th} and 90^{th} percentiles). Because all of the variables are expressed as a percent of total, the measures should range from 0 to 100. In all cases, the measures fall within this range. Eligibility for subsidized lunch is above the poverty line, thus we would expect that the subsidized lunch share should exceed the child poverty rate. This was the case for all parts of the distribution, and was true for all counties. As expected, the share of "at-risk" students as defined by the Census Bureau is substantially less than the child poverty rate and the share of children in single-parent households, because this is composite of both these measures. The share of LEP students as classified by MSDE is similar to the census measure of the percent of children growing up in households where English is spoken "not well" or "not at all".

Table 3-5. Descriptive Statistics for Student Need Variables

Student Need Variables	Mean	Average Variation	Minimum	10th Percentile	Median	90th Percentile	Maximum
Share of Subsidized Lunch Students	28.97	15.72	8.00	11.00	26.80	45.70	69.20
Census Child Poverty Rate (2000)	11.04	6.75	3.71	4.49	8.54	18.45	28.90
Census At-Risk Students (2000)	2.53	2.20	0.76	0.87	2.08	4.52	11.36
Title 1 Students	19.34	15.32	2.80	3.30	13.95	44.80	47.40
Student Mobility--Share New Students	9.71	4.49	4.80	5.00	9.00	14.20	25.20
Female-Headed Household with Children (2000)	22.53	9.25	12.04	14.58	19.26	33.37	54.10
Limited English Proficiency	1.53	1.77	0.00	0.10	0.85	3.90	7.60
English Spoken "Not Well" at Home (2000)	1.00	0.63	0.17	0.45	0.78	1.77	2.94
Special Education Students	12.88	2.16	8.90	10.50	12.55	15.70	17.80

Note: Data is for 2001 unless noted otherwise.

The second method for checking reliability is to look at the stability of the measure across time. If a measure is volatile when the underlying phenomenon is not, this suggests either measurement errors or changes in variable definition or collection methods. We would not expect large annual variations in the share of students living in poverty, or in the share of students with limited English proficiency or special needs at the district level. Exceptions might include small schools and districts. Annual rates of change of 10 percent or higher may indicate reliability problems, and could significantly increase the volatility of the GCEI.

In Table 3-6, we present several measures of the stability of student need variables based on at least 10 years of data. In the first column, the absolute change in each year is divided by the state average for the variable in that year, and then averaged over all years. This should capture cases where the variable fluctuates significantly in absolute terms across years.[30] The second measure (in column 2) is the average variation around a trend line fit to the data, divided

[30] A more intuitive measure might simply be an average of the absolute value of percent changes from the previous year. However, large percent changes can reflect trivial changes in the absolute number of high need students in districts with relatively few of these students.

by the overall state average for this variable (for all years). This measure should remove volatility caused simply by an increasing or decreasing trend in the data. The last three columns indicate the average percent of years where the annual percent change (same measure as column 1) exceeded 30 percent, 20 percent and 10 percent, respectively. All measures are calculated for each county individually and then averaged.

Table 3-6. Stability Analysis for Student Variables at District Level

District	Average Absolute Change as % of Annual State Average	Average Variation Around Trend Line As Percent of Overall State Average[1]	Percent of Years With Changes Above 30% Relative to State Average	Percent of Years With Changes Above 20% Relative to State Average	Percent of Years With Changes Above 10% Relative to State Average
Report Card Data (1992-2002)					
Subsidized Lunch	4.5	5.0	0.0	0.8	9.6
Title 1	21.1	28.4	20.4	31.7	49.2
Student Mobility (Entrants)	11.8	12.5	9.2	15.0	34.6
Limited English Proficiency	15.8	19.6	17.1	27.5	51.7
Special Education	4.8	5.3	0.0	2.1	11.3
Enrollment	2.0	1.3	0.0	0.4	2.9
Census Data (1990, 1995, 1997, 1999, 2000)					
Child Poverty[2]	9.0	18.5	0.8	2.1	17.5

[1]Calculated by fittlng a trend line through the data from 1992 to 2002, and taking the ratio of the standard error of estimate from trend line (average variation around the trend line) divided by the unweighted state average for all these years.

[2]Because the child poverty rate from the Census is not available for every year these estimates are only roughly comparable with those from the Report Card.

The share of students receiving subsidized lunch is actually quite stable. Average annual variation is around five percent, and almost no districts have variation greater than 20 percent. Ten percent of the time districts have variation over 10 percent. Surprisingly, this variable is more stable than the census child poverty measure, which has average variation between 9 and 20 percent, and over 20 percent of the districts with variation above 10 percent.[31] Title 1 students and student mobility rates are much less stable. The share of Title 1 students varies by 20 to 30 percent on average, and in close to 50 percent of the years the variation is over 10

[31] Because the Census child poverty measure is only available for a few years in the 1990s, measures of stability are not strictly comparable to those based on annual measures.

percent. Particularly troubling is that more than 20 percent of the time the variation exceeds 30 percent. The high volatility of this measure may reflect changing definitions of Title 1 students. Reauthorization of Title 1 in 1994 allowed schools meeting certain criteria to use Title 1 funds for implementing school-wide reforms. There has been a rapid nationwide growth in the use of school-wide reform models (AIR, 1999). If similar growth occurred in Maryland, then the volatility in Title 1 student counts could partially reflect the different definition of Title 1 students associated with these schools. The student mobility measure (share of new entrants) has average variation of 12 percent, and 35 percent of the years have a percent change greater than 10 percent. Based on stability, it would appear that the share of students receiving subsidized lunch is the strongest measure.

The only measure available on an annual basis for the share of LEP students is fairly unstable. On average, this share fluctuates between 15 and 20 percent per year, and over 50 percent of years have percent changes greater than 10 percent. Over 25 percent of the time this measure fluctuates more than 20 percent per year, and over 15 percent of the time this measure fluctuates more than 30 percent per year. While it is beyond the scope of this study to examine causes for this volatility, MSDE may want to consider such an investigation if this measure is going to be an important component of the GCEI. By contrast, the share of students with special needs is quite stable with annual fluctuations of approximately 5 percent.

An analysis of variable stability was also undertaken for student need variables available at the school level (Table 3-7).[32] We would expect school level variables to be more volatile, because of the lower enrollment in schools. An increase of 10 LEP students may have a large increase on the share of LEP students in a school, but a relatively small change on the district LEP share. As expected, measures of student need become more volatile at the school-level.

[32] To assure consistent measures of stability, the sample was limited to the 1,241 schools that had a complete set of student need measures available for all years from 1992 to 2002.

Average variation for subsidized lunch shares is now over 10 percent, and one-third of the time schools had changes over 10 percent. Of particular concern is the significant increase in the instability of LEP shares. The annual variation at the school level is approximately 30 percent, and almost 50 percent of the time the variation exceeded 10 percent. The volatility of the special education measure also increases significantly at the school-level. If school-level variables are going to be used in building the GCEI, steps may need to be taken (multi-year averages) to reduce this volatility.

Table 3-7. Stability Analysis for Student Variables At the School Level

District	Average Absolute Change as % of Annual State Average	Average Variation Around Trend Line As Percent of Overall State Average[1]	Percent of Years With Changes Above 30% Relative to State Average	Percent of Years With Changes Above 20% Relative to State Average	Percent of Years With Changes Above 10% Relative to State Average
Report Card Data (1992-2002)					
Subsidized Lunch	10.7	12.5	6.3	12.9	32.5
Title 1	30.3	49.5	16.1	18.5	22.1
Student Mobility (Entrants)	28.0	32.0	19.8	32.6	58.0
Limited English Proficiency	28.5	32.9	23.8	32.5	48.7
Special Education	15.1	17.4	8.6	18.3	44.2
Enrollment	5.6	7.4	1.8	3.7	13.7

[1]Calculated by fittlng a trend line through the data from 1992 to 2002, and taking the ratio of the standard error of estimate from trend line (average variation around the trend line) divided by the unweighted state average for all these years.

[2]Because the child poverty rate from the Census is not available for every year these estimates are only roughly comparable with those from the Report Card.

C. Validity Evaluation

Ideally, to evaluate the validity of at-risk student variables as measures of the working condition of teachers we would have measures capturing differences in classroom and school environment with different student bodies. Reliable and accurate measures of the share of students receiving discipline could be used to capture this environment. Because such measures are seldom available, researchers have relied on proxy measures that capture the share of at-risk students. There is significant empirical evidence indicating that child poverty and limited

English proficiency are related to school performance (Haveman and Wolf, 1994; Pollack and Ginther, 2003; Ladd and Ferguson, 1996; Jensen and Seltzer, 2000), so it is important to evaluate which measures best capture these dimensions.

The Census measure of the share of children of school age (5 to 17 years) living in poverty based on the decennial census seems to most directly capture the poverty status of students in school. However, the intercensal estimates of child poverty may be significantly less accurate, particularly at the local government level. The share of students receiving a subsidized lunch should (by definition) be highly correlated with the child poverty rate if there is full program participation. The share of Title 1 students, however, is only indirectly linked to child poverty. This is particularly the case for schools implementing school-wide reforms, because all students are classified as Title 1 students.

Other dimensions of student need that could be related to student performance in school include instability and lack of support in the home and frequent movement of students between schools. The share of new entrants into a school appears on its face to be a valid measure of mobility, as long as the definition is applied consistently. The share of female-headed single-parent households is often used as a proxy for a stressful home environment for the student (Duncombe and Yinger, 2000). The Census measure of "at-risk" (students living with a single mother who is not a high school graduate and whose income is under the poverty line) – is probably a better measure of this dimension.

To empirically evaluate the validity of the different measures of student need we estimated correlations and examined inconsistencies between these measures. Table 3-8 presents correlations between the district-level measures of student needs. Using the Census measure of child poverty as a benchmark, we evaluated how closely the other measures tracked with this measure. The correlation between the child poverty rate and subsidized lunch shares (0.93) is very strong, and the correlation with Title 1 shares (0.73) is moderately strong. The correlation between the subsidized lunch rate and Title 1 rate is also strong (0.83). Because these measures correlate so strongly only one measure is necessary. The Census measures of single-parent households and at-risk students are strongly correlated with the child poverty rate (over 0.82) and the subsidized lunch rate (0.77). The student mobility rate based on new entrants is weakly correlated with the Census poverty rate (0.29) and the subsidized lunch rate (0.37). It does have a moderately strong correlation with the share of single-parent households, and share of at-risk students (0.65). This variable appears to be picking up other factors besides poverty, and could serve as a proxy for family instability.

Table 3-8. Correlations Among Different Student Need Variables

Student Need Variables	Subsidized Lunch Rate	Census Child Poverty Rate	Census At-Risk Students	Title 1 Students	Limited English Proficiency	Census Poor English At Home	Female-Headed Household With Children	Special Education Students
Census Child Poverty Rate (2000)	**0.93**							
Census At-Risk Students (2000)	**0.77**	**0.82**						
Title 1 Students	**0.83**	**0.73**	**0.48**					
Limited English Proficiency	-0.05	-0.19	-0.12	-0.14				
English Spoken "Not Well" at Home (2000)	0.02	-0.14	-0.02	-0.03	**0.85**			
Female-Headed Household with Children (2000)	**0.83**	**0.81**	**0.90**	**0.55**	0.05	0.19		
Special Education Students	0.13	0.14	0.14	0.21	**-0.51**	**-0.44**	-0.06	
Student Mobility--Share New Students	0.37	0.29	0.65	0.09	0.16	0.27	**0.65**	-0.01

Note: Shaded cells have a correlation above 0.7. Cells in bold have correlations that are statistically significant from zero at 5 percent level.
Data is for 2001 unless noted otherwise.

If the share of students receiving subsidized lunch is going to be used as a proxy for child poverty it is important to evaluate the case for Maryland districts where they don't track closely. Table 3-9 provides a comparison for both rates and indicates the ranking of each district. In general, the subsidized lunch rate tracks closely with the child poverty rate, and the rank order correlation (0.93) is also very high. However, there are a few exceptions. Worcester County is ranked 4th in terms of the child poverty rate, but is ranked 10th on the subsidized lunch rate. On the other hand, Montgomery County is ranked 19th on the child poverty rate but 14th on the subsidized lunch rate.

Table 3-9. Comparison of Census Child Poverty Rate and Subsidized Lunch Rate

	Census Child Poverty (2000)		Subsidized Lunch (2000)	
District	Rank	Rate	Rank	Rate
Baltimore City	1	28.90	1	67.6
Somerset	2	25.35	2	51.7
Dorchester	3	18.45	4	45.6
Worchester	4	17.03	10	32.1
Garrett	5	16.39	5	44.6
Allegany	6	15.30	3	46.6
Kent	7	14.79	8	34.4
Wicomico	8	14.37	9	33.6
Caroline	9	14.21	7	40.5
Talbot	10	10.60	11	27.6
Washington	11	10.35	12	27.1
Prince George's	12	8.93	6	41
Cecil	13	8.15	15	21.4
St Mary's	14	7.79	16	21.4
Queen Anne's	15	7.29	18	15.9
Charles	16	6.70	17	19.6
Baltimore County	17	6.66	13	25
Anne Arundel	18	5.82	19	15.7
Montgomery	19	5.67	14	23.5
Calvert	20	5.10	20	13.1
Harford	21	5.08	22	11.2
Frederick	22	4.49	21	12.2
Carroll	23	3.85	24	8.6
Howard	24	3.71	23	9.8
Simple Correlation			0.94	
Rank Order Correlation			0.93	

The two measures of limited English proficiency are highly related to each other (0.86), suggesting that the classification of students as LEP tracks closely with the Census information on families where English is not spoken well at home. Table 3-10 compares the two measures for each district. A comparison of the district ranks for these two measures indicates that they are closely related, however, there are some anomalies as indicated by the lower rank order correlation (0.71). Talbot County is ranked 17^{th} on the Census measure and 8^{th} on the MSDE LEP rate. Somerset, and Washington Counties are also ranked much higher on the LEP rate than they are using the Census measure. The opposite is the case for Anne Arundel and St. Mary's

Counties. If the LEP rate is going to be used in the PCI, it may be important to understand the reasons for these discrepancies.

Table 3-10. Comparison of Census and MSDE Limited English Variables

District	English Spoken "Not Well" or "Not at All" at Home (2000 Census) Rank	Rate	Limited English Proficiency (2000) Rank	Rate
Montgomery	1	2.9	1	6.9
Prince George's	2	2.2	2	3.8
Wicomico	3	1.8	4	1.7
Caroline	4	1.6	5	1.6
St Mary's	5	1.4	11	0.7
Howard	6	1.2	3	2.4
Baltimore County	7	1.2	6	1.6
Anne Arundel	8	1.1	16	0.6
Baltimore City	9	1.1	12	0.7
Worcester	10	1.0	9	1.1
Kent	11	0.8	13	0.7
Frederick	12	0.8	14	0.7
Dorchester	13	0.8	10	0.8
Harford	14	0.7	17	0.6
Cecil	15	0.7	19	0.4
Charles	16	0.7	18	0.5
Talbot	17	0.7	8	1.4
Queen Anne's	18	0.7	20	0.4
Allegany	19	0.6	23	0
Calvert	20	0.5	22	0.2
Carroll	21	0.5	21	0.3
Somerset	22	0.4	7	1.6
Washington	23	0.3	15	0.7
Garrett	24	0.2	24	0
Simple Correlation			0.86	
Rank Order Correlation			0.71	

Neither the LEP rate or share of special needs students is highly related to the poverty measures, but there is a moderately negative correlation (-0.51) between them. The lack of a relationship between LEP and subsidized lunch is confirmed by examining the relative ranking of each county on these measures (Table 3-11). The low correlations suggest that these variables are measuring distinct phenomena, and could be included separately in the teacher wage model.

Table 3-11. Comparison of Subsidized Lunch Rate and Limited English Proficiency Rate

	Subsidized Lunch (2001)		Limited English Proficiency (2001)	
District	Rank	Rate	Rank	Rate
Baltimore City	1	69.2	12	0.9
Somerset	2	54.4	7	1.8
Allegany	3	45.7	23	0
Garrett	4	43.9	24	0
Prince George's	5	43	2	4.9
Dorchester	6	42.9	11	1
Caroline	7	39.9	5	2
Wicomico	8	36.9	8	1.7
Kent	9	36.8	19	0.4
Worcester	10	31.2	3	3.9
Talbot	11	29.2	6	2
Baltimore County	12	26.9	9	1.7
Washington	13	26.7	14	0.7
Montgomery	14	22.7	1	7.6
St Mary's	15	21.7	13	0.8
Charles	16	17.4	16	0.6
Anne Arundel	17	16.5	10	1.2
Cecil	18	16.4	17	0.6
Harford	19	16.3	18	0.6
Queen Anne's	20	15.9	20	0.4
Frederick	21	13.2	15	0.7
Calvert	22	11	22	0.1
Howard	23	9.4	4	2.8
Carroll	24	8	21	0.3
Simple Correlation			-0.05	
Rank Order Correlation			0.15	

5. Cost-of-Living and Other Economic Measures

Another important factor in the hedonic wage model is the geographic cost-of-living of an area. Cost-of-living (COL) factors are included in teacher wage models to reflect differences in the required salary to maintain the same standard of living across local governments. The lack of information on where teachers live (compared to where they work) leads to the (often implicit) assumption that price differences affecting standards of living are determined by the county of employment, not the county of residence (if they are different). We begin this section by discussing possible cost-of-living measures, and then provide an evaluation of these and other economic measures.

A. Measures

DBED cost-of-living index: The most obvious COL factor to include in the model is the COL index developed by DBED. The DBED measure is based on a fixed market basket approach, which involves several steps. First, the share of a consumer's budget spent on certain items must be estimated. DBED uses the BLS Consumer Expenditure Survey for the southern region to establish budget shares.[33] Second, price indices need to be developed for each broad expenditure category. DBED allows prices to vary across Maryland counties for four expenditure categories: housing, food and apparel, utilities, and insurance. The final cost of living index is a weighted average of the budget share multiplied by price index for each expenditure category.

In the DBED measure, housing and food and apparel are by far the more important cost categories allowed to vary across counties.[34] They calculate the housing price index using median house sales prices from the Maryland Association of Realtors, and median gross rent from the 1990 Census of Housing using a weight of 75 percent for owner occupied housing and 25 percent for renter occupied housing.[35] We correlated the index with just the median sales prices for houses in 2000 and got a correlation of 0.95 (Table 3-12).

[33] See Shahrohk (2002) for a description of the method used to develop the DBED COL index.
[34] Housing and food and apparel are given weights of 17 percent and 50 percent. Because 38 percent of the market basket is assumed to have constant prices across counties, housing, food and apparel represent 85 percent of the components in the index that vary.
[35] Median gross rent is inflated to 2000 dollars using the House Price Index as reported by the Office of Federal Housing Enterprise Oversight.

Table 3-12. Comparison of DBED Housing COL Index and Median House Prices

District	DBED Housing COL Rank	DBED Housing COL Index	Medan Sales Price of Houses (2000) (Maryland Asso. of Realtors) Rank	Medan Sales Price of Houses (2000) (Maryland Asso. of Realtors) Value
Montgomery	1	138.5	1	190,000
Howard	2	128.3	2	176,690
Calvert	3	121.6	6	165,000
Charles	4	115.5	8	149,000
Anne Arundel	5	114.6	7	156,850
Carroll	6	112.2	4	169,000
Talbot	7	112.1	3	176,000
Queen Anne's	8	110.3	5	166,900
Prince George's	9	105.7	12	135,000
Harford	10	96.2	11	136,250
Frederick	11	95.6	9	148,000
Cecil	12	91.1	14	127,000
Baltimore Co.	13	90.9	17	119,000
St. Mary's	14	89.5	10	145,804
Worcester	15	87.8	13	129,833
Kent	16	87.0	15	127,000
Wicomico	17	80.2	19	108,750
Garrett	18	79.9	16	125,000
Washington	19	77.1	18	112,850
Somerset	20	75.1	22	85,000
Caroline	21	70.3	20	100,000
Dorchester	22	62.7	21	86,725
Baltimore City	23	57.5	24	65,000
Allegany	24	49.3	23	$65,000
Simple Correlation			0.95	

The largest component of the COL index is food and apparel, which have a combined weight of 33 percent. Because the product prices for food and apparel are assumed to be constant, the only variation in retail costs is in the salaries of retail workers. The index reflects the variation in the average wages in the retail trade sector. The correlation between this index and private wages in general (from the BLS) is 0.77 (Table 3-13).[36] The COL index assumes that transportation costs are constant across counties, but auto insurance costs are allowed to vary and are estimated based on a survey of insurance companies. Utility costs are intended to reflect differences in costs for electricity, heating oil and natural gas. Supposedly, local electricity

[36] Because of changes in industrial classification systems in 2001, it is not possible using readily available data at the county level to get information directly on the retail trade sector.

prices were collected for each county, but it is not clear if similar information was collected for oil and natural gas.

Table 3-13. Comparison of DBED Food and Apparel COL Index and Private Sector Wages

	DBED Food and Apparel COL		Private Weekly Wages (BLS)	
District	Rank	Value	Rank	Value
Prince George's	1	119.5	5	710
Montgomery	2	117.3	1	873
Howard	3	107.9	2	809
St. Mary's	4	107.8	7	648
Anne Arundel	5	103.9	4	716
Baltimore Co.	6	102.4	6	698
Caroline	7	99.7	22	470
Harford	8	97.2	12	555
Cecil	9	96.8	10	592
Baltimore City	10	95.4	3	794
Talbot	11	94.4	14	544
Frederick	12	92.3	8	633
Washington	13	88.8	11	563
Charles	14	88.3	16	536
Carroll	15	85.8	15	540
Worcester	16	85.2	24	388
Calvert	17	85.0	9	614
Queen Anne's	18	85.0	21	472
Wicomico	19	82.5	13	547
Somerset	20	81.7	18	479
Garrett	21	80.3	23	420
Kent	22	72.4	19	473
Dorchester	23	72.1	17	488
Allegany	24	70.6	20	473
Simple Correlation			0.77	

In summary, the COL developed by DBED appears, primarily, to be a weighted average of median housing prices and wages in the retail sector. Our approach is to focus instead on the major source of variation in the COL, which is housing prices.

Housing price measures: Housing prices are often the largest source of variation in the cost-of-living, because they reflect unique conditions of the local area (i.e., the prices are not set in a national market). When developing housing price measures to use in the teacher wage equation it is important to identify the source of variation in average (or median) house prices.

Average housing prices may vary because of higher land prices, construction costs, higher quality housing stock, and larger houses. Ideally, the housing price measure used in the teacher wage model should reflect price differences for equal quantity and quality housing. Unfortunately, neither of the most readily available measures of county-level housing prices—the Census estimate of median house value, and average and median house sales price estimates from the Maryland Association of Realtors—adjusts for the size and condition of the house (Table 3-14). It is possible to make some simple adjustments to these housing prices using housing information in the *2000 Census of Housing*.

Table 3-14. Descriptive Statistics for Economic Variables

Variable	Mean	Average Variation	Minimum	10th Percentile	Median	90th Percentile	Maximum
DBED Cost-of-Living Index (2000)	97.2	7.1	82.9	89.1	97.0	107.7	112.7
Median Home Price (Realtors)	$138,589	$40,279	$62,500	$69,999	$139,500	$183,500	$215,000
Median Home Price (SDAT)	$134,620	$39,474	$65,000	$72,750	$139,447	$173,900	$200,000
Median House Value (2000 Census)	$133,113	$39,938	$69,100	$81,100	$138,950	$169,200	$221,800
Per Capita Income	$30,565	$7,525	$18,641	$20,962	$31,004	$39,675	$50,919
Wealth	$240,974	$86,571	$132,823	$154,119	$209,833	$406,071	$449,227
Unemployment Rate	4.7	2.3	2.3	2.5	4.0	7.9	9.6

Note: Data is for 2001 unless noted otherwise.

Fortunately, there is an alternative data source for housing information in the state of Maryland. The Sales History File produced by the State Department of Assessment of Taxation (SDAT) collects information on property sales during each calendar year. Information is available on the type of unit (house, townhouse, condominium), age of the unit, the size of the unit (and size of lot), number of stories, and various characteristics of the unit collected as part of Maryland's Computer Aided Mass Appraisal (CAMA) system. In consultation with SDAT staff, we limited the sample to only residential property sold in traditional private sales (single-unit, arms-length transaction), and where the CAMA records on the age and condition of the house were complete. The resulting sample of house sales in 2001 was 62, 436.[37]

SDAT also estimates median housing prices in each county (Table 3-14), which match quite closely with Census prices and with those from the Maryland Association of Realtors. There is significant variation in median housing prices at the county level ranging from $200,000 (in 2001) in Montgomery County to $65,000 in Allegany County. Not surprisingly, the variation is even larger when looking at individual home sales (Table 3-15).

Table 3-15. Descriptive Statistics for Housing

Variable	Mean	Average Variation	Minimum	10th Percentile	Median	90th Percentile	Maximum
House Sales Price	$193,035	$109,171	$45,100	$92,900	$162,100	$335,900	$749,224
Age	28	24	0	3	21	59	211
Size of Structure (square feet)	1641	676	0	1020	1428	2540	8506
Height of House:							
1 Story	0.21	0.41	0.00	0.00	0.00	1.00	1.00
Over 2 Stories	0.04	0.19	0.00	0.00	0.00	0.00	1.00
Detached House	0.91	0.29	0.00	1.00	1.00	1.00	1.00
Standard Housing Unit	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Brick or Stone Construction	0.23	0.42	0.00	0.00	0.00	1.00	1.00
Housing Condition:							
Worse Than Average	0.01	0.11	0.00	0.00	0.00	0.00	1.00
Better Than Average	0.01	0.11	0.00	0.00	0.00	0.00	1.00

Note: Data is for 2001.

Table 3-15 presents descriptive statistics for variables in the housing price model. An average house in 2001 was 28 years old with over 1,600 square feet, and two stories (21 percent had 1 story, and 4 percent had more than 2 stories). Most of the residential sales were in traditional detached houses (not townhouses or condominiums) in average condition (very small percent classified in poor quality or very good quality). Approximately 23 percent of houses

[37] The number of qualifying sales in 1998, 1999 and 2000 were 63,946, 72,839, and 58,239, respectively. The age of the house was limited to be between 0 and 250 years old. Any observations with missing CAMA variables for grade, construction, story, and dwelling type were dropped from the analysis. To reduce the influence of outliers, we trimmed the sample by removing observations with sales prices in the bottom 1 percent or top 1 percent.

were of brick or stone construction. For the condition variables (construction and condition), we have included dichotomous variables for the non-typical cases to try to identify the impact on price of houses in particularly good or poor condition.

Other economic variables: Salaries required to attract teachers of a given quality may depend on the availability of acceptable alternatives. During a period where available jobs are relatively scarce, teachers may be willing to accept lower wage jobs than during periods of abundant employment opportunities. While imperfect, the unemployment rate developed by BLS is the most commonly used measure of the tightness of the labor market. The key weakness of this measure is that unemployment rates are affected by both the change in the number of unemployed and the size of the labor force. The labor force may decrease because of demographic changes and "discouraged workers" that stop looking for work.

Due to limitations of both the hedonic wage model, and the housing price model, it may be important to control for the fiscal capacity of the district in these models. By fiscal capacity we are referring to the local governments' available tax bases, which in Maryland include property taxes and income taxes. Accordingly, we have looked at two fiscal capacity measures: per capita personal income produced by the Bureau of Economic Analysis, and a measure of "wealth" which is a composite of personal property, real property, and income.[38]

B. Constructing Comparable Housing Prices

Several modifications need to be made to the housing price before it represents an appropriate cost-of-living measure. First, housing prices need to be adjusted for the differences in housing quality and quantity. We make this adjustment using the SDAT "Sales History File,"

[38] Total wealth in a district is calculated as the sum of 100 percent of the assessed value of the operating real property of public utilities, 40 percent of real property assessable base, 50 percent of personal property assessable base, and net taxable income.

and a housing price regression. Second, to use housing prices as a measure of cost-of-living, it is necessary to assume that all teachers live in the county they work. To account for the possibility of teachers commuting into the county, we develop a regional housing price.

Housing price model: Access in Maryland to the SDAT "Sales History File" permits careful adjustment of housing prices for house size and quality differences on an annual basis. We have included most of the CAMA (Computer Aided Mass Assessment) variables in this dataset, as well as measures of house age and house size.[39] Table 3-16 reports the results for the housing price model for 2001.[40] We estimated the model separately for each year to allow the model to adapt to changing circumstances in the housing market in Maryland.[41]

Since the dependent variable is house sales price, the coefficients in the regression can be expressed in dollars. Almost all of the regression coefficients are statistically significant from zero because of the large sample size. To indicate the relative effects of the assorted variables on housing prices, we also reported the standardized coefficients. The larger the standardized coefficient, the more important an explanatory variable is. The housing price model explains approximately 70 percent of the variation in house sales prices.

---

[39] A list of variables in the sales history file is available from SDAT at the following website: http://www.dat.state.md.us/sdatweb/salemstr.html. Information on the CAMA system is available at: http://www.dat.state.md.us/sdatweb/real/CAMA_index.html.

[40] The housing price model is estimated with a linear function, which fit the data slightly better than a log-linear function; furthermore, interpretation of the coefficients on the continuous variables (age and size) makes more intuitive sense using a linear model. Results for 1998-2000 are report in appendix Tables B-2 to B-4.

[41] We did a Chow test to check for pooling across years, and were able to reject at the 1 percent level the null hypothesis that the coefficients in each year are the same.

Table 3-16. Results of Housing Price Model (2001)

Variable	Coefficient	t-statistic	Standardized Coefficient
Intercept	-$25,707	-14.22	
Age	-$687	-22.60	-0.15167
Age Squared	$5	17.15	0.10406
Size of Structure (Square feet)	$95	198.19	0.58868
Height of House:			
1 Story	$7,717	10.38	0.02881
Over 2 Stories	-$36,549	-26.92	-0.06353
Detached House	$5,003	5.16	0.01337
Standard Housing Unit	$32,784	48.72	0.14959
Brick or Stone Construction	$25,643	37.11	0.09847
Housing Condition:			
Worse Than Average	-$15,670	-6.98	-0.01593
Better Than Average	$168,734	76.30	0.17501
County Variables:			
Allegany	-$57,109	-16.40	-0.03822
Anne Arundel	$61,374	42.42	0.18813
Baltimore	$24,366	17.83	0.07596
Calvert	$35,854	15.52	0.04177
Caroline	-$26,831	-6.29	-0.01450
Carroll	$31,161	16.39	0.04826
Cecil	$9,118	3.83	0.01006
Charles	$8,742	4.54	0.01365
Dorchester	-$24,276	-5.85	-0.01353
Frederick	$32,756	20.00	0.07204
Garrett	-$42,699	-6.97	-0.01572
Harford	$11,562	6.86	0.02318
Howard	$65,598	40.95	0.14662
Kent	$10,538	2.01	0.00453
Montgomery	$108,999	81.13	0.39771
Prince George's	$32,346	22.64	0.09983
Queen Anne's	$41,143	14.70	0.03668
St. Mary's	$4,694	1.99	0.00531
Somerset	-$47,982	-7.32	-0.01640
Talbot	$30,373	9.58	0.02322
Washington	-$23,367	-11.28	-0.03021
Wicomico	-$31,800	-13.54	-0.03621
Worcester	$3,272	1.07	0.00265
Adjusted r-square		0.6987	
Sample size		62436	

Note: Dependent variable is the housing sales price. Estimated with ordinary least squares regression.

To account for the possible nonlinear relationship between house age and housing prices, we included age and age squared in the regression model. As expected, the older a house gets the lower its value, at least up to a certain point (holding all other factors in the model constant). The rate of decline decreases as a house get older and by the age of 72 the value of a house begins to increase again.[42] The upturn in housing prices at this point is probably due to better materials in old houses, and demand for unique historical property.

A square foot increase in house size is associated with a \$95 increase in housing prices.[43] Among house size/quality variables, house age and size are the most important (as indicated by the standardized coefficients). Houses with one story have prices higher by \$7,717 on average, and houses with over two stories have prices lower by \$36,549 (compared to houses with two stories). The latter result is probably due to the fact that most housing units with over two stories are townhouses. Standard detached houses as identified either by the dwelling type code (standard unit), or land use code (residential) have prices from \$5,003 to \$32,784 higher (holding other variables constant) compared to townhouses or condominiums. Houses of brick or stone construction have prices \$25,643 higher than other types of construction. Finally, houses in below average (above average) condition sell for significantly lower (higher) prices.

Constructed housing prices: The reason for estimating the housing price is to determine the impact of being located in a particular county on housing prices, holding housing quantity and quality constant. Baltimore City serves as the benchmark to which the other counties are being compared. In Allegany County, for example, 2001 housing prices were \$57,000 lower than in Baltimore City, holding other housing factors constant (Table 3-16). By contrast, housing prices in Montgomery County were \$109,000 higher than in Baltimore City. The

[42] Interestingly, the age at which the value of the house begins to increase again (minimum price age) dropped from 1998 to 2002 from 100 years old in 1998 to 72 years old in 2001 and 2002.
[43] The value of a square foot of space grew from \$75 in 1998 to \$95 in 2001 and 2002. Most of that growth was between 1999 and 2000.

coefficients on the county variables can be used to construct housing prices for each county, controlling for house quantity and quality (see Chapter 2); these prices are then used in the teacher salary hedonic regression.

To facilitate making comparisons across counties and years, we have developed housing price indices for each district for 1998 to 2002. A simple average of district housing prices for each year is used to center the index (at 1). In addition, Table 3-17 reports the regional constructed housing prices, which are calculated as the average of the adjusted housing price in a district and its neighboring counties in the state of Maryland.[44] As expected, the rural counties of Allegany, Garrett, Somerset, and Wicomico have housing prices well below the state average. Baltimore City has below average housing prices, even after accounting for the smaller and older houses in the City. Wealthy suburbs, such as Montgomery, Howard, and Anne Arundel have housing prices well above the state average. The use of regional housing prices dampens the variation in housing prices, especially for counties in urban areas. For example, the regional housing price for Baltimore City is slightly above average rather than below average. The regional housing price for Montgomery county is 25 to 35 percent above average compared to housing prices in the county itself that are 45 to 70 percent above average.

---

[44] Maryland borders 4 states and Washington DC, and most counties in Maryland border at least one state. Thus, regional housing prices would ideally include housing prices in counties in other states as well as those in Maryland. The SDAT data is only available for house sales in Maryland. To get a sense of how important including other states might be to regional adjusted housing prices, we estimated adjusted Census housing prices for Maryland and all adjacent counties in neighboring states. We used these to compare regional housing prices based only on Maryland counties with regional housing prices using counties in other states as well. On average, regional housing prices are 1 percent lower when housing prices in other states are used. The largest differences were in Allegany, Caroline, and Kent Counties where the difference was slightly over 5 percent. One third of the counties had differences of less than 1 percent. The results are reported in Appendix Table B-5.

Table 3-17. Constructed Housing Prices for Houses of Equal Quality and Quantity (Index Relative to Simple Statewide Average)

	Constructed Housing Price					Regional Constructed Housing Price[1]				
District	**1998**	**1999**	**2000**	**2001**	**2002**	**1998**	**1999**	**2000**	**2001**	**2002**
Lea 1, Allegany	0.66	0.64	0.57	0.57	0.54	0.75	0.73	0.69	0.67	0.65
Lea 2, Anne Arundel	1.27	1.28	1.33	1.32	1.36	1.14	1.14	1.17	1.17	1.20
Lea 3, Baltimore	1.10	1.10	1.10	1.09	1.07	1.09	1.09	1.09	1.09	1.10
Lea 4, Calvert	1.15	1.14	1.18	1.16	1.16	1.12	1.12	1.13	1.11	1.11
Lea 5, Caroline	0.79	0.79	0.75	0.76	0.77	0.94	0.93	0.96	0.96	0.95
Lea 6, Carroll	1.14	1.15	1.16	1.13	1.15	1.16	1.17	1.17	1.17	1.19
Lea 7, Cecil	1.00	1.01	1.01	0.99	0.95	0.99	0.99	0.97	0.99	0.95
Lea 8, Charles	1.03	1.01	1.00	0.99	0.99	1.08	1.08	1.09	1.06	1.06
Lea 9, Dorchester	0.80	0.83	0.79	0.78	0.75	0.86	0.86	0.85	0.85	0.83
Lea 10, Frederick	1.13	1.13	1.13	1.14	1.16	1.17	1.18	1.19	1.20	1.24
Lea 11, Garrett	0.73	0.71	0.68	0.66	0.63	0.69	0.67	0.62	0.62	0.58
Lea 12, Harford	1.04	1.04	1.04	1.01	0.99	1.04	1.05	1.05	1.02	1.00
Lea 13, Howard	1.31	1.32	1.31	1.34	1.40	1.18	1.19	1.21	1.22	1.25
Lea 14, Kent	0.94	0.93	0.87	1.00	0.92	1.02	1.01	1.03	1.05	1.02
Lea 15, Montgomery	1.44	1.49	1.56	1.62	1.72	1.25	1.27	1.28	1.30	1.35
Lea 16, Prince George's	1.15	1.15	1.15	1.14	1.14	1.22	1.23	1.25	1.25	1.29
Lea 17, Queen Anne's	1.13	1.10	1.22	1.19	1.22	1.03	1.02	1.05	1.07	1.07
Lea 18, St. Mary's	1.03	1.02	1.03	0.96	0.95	1.06	1.05	1.06	1.03	1.03
Lea 19, Somerset	0.66	0.65	0.63	0.63	0.58	0.78	0.79	0.77	0.77	0.77
Lea 20, Talbot	1.07	1.03	1.10	1.12	1.09	0.94	0.93	0.96	0.96	0.95
Lea 21, Washington	0.87	0.86	0.82	0.79	0.79	0.88	0.87	0.84	0.83	0.83
Lea 22, Wicomico	0.78	0.80	0.76	0.73	0.71	0.78	0.80	0.77	0.77	0.76
Lea 23, Worcester	0.91	0.94	0.92	0.95	1.02	0.78	0.79	0.77	0.77	0.77
Lea 24, Baltimore City	0.88	0.86	0.88	0.93	0.93	1.04	1.04	1.04	1.08	1.06

[1]Average of constructed housing price in district and its instate neighbors.

C. *Reliability Evaluation*

For several of these variables, we were able to look at their stability across time (Table 3-18). Unemployment rates are fairly unstable, with average variation of 10 to 12 percent and variation exceeding 10 percent, 46 percent of the time. Median housing prices are fairly stable, even with the rapid growth in housing prices in Maryland over the last five years, with average variation of 5 percent or less. For the SDAT data, median housing price variation exceeded 10 percent less than 10 percent of the time. The median housing prices from the Maryland Association of Realtors are less stable. Finally, the fiscal capacity variables—income and wealth—are quite stable.

Table 3-18. Stability Analysis for Economic Variables

District	Average Absolute Change as % of Annual State Average	Average Variation Around Trend Line As Percent of Overall State Average[1]	Percent of Years With Changes Above 30% Relative to State Average	Percent of Years With Changes Above 20% Relative to State Average	Percent of Years With Changes Above 10% Relative to State Average
Maryland Realtors:					
Average House Price[2] (1995-2002)	15.8	4.9	2.7	9.5	28.0
Median House Price[2] (1995-2002)	5.3	4.2	2.9	5.3	18.5
SDAT:					
Median House Price (1994-2002)	4.7	3.7	0.0	1.0	8.9
Fiscal Capacity Measures:					
Per Capita Income (1993-2001)	4.3	1.9	0.0	0.0	2.1
Wealth (1992-2002)	3.3	2.4	0.0	0.4	3.3
Unemployment Rate (1993-2002)	12.4	10.5	8.3	18.5	46.3

[1]Calculated by fittlng a trend line through the data from 1992 to 2002, and taking the ratio of the standard error of estimate from trend line (average variation around the trend line) divided by the unweighted state average for all these years.
[2]Data is not available for all districts for all years. Only years where data was available was used to develop estimates.

To look at the stability of the adjusted housing price indices, we calculated correlations across years for both adjusted prices and regional prices. As indicated in Table 3-19 (shaded areas) the adjusted housing price measures are quite stable with correlations well above 0.90.

Table 3-19. Stability Analysis for Housing Price Indices (Correlations)

	Constructed Housing Price					Regional Constructed Housing Price			
	1998	**1999**	**2000**	**2001**	**2002**	**1998**	**1999**	**2000**	**2001**
Adjusted Housing Prices:									
1999	0.996								
2000	0.993	0.991							
2001	0.983	0.982	0.987						
2002	0.977	0.979	0.984	0.994					
Adjusted Regional Housing Prices:									
1998	0.890	0.881	0.863	0.857	0.836				
1999	0.892	0.886	0.867	0.862	0.843	0.998			
2000	0.893	0.885	0.870	0.868	0.847	0.997	0.997		
2001	0.888	0.882	0.869	0.876	0.855	0.990	0.992	0.995	
2002	0.895	0.891	0.877	0.882	0.867	0.987	0.991	0.993	0.996

Note: Shaded correlations are those for the same index across different years.

Constructed prices for each district and regional constructed prices are also strongly correlated, with correlations between 0.85 and 0.90. The stability of the housing measures across time suggest that multi-year averages may not be necessary for constructed housing prices to maintain the stability of the GCEI.

D. Validity Evaluation

The key validity issue in this section is whether the DBED COL index should be used as is, or whether modifications should be made to this measure. In our view, the housing component of this COL index is inadequate, because it does not account for differences in housing quantity and quality across districts. Using the SDAT Sales History File, we have constructed a quality and quantity adjusted housing price measure, which should be a better measure of housing prices. The use of variation in private wages to proxy "food and apparel" cost differences is an indirect measure at best. Use of private wage data is an alternative to the hedonic approach, and we compare the results of these two approaches later in the report.

Table 3-20 presents the correlation among the different measures presented in this section. As expected, correlations between the different housing price measures are quite high. Median house value as determined by the Census has a correlation of 0.93 with median house sales prices collected by the Maryland Association of Realtors, and a correlation of 0.98 with the SDAT median housing price. Given that the Census housing price is not based on a sample, this gives us confidence that the sample of houses selling in Maryland in 2001 is representative of the underlying population. Per capita income is highly correlated with housing prices, while somewhat surprisingly the wealth measure (which includes real property values) has a lower correlation. Finally, the unemployment rate is highly correlated with several of the housing variables and wealth. The high inter-correlations suggest using caution in deciding which variables are introduced into the model.

Table 3-20. Correlations Among Economic Variables

Variable	DBED Cost-of-Living Index	Median Home Price (Realtors)	Median Home Price (SDAT)	Median House Value (Census)	Per Capita Income	Wealth
Median Home Price (Realtors)	**0.60**					
Median Home Price (SDAT)	**0.64**	**0.93**				
Median House Value (Census)	**0.70**	**0.93**	**0.98**			
Per Capita Income	**0.72**	**0.80**	**0.83**	**0.88**		
Wealth	**0.51**	**0.64**	**0.52**	**0.57**	**0.68**	
Unemployment Rate	**-0.48**	**-0.72**	**-0.83**	**-0.67**	-0.17	**-0.79**

Note: Shaded cells have a correlation above 0.7. Cells in bold have correlations that are statistically significant from zero at 5 percent level. Data is for 2001 unless noted otherwise.

6. Measures of Other Cost and Amenity Factors

A range of factors related to amenities associated with living in a particular county has also been evaluated for use in the teacher wage model. These variables are meant to capture other dimensions of a geographic area that may make it more or less attractive to a teacher. In this section we briefly describe these measures, and provide some assessment of their strengths and weaknesses.

A. Measures

Crime rates: Crime rates could influence teacher decisions in several ways. First, a teacher may use them as a proxy for safety in the public schools. Second, if the teacher prefers to live in the county where s/he works, crime rates could be used to judge the general level of safety in a community. The principal source of crime rate data is the Uniform Crime Reporting (UCR) System, administered by the FBI and state agencies such as the Maryland State Police. The most commonly reported crime rate is for seven “index” crimes per population of 100,000 (violent crimes, such as murder and non negligent manslaughter, rape, robbery, and aggravated assault, and the property crimes of burglary, larceny-theft, and motor vehicle theft). We have collected information on the total index crime rate, and violent crime rate for a number of years.

Weather: Weather may influence location decisions for teachers who have strong preferences for a certain type of climate. Common weather variables include measures of summer or winter temperatures (average, minimums or maximums), levels of precipitation and snowfall, and the number of hot and cold days. We have collected from NOAA and the Maryland Climatologist Office annual information from 1994 to 2002 for precipitation, heating degree days (cold days), and cooling degree days (hot days).[45] In selecting the time period for climate measures, a balance must be struck between the short-run and long-run. It is unlikely that people's location choice is based heavily on last year's weather; however, a long-run average is also likely to be inappropriate. We try averages of several different lengths in estimating the hedonic wage model.

Traffic congestion during commuting: Employment and residential decisions may be influenced by the potential time it takes to commute to work. We try several different measures of travel time to work from the *2000 Census of Population*. In addition, we have collected a measure of the traffic volume on roads in a county from the Maryland Department of Transportation. Specifically, we divide the traffic volume (vehicles miles) by the number of road miles (lane miles) to get a measure of the relative traffic volume in a county. Finally, it is possible that commuting distance to a major airport might influence location decisions of some personnel. DBED has developed an estimate of the distance to a major airport by measuring the distance between the county seat and the nearest primary hub airport.

---

[45] A heating (cooling) degree day is calculated as the number of degrees that the daily mean temperature is below (above) 65 degrees Fahrenheit. For instance, if the average temperature on a particular day is 25 degrees, then this will be recorded as 40 heating degree days.

***Other Amenities*:** Ready availability of a major recreational amenity, such as an ocean beach, could influence location choices of some teachers. We have tried the number of shoreline miles developed by DBED as another amenity variable. Urban areas have some characteristics that are potentially attractive to teachers, and other characteristics that may be viewed negatively. Urban areas are more apt to have cultural and entertainment amenities. However, urban school districts and schools are often large in size, which may be unattractive to some teachers. We consider several variables related to urbanization and the size of the student body.

Education: Several education-related variables could influence teacher location decisions. Close proximity to a 4-year college could be particularly attractive to a teacher, because of certification and continuing education requirements. In addition, teachers may prefer to teach in schools with more highly educated parents, because these parents may provide more educational opportunities and have higher expectations for their children.

B. Reliability Analysis

Most of the cost and amenity variables come from established data sources, therefore measurement errors will be difficult to detect. Table 3-21 provides descriptive statistics for several of the factors available in the database. Most variables fall within reasonable ranges and outliers tend to fit expectations. For example, Baltimore City is the main outlier for crime rates, population and enrollment. The longest travel times to a major airport are counties in the western and southeastern parts of the state. Miles of shoreline are the greatest in Somerset, Dorchester and Talbot Counties. The actual mileage numbers seem large, but probably reflect the irregular shape of the shoreline. The highest temperatures tend to be in the most urbanized counties, and the lowest temperatures are in counties in the north and west (see Table 3-24 for heating and cooling degree days).

Table 3-21. Descriptive Statistics for Amenity

Variable	Mean	Average Variation	Minimum	10th Percentile	Median	90th Percentile	Maximum
Total Crime Rate	3,679.4	1,831.0	1,856.2	2,215.6	3,157.4	5,839.8	10,257.3
Violent Crime Rate	558.4	466.2	154.1	214.5	443.1	912.1	2,462.6
Miles of Shoreline (2002)	184.3	186.9	0.0	0.0	141.5	442.0	619.0
Precipitation	42.5	4.0	31.8	37.0	42.7	46.2	48.8
Vehicle Miles per Lane Mile	590,630	308,619	237,139	257,040	503,547	1,083,557	1,253,420
Average Travel Time to Work (2000)	29.1	5.2	20.9	22.6	29.1	35.9	39.8
Distance to Nearest Major (Hub) Airport	61.1	40.2	9.8	17.8	61.1	126.7	139.8
Population Density	769.7	1,634.8	46.1	68.7	254.2	1,651.1	8,058.4
Enrollment	35,470	41,821	2,795	4,521	16,038	106,898	134,180
Number of 4-Year Colleges (2003)	1.6	3.0	0.0	0.0	1.0	4.0	14.0
% College Graduates (2000)	24.0	11.0	11.7	12.1	22.2	30.6	54.6

Note: Data is for 2001 unless otherwise noted.

We have multiple years of data for only a few of these variables (Table 3-22). Total crime rates are fairly stable across time (6 percent), while violent crime rates are significantly less stable (10 percent). For total crime rates, 20 percent of the time the variation exceeds 10 percent, while this is close to 40 percent for violent crime. If violent crime is determined to be the better of the two measures to use in the hedonic wage model, it may make sense to use a multi-year average for this variable. The weather variables (annual data) are fairly unstable, with average variation of between 10 percent and 20 percent, and the variation exceeding 10 percent well over half the time. This suggests that multi-year averages for weather are not only a good idea conceptually, but will improve the stability of the GCEI if they are included in the final model. Finally, the traffic volume measure—vehicles per lane mile—is very stable across the five years for which we have data.

Table 3-22. Stability Analysis for Amenity Variables

District	Average Absolute Change as % of Annual State Average	Average Variation Around Trend Line As Percent of Overall State Average[1]	Percent of Years With Changes Above 30% Relative to State Average	Percent of Years With Changes Above 20% Relative to State Average	Percent of Years With Changes Above 10% Relative to State Average
Crime Rates (1991-2001)					
Total Crime Rate	6.3	6.6	1.3	5.0	20.0
Violent Crime Rate	10.6	10.4	5.4	15.8	38.3
Weather Measures (1994-2002)					
Precipitation	20.4	15.7	19.4	39.4	69.6
Heating Degree Days	11.7	9.2	2.6	8.9	58.3
Cooling Degree Days	15.4	14.6	6.3	29.0	64.1
Vehicles Per Mile (1998-2002)	2.8	1.7	0.0	0.0	1.0

[1]Calculated by fitting a trend line through the data from 1992 to 2002, and taking the ratio of the standard error of estimate from trend line (average variation around the trend line) divided by the unweighted state average for all these years.
[2]Data is not available for all districts for all years. Only years where data was available was used to develop estimates.

C. *Validity Evaluation*

In general, the set of variables listed in Table 3-21 appear to be reasonable proxies for the underlying factors of safety, weather, distance, urbanization, and education. The crime rate is probably the weakest measure because of the significant underreporting of crime, particularly for certain crimes and demographic groups. While the U.S. Bureau of Justice Statistics conducts a National Crime Victimization Survey, the results of this survey are not available at the local level. However, crime rates from the UCR system are likely to be the only measures of public safety readily available to the public.

Looking at the correlations between the cost and amenity factors, only a few correlations are high (Table 3-23). Population density is strongly correlated with the number of 4-year colleges in a county and the crime rate, which is driven heavily by the city of Baltimore. Once Baltimore is removed, the correlation between crime rates, population density and the number of 4-year colleges drops significantly. Baltimore is clearly an extreme outlier when it comes to 4-year colleges, which suggests this variable may pick up other effects related to Baltimore besides the existence of a number of higher education institutions. Very few of the other correlations in Table 3-21 are even moderate in size, and most are not statistically significant from zero.

Table 3-23. Correlations Among Amenity Factors

Variable	Total Crime Rate	Violent Crime Rate	Miles of Shoreline	Precipitation	Vehicle Miles	Average Travel Time To Work	Distance To Nearest Major Airport	Population Density	Enrollment	Number of 4-Year Colleges
Violent Crime Rate	**0.94**									
Miles of Shoreline (2002)	0.00	-0.03								
Precipitation	-0.02	0.02	**0.51**							
Vehicle Miles per Lane Mile	0.34	0.20	-0.30	-0.18						
Average Travel Time to Work (2000)	-0.02	0.05	-0.29	-0.01	0.38					
Distance to Nearest Major (Hub) Airport	-0.25	-0.25	0.20	-0.12	**-0.73**	**-0.64**				
Population Density	**0.81**	**0.86**	-0.22	-0.18	0.41	0.19	**-0.45**			
Enrollment	**0.55**	**0.45**	-0.31	-0.08	0.86	0.36	**-0.65**	**0.63**		
Number of 4-Year Colleges (2003)	**0.81**	**0.85**	-0.23	-0.10	0.47	0.16	-0.44	**0.96**	**0.73**	
% College Graduates (2000)	-0.03	-0.20	-0.26	-0.06	**0.70**	0.28	**-0.58**	0.14	**0.55**	0.16

Note: Shaded cells have a correlation above 0.7. Cells in bold have correlations that are statistically significant from zero at 5 percent level.

7. Measures Used in Constructing the Energy Cost Index

As discussed in Chapter 2, the only non-wage object of expenditure for which we calculate a separate index is energy costs. Other contracted services used by the district are assigned to the PCI for the particular functional area they are associated with (instruction, administration, operating and maintenance), and local prices for supplies and materials are assumed not to vary. The energy cost model is meant to capture those discretionary and cost factors affecting the energy expenditures per student in the district. Among the discretionary factors is the type of energy source used by the district, the age (and condition) of buildings, the relative size of buildings, and whether to have central air conditioning in the school. Cost factors include the size of the district (which potentially affects the energy prices the district pays) and the existence of cold or hot weather.

A. *Reliability Analysis*

Table 3-24 presents descriptive statistics for the major variables used in the energy cost model. These measures appear reasonable, suggesting that major measurement errors in the data are not likely. Energy expenditures average only $150 per pupil, and have an average variation of $27 dollars. Heating and cooling degree days also vary significantly across counties. Most districts rely heavily on natural gas and electric, but there are some districts which use heating oil and coal. Adjusted building age is calculated as the weighted average of the share of the building space (square feet) built or renovated in a particular year. For example, if a school was built in 1960, and half the school was renovated in 1990, then the school would have an adjusted age of 25 years in 2000 (40 years x 50 percent + 10 years x 50 percent). The typical building is 20 years old, and age varies by 5 years across districts on average. Finally, districts have a fair amount of variation in the physical capacity per student that needs to be heated or cooled. Except for the weather variables, we only have data on these variables for four years. In lieu of assessing stability of the underlying data, we will examine stability of the energy cost index later in the report.

Table 3-24. Descriptive Statistics for Energy Model

Variable	Mean	Average Variation	Minimum	10th Percentile	Median	90th Percentile	Maximum
Energy Expenditures per Pupil	$149.8	$27.8	$105.3	$117.6	$146.9	$190.8	$238.8
Heating Degree Days	4391.4	677.9	2781.5	3630.0	4345.8	5302.0	6489.0
Cooling Degree Days	1234.4	352.5	352.5	869.4	1203.9	1663.5	2493.3
Percent of Energy Expenditures in Natural Gas and Electric	86.7%	8.0%	67.2%	75.5%	88.7%	96.7%	99.7%
Adjusted Building Age	23.3	4.7	15.0	18.2	22.1	30.5	36.0
Building Capacity per Pupil	155.2	21.3	121.7	134.1	149.6	187.1	218.1

Note: Data is for 2001 unless otherwise noted.

B. Validity Evaluation

Most past estimates of GCEI we are aware of have not attempted to estimate energy cost models. Thus, we cannot use past research as a guide to what to include in this model. Instead, we have discussed the factors affecting energy costs with school business officials in the state of Maryland, and several officials at utilities. It is clear from these discussions that the determinants of the price of energy in a district are complex, particularly in an environment of energy choice. The official pricing schedules for utilities that have traditionally served school districts are complex enough. With energy choice it is now possible for energy providers to market energy from non-Maryland sources, and to negotiate with districts on a school-by-school basis. Given this complexity, it is not surprising that energy costs per pupil are only weakly related to the variables we include in the model (Table 3-25). Very few of these variables are even moderately related to each other. This suggests that the results of the energy analysis should be used cautiously, and the issue of whether to include an energy cost index in the GCEI should be explored in a couple of years, when energy choice becomes more widespread.

Table 3-25. Correlations Energy Model

Variable	Energy Expenditures Per Capita	Heating Degree Days	Cooling Degree Days	Percent Gas & Electric	Adjusted Building Age	Building Capacity	Wealth
Heating Degree Days	-0.07						
Cooling Degree Days	-0.08	**-0.76**					
Percent of Energy Expenditures in Natural Gas and Electric	**-0.30**	0.16	-0.17				
Adjusted Building Age	-0.08	-0.08	0.18	-0.09			
Building Capacity per Pupil	**0.38**	**0.23**	**-0.27**	-0.10	**0.42**		
Wealth	0.12	-0.08	0.06	**0.38**	**-0.27**	-0.33	
Enrollment	**-0.30**	0.05	0.09	**0.32**	**0.43**	-0.09	0.14

Note: Shaded cells have a correlation above 0.7. Cells in bold have correlations that are statistically significant from zero at 5 percent level.

8. Conclusions

The objective of this chapter is to present the variables considered for use in the hedonic salary models and energy cost models (and housing price model). For each variable, we have examined its validity both in terms of how closely it relates to the underlying factor we want to measure and how closely it correlates with similar (or dissimilar) variables. Reliability was examined for each variable both in terms of measurement error and stability of the measure across time. In general, most variables seem to be both reliable and valid. Therefore, we select variables for the final hedonic models that can be updated on a regular basis.

Among the key variables in the hedonic wage models is a measure of cost-of-living. We are recommending the use of a constructed housing price for the cost-of-living measure. Using data on individual house sales in Maryland, we can develop a measure of housing price differences across counties that controls for house size, age, and condition. To allow for the possibility that teachers (and other staff) may commute across county borders, we have also calculated a regional housing price that is the average of the constructed housing price in the county and its neighbors (in Maryland).

The limited number of school districts in Maryland limits the number of variables we can include in the model. Moreover, a number of the student need and amenity variables are highly related to each other. Thus, it will be important to carefully select the small set of "cost" variables to include in the final model. The analysis presented in this chapter serves as the basis for variable selection. Among student need variables, the share of students participating in subsidized lunch is highly related with Census child poverty rates, can be updated every year, and is also stable across time. For cost of living, the constructed housing price or the regional constructed housing price capture the most important factor affecting cost-of-living differences, control for housing quantity/quality differences across counties, and are relatively stable across time. Among amenity variables, measures of crime rate and commuting time (or traffic volume) are potentially important factors affecting staff salaries, and vary significantly across counties.

Chapter 4

Results of Hedonic Wage Models, and Estimates of Components of GCEI

The objectives of this chapter are fivefold. First, we review some of the methodological issues that arise in attempting to accurately capture the factors that make school districts in Maryland relatively attractive or unattractive places to work. Second, we describe in detail the process used to choose the variables to include in the hedonic models, and the impact of different variable choices on the resulting cost indices. The index values for the different components of a teacher cost index (TCI) are calculated, and their stability across time is examined. In addition, we test whether it is possible to combine teachers and other professional staff into a professional salary index (PPCI), or whether it is more appropriate to separately calculate a non-teaching professional cost index (NTPCI). Third, we estimate a non-professional personnel cost index (NPCI). Fourth, we estimate an energy cost model, and calculate the energy cost index (ECI). Finally, using budget shares developed by MSDE, we combine personnel cost indices with an energy cost index to create a GCEI.

1. Hedonic Salary Model Methodology and Calculation of Cost Indices

Here we describe the estimation of the teacher cost index (TCI), however, the process used in the estimation of the various cost indices is qualitatively similar. As reviewed in Chapter 3, there are a number of variables that can be used in a hedonic wage model, however the fact that there are only twenty-four school districts in the state severely limits the number of variables that we can include in this model. This is because a smaller sample provides less information about how cost factors are related to teacher salaries, and some of the district factors experience relatively little variation. Consequently, it will likely be more difficult to estimate the relationship between district variables and teacher salaries with precision, and coefficient estimates on district variables can be quite sensitive to model specification. Furthermore, the fact that our data are hierarchical – e.g. teachers are employed within school districts – implies that it is appropriate to account for "clustering" (similarly, it is important to account for the fact that some teachers appear in our dataset more than once). We discuss the correction for clustering in more detail below in subsection 4.2.H.

We have salary information for each teacher, and based on this we are attempting to accurately estimate the impacts the various discretionary (those factors that are within a district's control) and cost (those factors that are outside of a district's control) factors have on teachers' salaries. In estimating this model we use a log-linear model specification, meaning that we are estimating the natural logarithm of teachers' salaries as a function of discretionary and cost factors. The use of this log-linear specification is consistent with much of the literature on human capital (Mincer, 1974; Heckman et al, 1996). The logarithmic specification of the dependent variable means that the coefficients estimated from our models should be interpreted as describing the percentage change in salaries resulting from a one-unit change in an independent variable, holding all other variables in our model constant.

We employ a consistent set of discretionary teacher variables, which are similar to the set of personnel variables used in past research on the determinants of teacher salaries (Chambers, 1997; Goldhaber, 1999). The personnel variables we include are teacher race, gender, and ethnicity, licensure status, teaching experience, degree level, certification status, and licensure test performance. Teachers' salaries are typically defined by experience and degree level, while licensure status and test performance serve as proxies for teacher quality.

The models we estimate are pooled across time meaning that we treat each teacher observation in each year as an independent observation. To account for changes in salaries that occur over time, due either to cost of living adjustments or changes in the structure of districts' salary schedules, we include year dummy variables. This specification of the model assumes that the coefficients of all the variables in the model are consistent across years. We later relax this assumption, as we describe in subsection 4.2.G below, and test whether the coefficients are different (from a statistical perspective) across years. This provides a sense of the need to re-calibrate the model.

One decision we must make before estimating models is how to align the different time periods represented by our data. Our personnel data are based on the school year, which runs from September to June, while the district-level variables represent several time periods. Some district variables are based on changes or averages over a calendar year (e.g., housing prices, crime rates, weather variables, per capita income). Other district (or school) variables are collected at a given point in time during the year, ranging from early fall (enrollment—September 30) to the end of the school year (e.g., student need variables). Methodologically it is important that the explanatory variables in the model are either based on the same time period or precede the dependent variable. To ensure this, we link teacher observations with district information from the immediate prior year, believing that this information is likely to be most relevant to teachers that are making employment decisions. For example, teacher information from the year 2000 was linked with district-level variables from 1999.

Initially we start by estimating simple Ordinary Least Squares (OLS) regressions. OLS does not account for clustering (the issue of teachers being grouped in schools and districts that are described in Chapter 2), however, the procedure that does account for clustering is somewhat computer intensive. We begin with OLS models, because they provide a way to pare down the number of variables in our models and determine the maximum number that we are likely to be able to include in a final specification that does account for clustering.

We then go through a step-by-step process where we hold constant the personnel discretionary variables in the model and two of the three sets of cost factor variables, while experimenting with the third set of cost variables to determine which are the most appropriate variables for capturing the concept of the category. As an example, we hold the discretionary personnel variables, cost of living variables, and quality of life variables constant and experiment with using different working conditions variables (e.g., free and reduced price lunch or child poverty defined by the Census) to see how the use of a particular variable (or set of variables) affects the stability of the resulting index. We estimate models that include single variables to capture the concepts of working conditions, quality of life, and cost of living (e.g. using census poverty figures to capture working conditions), as well as models that include multiple variables, and models that include interactions between various variables. For example, one might imagine that poverty in rural areas is viewed differently by teachers (or other school personnel) than poverty in more densely populated urban areas. To account for the potential of this type of interaction (i.e. the interaction between poverty and urbanicity), we might estimate a model that includes poverty, population density, and an "interaction" variable between the two.

In evaluating the impact of the cost variables on teachers' salaries, it important to focus on both the sign and magnitude of each of the coefficients, and also on the statistical significance of the coefficients. The reason is that the TCI (as well as any of the other cost indices that we discuss) is calculated based on the coefficients for the cost variables only. We do not want to use coefficients to construct the TCI unless we can conclude with a high degree of confidence (the 95 percent confidence level is the traditional level used by statisticians) that these coefficients are in fact different from zero, implying they have a real impact on salaries.

2. Choice of Hedonic Models

As we described in the previous chapter, there are a number of different cost variables that we might employ to capture differences in the attractiveness of jobs resulting from variation in working conditions, quality of life, and cost of living factors. In fact, holding constant the discretionary variables, there are over 20,000 different combinations of cost variables that we could potentially choose from. Thus, as described above, we start with a basic set of cost variables and observe how the calculated TCIs are affected by changes in this basic set.

We focus on the cost variables because there is little choice over which discretionary variables to include in the models, and because these variables are held constant when calculating the TCI for each district. Furthermore, the sign, magnitude and statistical significance of the personnel coefficients remain remarkably consistent, regardless of the model specification we employ. Thus, for all of the models described in this subsection we include a constant set of personnel and year variables including: teacher race, gender, and ethnicity, licensure status, teacher experience, degree level, certification status, and licensure test performance. We also consistently include controls for the percentage of property that is commercial and the per capita income of each district, and for each school year.[46]

In the next set of subsections, we describe some of the model specifications that we used to determine which set of variables to include in the final TCI. These specifications represent a small subset of the total number of model specifications that we actually examined, and are included to illustrate why we chose particular variables for the final teacher salary model specification. We start with the same basic set of cost factors, and vary one-by-one different cost factors to observe the impact they have on the model.

[46] In subsection 4.2.H, we present another method, district "fixed effects," in order to control for potentially important variables omitted from the model.

A. Choice of Working Conditions Variables

We begin our experimentation with various sets of cost variables by holding constant the cost of living and quality of life variables and allowing the working conditions variables to vary. As we describe in Chapter 3, the various working conditions variables are highly correlated to one another, which, as stressed above, suggests that we are limited in our choices. We experiment primarily with various measures of student needs including measures of child/student poverty (e.g. free-reduced price lunch status, census poverty, etc.), special education and limited English proficient (LEP) status, and interactions between these and other cost factor variables.

Table 4-1 describes some of the various model specifications that we utilize in trying to determine the most appropriate set of cost variables to capture the differences in working conditions between districts. (Working condition variables are indicated in italics.)

Table 4-1. Model Specifications, Experimenting with Working Conditions Variables

Specification 1	Personnel, Fiscal Capacity, & Year variables + *Percent of Students Eligible for Free/Reduced Lunch in Each School*, Rate of Violent Crime, Average Commute Time, Constructed Average House Value
Specification 2	Personnel, Fiscal Capacity, & Year variables + *Percent of Students Eligible for Free/Reduced Lunch in Each District,* Rate of Violent Crime, Average Commute Time, Constructed Average House Value
Specification 3	Personnel, Fiscal Capacity, & Year variables + *Percent of Students Eligible for Free/Reduced Lunch in Each School and an interaction of this variable with Population Density,* Rate of Violent Crime, Average Commute Time, Constructed Average House Value
Specification 4	Personnel, Fiscal Capacity, & Year variables + *Percent of LEP Students,* Rate of Violent Crime, Average Commute Time, Constructed Average House Value
Specification 5	Personnel, Fiscal Capacity, & Year variables + *Percent of School Aged (ages 5-17) Children Living in Poverty in Each District,* Rate of Violent Crime, Average Commute Time, Constructed Average House Value
Specification 6	Personnel, Fiscal Capacity, & Year variables + *Percent of Students Receiving Title 1 Assistance in Each School,* Rate of Violent Crime, Average Commute Time, Constructed Average House Value

Specification 7	Personnel, Fiscal Capacity, & Year variables + *Student Mobility (Annual Percent of New Entrants in Each School),* Rate of Violent Crime, Average Commute Time, Constructed Average House Value
Specification 8	Personnel, Fiscal Capacity, & Year variables + *Percent of Students Enrolled in Special Education in Each School,* Rate of Violent Crime, Average Commute Time, Constructed Average House Value

As we show in Table 4-2, the TCIs corresponding with the various model specifications listed in Table 4-1 are very highly correlated to one another, with correlations between specifications of well over 0.9. This suggests that we face few trade-offs here in terms of validity; in other words, the variables in the model appear to be capturing the same underlying concepts regardless of which set we choose.

Table 4-2. Correlations of TCI Across Different Working Conditions Specifications

	Spec. 1	Spec. 2	Spec. 3	Spec. 4	Spec. 5	Spec. 6	Spec. 7	Spec. 8
Spec. 1	1							
Spec. 2	0.9876	1						
Spec. 3	0.9913	0.9884	1					
Spec. 4	0.9979	0.9882	0.9850	1				
Spec. 5	0.9962	0.9891	0.9817	0.9995	1			
Spec. 6	0.9973	0.9898	0.9840	0.9996	0.9998	1		
Spec. 7	0.9961	0.9893	0.9818	0.9995	1.0000	0.9998	1	
Spec. 8	0.9962	0.9894	0.9822	0.9995	1.0000	0.9998	1.0000	1

In Table 4-3 we report the stability of each model specification as measured by the average coefficient of variation of the TCI over time (1999 to 2002). The coefficient of variation is a measure of the average variation over time in a factor as a percent of its average (thus it is computed as the ratio of the standard deviation to the mean), and it is reported as a percentage (i.e. it is multiplied by 100). For instance, a coefficient of variation of 1 indicates that this variable fluctuates over time on average by 1 percent relative to its average. This is a useful measure of dispersion because it allows for comparisons of relative variation across districts when they have different average values. The coefficient of variation for each specification is similar and very small implying that the TCI are stable regardless of the variables chosen to capture working conditions.[47]

Table 4-3. Stability Over Time of TCI Based on Various Working Conditions Specifications

Specification	Average Coefficient of Variation Across Time
Specification 1	0.15%
Specification 2	0.10%
Specification 3	0.09%
Specification 4	0.12%
Specification 5	0.12%
Specification 6	0.13%
Specification 7	0.12%
Specification 8	0.12%

Two other findings are notable. First, coefficients on the variables identifying the percentage of students in a district who are in special education, the percentage of students that are LEP, and student mobility are insignificant in many specifications. For the reasons discussed above we do not wish to use variables that are not statistically significant, so we do not recommend the use of these three variables in the TCI model. Second, the coefficients on working conditions variables (when specified at the school-level) and the various interaction terms we used in the model are all quite sensitive to model specification.[48] For this reason we would not recommend using these variables at the levels specified. This leaves a choice of measuring the concept of working conditions using one of the district level measures, for instance, the percentage of children aged 5-18 who are in poverty, as defined by the census or the percentage of students at the *district level* who are on free or reduced price lunch. The district

[47] By means of comparison, the coefficient of variation on the 2002 SAT test (based on college bound seniors who took the test) is about 20 percent (College Board, 2002).
[48] The sensitivity of the interaction terms to model specification is likely due to a high correlation between these and other cost variables in the model. The sensitivity of free or reduced price lunch when specified at the school level may result from sorting of teachers across schools within districts that results in a high correlation between teacher characteristics and this variable.

free or reduce priced lunch variable is more consistent in sign and magnitude than the other measures. Based on that, and the fact that it can be annually updated, ***we recommend, in the OLS specification of the model, using the percentage of students in each district eligible for free or reduced price lunch as the measure of working conditions in the final TCI model specification.***

B. *Choice of Quality of Life Variables*

To determine the quality of life variable(s) to use in the final TCI model specification, we experiment with various quality of life variables while holding constant the working conditions and cost of living variables. Some of the quality of life variables are highly correlated with one another, but this is less so than with the working conditions variables since these variables measure very different dimensions of quality of life (e.g. crime and weather).

Table 4-4 describes some of the various model specifications that we utilize in trying to determine the most appropriate set of cost variables to capture the differences between districts in quality of life. (Quality of life variables indicated in italics.)

Table 4-4. Model Specifications, Experimenting with Quality of Life Variables

Specification 1	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/Reduced Lunch in Each School, *Rate of Violent Crime, Average Commute Time, Miles of Shoreline*, Constructed Average House Value
Specification 2	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/Reduced Lunch in Each School, *Rate of Violent Crime, Miles of Shoreline*, *Distance to the Nearest Airport, Number of 2-year Colleges,* Constructed Average House Value
Specification 3	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/Reduced Lunch in Each School, *Rate of Total Crime, Average Commute Time, Miles of Shoreline,* Constructed Average House Value
Specification 4	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/Reduced Lunch in Each School, *Miles of Shoreline*, *Population Density,* Constructed Average House Value

Specification 5	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/Reduced Lunch in Each School, *Rate of Violent Crime, Miles of Shoreline*, *Traffic Volume (Vehicles per Lane Mile)*, Constructed Average House Value
Specification 6	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/Reduced Lunch in Each School, *Rate of Violent Crime, Traffic Volume (Vehicles per Lane Mile), Average Number of Heating Degree Days,* Constructed Average House Value
Specification 7	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/Reduced Lunch in Each School, *Rate of Violent Crime, Traffic Volume (Vehicles per Lane Mile)*, Constructed Average House Value
Specification 8	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/Reduced Lunch in Each School, *Percent of Population Commuting Over an Hour to Work*, Constructed Average House Value

As we show in Table 4-5, in contrast with the various working conditions model specifications, the quality of life model specifications are not always highly correlated to one another. This is perhaps not surprising, given that the variables in the assorted specifications are quite different from one another in terms of what they are measuring. For example, some measure weather conditions while others measure commuting time.

Table 4-5. Correlations of TCI Across Different Quality of Life Specifications

	Spec. 1	**Spec. 2**	**Spec. 3**	**Spec. 4**	**Spec. 5**	**Spec. 6**	**Spec. 7**	**Spec. 8**
Spec. 1	1							
Spec. 2	0.5604	1						
Spec. 3	0.9944	0.5180	1					
Spec. 4	0.5210	0.9856	0.4842	1				
Spec. 5	0.5038	0.9420	0.4862	0.9639	1			
Spec. 6	0.4468	0.6460	0.4638	0.6623	0.7895	1		
Spec. 7	0.4968	0.9181	0.4717	0.9344	0.9174	0.7136	1	
Spec. 8	0.8447	0.8427	0.8224	0.8268	0.7972	0.6580	0.8423	1

Table 4-6 shows the stability of the various indices over time. All are extremely stable, with average variation of less than one-half of one percent. The high stability is not surprising since many of the quality of life variables are from the *2000 Census of Population and Housing* so do not change from year to year.

Table 4-6. Stability Over Time of TCI Based on Various Quality of Life Specifications

Specification	Average Coefficient of Variation Across Time
Specification 1	0.14%
Specification 2	0.38%
Specification 3	0.19%
Specification 4	0.36%
Specification 5	0.38%
Specification 6	0.34%
Specification 7	0.39%
Specification 8	0.25%

The fact that different model specifications appear to produce somewhat different results makes the choice of a particular model difficult, in that the choice matters from a substantive point of view in effecting the calculation of the TCI. Unfortunately, there is little difference in the overall fit of the particular models with different variables and therefore relatively little in the way of empirical results to guide our decision-making.

Many of the specific variables that we use in the model have coefficient estimates that are sensitive to model specification. For example, the sign on the coefficient of the unemployment rate is sometimes significant and positive, which is contrary to expectations as it implies that school systems pay more where there is high unemployment.[49] In virtually all of the models where we include the variables that are influenced by labor market conditions, unemployment and crime rates, the signs on one or both of these variables is contrary to expectations. Thus, we opt to only include violent crime (the fit of the model is slightly better with violent crime than overall crime rates). We believe it was appropriate to include a measure of commuting given our decision, discussed below, to use a regional housing cost measure. We found the percent of commuters traveling an hour or more each day to have a significant and positive coefficient regardless of the other variables in the model, whereas some of the various commuting measures

[49] They should be able to offer less since a high unemployment rate implies a slack labor market.

were found to have unstable coefficient estimates. Few of the remaining variables had coefficient estimates that were consistently significant with the expected sign. Based on this, ***we recommend using two quality of life variables in the OLS specification of the model: the violent crime rate, and the percentage of commuters who travel over 60 minutes to get to work.***

C. Choice of Cost of Living Variables

As was the case above, when experimenting with the cost of living variables, we hold constant the other two variable categories. There are relatively few choices of variables to use in calculating cost of living, and, as we discussed in Chapter 3, most are based on measures of housing cost. We describe the various cost of living specifications we experiment with in Table 4-7, all of which are based on different housing cost calculations (which are described in detail in Chapter 3).

Table 4-7. Model Specifications, Experimenting with Cost of Living Variables

Specification 1	Personnel, Fiscal Capacity, & Year variables + Percentage of Students Eligible for Free/ Reduced Lunch in Each School, Rate of Violent Crime, Average Commute Time, C*onstructed Average House Value*
Specification 2	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/ Reduced Lunch in Each School, Rate of Violent Crime, Average Commute Time, *Constructed Regional Average House Value*
Specification 3	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/ Reduced Lunch in Each School, Rate of Violent Crime, Average Commute Time, *Constructed Regional Minimum House Value*
Specification 4	Personnel, Fiscal Capacity, & Year variables + Percent of Students Eligible for Free/ Reduced Lunch in Each School, Rate of Violent Crime, Average Commute Time, *Median House Value (from Census)*

As we report in Table 4-8, most of the cost-of-living specifications are highly correlated (the lowest correlation coefficient is .85) and fairly stable (Table 4-9). Thus, the choice of the particular variable has relatively little substantive impact on the estimate of the TCI.

Table 4-8. Correlations of TCI Across Different Cost of Living Specifications

	Spec. 1	Spec. 2	Spec. 3	Spec. 4
Spec. 1	1			
Spec. 2	0.9920	1		
Spec. 3	0.8480	0.8650	1	
Spec. 4	0.9950	0.9894	0.8572	1

Table 4-9 reports the average coefficient of variation of the TCI over time with various cost of living specifications. Again, as was the case with working conditions and quality of life, all of the various cost of living specifications are quite stable over time.

Table 4-9. Stability Over Time of TCI Based on Various Cost of Living Specifications

Specification	Average Coefficient of Variation Across Time
Specification 1	0.15%
Specification 2	0.12%
Specification 3	0.24%
Specification 4	0.08%

Since specifications 1, 2, 3, and 4 are all highly correlated and stable over time, we have some flexibility in selecting which housing measure to use in the TCI. We wish to have an "apples" to "apples" comparison of housing costs in one district relative to another, and as we describe in the previous chapter, measures such as the census housing value do not provide such a comparison. We feel it is more appropriate to use one of the adjusted housing cost measures based on the housing price model discussed in Chapter 3, so we are left with a choice between specifications 1-3. Given the possibility that many teachers may live outside of the district in which they are employed, we believe it makes sense to use a regional housing cost measure, and since specification 2 (constructed regional average house value) is more stable than specification 3 (the constructed minimum house value), ***we recommend, in the OLS specification of the model, using the constructed regional average house value as our cost of living variable.***[50]

D. TCI Calculations Based on Recommended Model Specification

Based on the findings above, we have picked what we refer to as our "preferred" OLS model specification, and we report the regression results from this preferred specification in Table 4-10. The table shows the coefficient estimates and the t-statistics, which identify how confident we are that the coefficient estimates are statistically different from zero (meaning the variable has no impact on salaries). We also report the "standardized coefficient", which is the effect of the coefficient in standard deviation units. Standardized coefficients are a way of comparing the relative effects of variables that are specified in different units (e.g. experience is measured in months and housing value is measured in dollars).

We are confident that this preferred OLS model does a good job of identifying the factors that influence salaries, as the variables in the model account for a significant share (about 83 percent) of the overall variation in teachers' salaries. Because the dependent variable is specified in log form, as mentioned above, the coefficient estimates should be interpreted as the percentage change in salaries resulting from a one-unit change in an independent variable. Prior to reporting the TCIs calculated from our preferred specification, it is worth discussing some of the estimated coefficients.

[50] This housing cost measure also has the advantage of producing one of the more stable TCI measures.

Table 4-10. Results of Preferred Teacher Salary (TCI) Model (Estimated with OLS)

Variable	Coefficient	t-statistic	Standardized Coefficient
Teacher Demographics			
Native American	-0.0269	-4.88	-0.0046
Black/ African- American	-0.0082	-11.42	-0.0129
Asian	-0.0183	-7.79	-0.0073
Male	-0.0079	-13.15	-0.0127
Teacher Credentials			
MA (and BA+30)	0.1399	216.47	0.2644
MA30	0.2157	227.17	0.2689
PhD	0.2221	69.51	0.0658
Years of Teaching Experience	0.0151	455.79	0.6143
Alternative	-0.0423	-6.30	-0.0059
Provisional	-0.0500	-48.92	-0.0544
NTE Communication Score	-4.81E-05	-0.77	-0.0592
NTE General Knowledge	0.0002	3.87	0.2666
NTE Professional Knowledge Score	-0.0008	-12.17	-0.9760
Praxis Reading Score	-0.0020	-6.81	-0.2731
Praxis Math Score	-0.0003	-1.69	-0.0482
Praxis Writing Score	-0.0007	-1.91	-0.0906
Computer Based Praxis Reading Score	-0.0013	-3.94	-0.2785
Computer Based Praxis Math Score	-8.02E-05	-0.45	-0.0167
Computer Based Praxis Writing Score	-0.0011	-4.07	-0.2243
Year and Fiscal Capacity Variables			
Observation Year: 2000	0.0474	66.20	0.0772
Observation Year: 2001	0.0884	121.41	0.1459
Observation Year: 2002	0.1030	133.94	0.1710
Per Capita Income	6.95E-06	95.38	0.2048
% of Designated Commercial Land	-0.2076	-16.25	-0.0358
Cost Factor Variables			
% of students receiving Free/Reduced Lunch (district level)	5.82E-04	15.35	0.0375
Measure of Violent Crime	1.73E-05	19.19	0.0458
Proportion of Working Population that Commutes over 60 Minutes	0.1976	23.49	0.0320
Constructed Regional Average House Value	6.16E-07	24.67	0.0507
Adjusted R-Squared		0.8258	
Sample size		199,578	

Note: The model also includes dichotomous variables identifying missing values of the various test score variables.

***Discretionary Variables*:** Most of the personnel coefficients are statistically significant and appear to have a great deal of face validity. Not surprisingly, the experience and degree level variables have the largest relative (based on the standardized beta) impact in determining salaries. Salaries are predicted to increase by 1.5 percent for each additional year of experience a teacher gains. Based on a mean salary of about $45,000, this represents an increase of about $675. This figure is quite similar to increases reported for the average steps on the salary scales of many of the large districts in the state (MSDE, 2002). Teachers with Master's Degrees (or Bachelor's plus 30 credits) are predicted to earn about 14 percent more ($6,300) than those with a BA only, and teachers with either a Master's Degree plus 30 credits or a Ph.D. are predicted to earn about 22 percent more ($9,450) than those with only a BA. Again, the premiums paid for advanced degrees appear to be quite consistent with reported state figures.

There are some surprising personnel coefficients. For instance, minority teachers are predicted in some cases to earn slightly less than white teachers (between 1 and 3 percent less depending on the minority group), and male teachers earn about 1 percent less than female teachers. One might have guessed there would not be any differences by race or gender in teachers' salaries given that teachers are generally paid according to a salary schedule. One possible explanation for these differences is that the years of experience variable in the model is an imprecise measure of the actual years of experience that teachers are credited as having for salary purposes, and race and gender are picking up the true effects of experience.[51] As we discuss in Chapter 3, there are some problems with the experience variable prior to 2002 so this does not seem implausible.

The estimated effects of the teacher licensure status variables show that teachers with less than full licensure earn 4 to 5 percent less than those with full state credentials. The signs on the

[51] For instance, minority and male teachers may tend to be employed in districts that tended to overstate experience levels in their reports to the state.

various licensure tests variables are sometimes positive, but often negative, which may at first blush seem contrary to expectations, as the negative signs imply that teachers who do better on licensure tests tend to receive lower salaries. There are two possible explanations for this finding. The first is that school systems are not terribly discriminating in their hiring practices, at least in regard to teacher performance on licensure exams (Ballou, 1996). The second is that, consistent with the literature on teacher labor markets (e.g. Lankford et al., 2002), teachers in Maryland tend to be unequally distributed across school districts based on student demographics. Teachers with higher test scores might sacrifice higher salaries for employment in what they consider to be more attractive working conditions (Hanushek et al., 2004; Lankford et al., 2002).

Cost Factor Variables: The cost factor variables in the base model are all statistically significant, however the effect of these variables on teachers' salaries tend to be far smaller than personnel variables such as experience (again, this is based on the standardized coefficient). Salaries are predicted to vary positively with the percentage of students that are on free or reduced price lunch, the variable we designed to capture the concept of working conditions. For a ten percent increase at the mean in the percentage of students in a district receiving free or reduced price lunch (which is an increase of about 2.95 percentage points), we estimate that districts are required to offer salaries that are 0.18 percent higher. These findings are sensible considering that jobs in schools with more needy students are likely to entail more difficult working conditions.

Our measures of quality of life, violent crime rates and the percentage of the population that has to commute over an hour also have a small impact on teachers' salaries. An increase of ten percent in the state average violent crime rate (which is an increase of 78 crimes per 100,000 population) is predicted to lead to an increase in the salary offered by districts of about 0.1 percent, and a 10 percent increase in the state mean value of the percentage of the population commuting over an hour (which is an increase of about .013) is predicted to lead to salaries that are about 0.2 percent higher. Finally, salaries vary positively with constructed regional housing prices, with a ten percent increase in the state mean regional housing value (which is equivalent to an increase of about $17,000) associated with salaries that are about one percent higher.

The magnitudes of the effects of the various cost factor variables on what we predict districts must offer to hire teachers of a comparable skill level may best be illustrated with some examples of hypothetical school districts with different working conditions, quality of life, and cost of living characteristics. Table 4-11 does this by showing simulated TCIs for 2002 for districts with various costs factors (these are calculated based on the regression results reported in Table 4-10). No school district in the state actually has characteristics that mirror those of the districts in the table; rather, the values of the cost variables in the table are based on the combined characteristics from districts in Maryland. Hypothetical District 1 has a combination of the "worst" cost factors making it the most difficult place to attract teachers; Hypothetical District 4 has a combination of the "best" cost factors making it relatively easy to attract teachers; and Hypothetical Districts 2 and 3 fall somewhere in between.

Table 4-11. 2002 TCIs for Hypothetical School Districts

District	Value of Cost Variables	Predicted 2002 TCI
Hypothetical District 1 Working Conditions: Poor Quality of Life: Low Cost of Living: High	Free/reduced lunch = 69.39% Violent crime = 2245/100,000 pop. Commute = 25.36% Housing value= $208,235	1.114
Hypothetical District 2 Working Conditions: Good Quality of Life: Low Cost of Living: High	Free/reduced lunch = 8.96% Violent crime = 2245/100,000 pop. Commute = 25.36% Housing value= $208,235	1.075
Hypothetical District 3 Working Conditions: Good Quality of Life: High Cost of Living: High	Free/reduced lunch = 8.96% Violent crime = 89.1/100,000 pop. Commute = 4.37% Housing value= $208,235	0.994
Hypothetical District 4 Working Conditions: Good Quality of Life: High Cost of Living: Low	Free/reduced lunch = 8.96% Violent crime = 89.1/100,000 pop. Commute = 4.37% Housing value= $98,407	0.929

As we would expect, the value of the TCI decreases markedly from District 1 to District 4 as the characteristics of the districts make them progressively more attractive places in which to work (recall that an index value of one indicates a district with characteristics that make it about as attractive a place to work as the average district). The range of the TCIs (0.93 to 1.11) is larger than what we actually observe in the state. As we show in Table 4-12, which reports the TCI calculated for each district in each year of our data based on actual district characteristics, the range in any single year is just over 0.1. This suggests, at least by our hedonic measure, that at the extreme, some high cost districts (e.g., LEA 30, Baltimore City) may have to pay about 10 percent more to attract the same teacher as a low cost district (e.g., LEA 11, Garrett).

Table 4-12. TCI Estimates

	1999	2000	2001	2002
LEA 1, Allegany	0.977	0.976	0.972	0.968
LEA 2, Anne Arundel	1.003	1.003	1.008	1.011
LEA 3, Baltimore	1.002	1.002	1.001	1.003
LEA 4, Calvert	1.024	1.024	1.026	1.024
LEA 5, Caroline	1.004	1.006	1.005	1.001
LEA 6, Carroll	1.004	1.004	1.007	1.006
LEA 7, Cecil	0.989	0.990	0.987	0.986
LEA 8, Charles	1.029	1.029	1.029	1.026
LEA 9, Dorchester	0.991	0.990	0.988	0.987
LEA 10, Frederick	1.014	1.015	1.017	1.019
LEA 11, Garrett	0.966	0.962	0.960	0.955
LEA 12, Harford	0.990	0.990	0.987	0.987
LEA 13, Howard	0.998	0.999	1.001	1.003
LEA 14, Kent	0.997	0.996	0.998	1.002
LEA 15, Montgomery	1.015	1.016	1.019	1.022
LEA 16, Prince George’s	1.044	1.041	1.047	1.051
LEA 17, Queen Anne’s	1.003	1.001	1.004	1.009
LEA 18, St. Mary’s	1.000	0.998	1.000	0.997
LEA 19, Somerset	0.981	0.983	0.979	0.979
LEA 20, Talbot	0.984	0.982	0.983	0.983
LEA 21, Washington	0.980	0.977	0.975	0.974
LEA 22, Wicomico	0.969	0.976	0.973	0.978
LEA 23, Worcester	0.974	0.972	0.971	0.968
LEA 30, Baltimore City	1.061	1.069	1.061	1.062

F. Testing the Need to Estimate Separate Non-Teaching Professional Salary Models

Non-teaching professionals (counselors, library and media specialists, principals, and vice-principals) are certainly distinct from teachers in terms of their jobs, but we might expect the impact of the various cost factor variables to be the same for both teachers and non-teaching professionals. We examine this hypothesis by estimating separate regressions for teachers and non-teaching professionals and test whether the coefficients are statistically different for these two groups (Chow, 1960). This test rejects the hypothesis that the coefficients for teachers and non-teaching professionals are the same, suggesting from a statistical standpoint that it is appropriate to estimate separate models.

Though we do not report them here, the coefficient estimates from various specifications of the NTPCI are quite sensitive to model specification. This is to be expected given that our sample of non-teaching professionals, 23,205, is only about ten percent as large as the teacher sample, and includes several types of personnel. Given the instability of the coefficient estimates of the NTPCI models, and the fact that it is more complex to go through a two step process to derive a professional personnel cost index (PPCI), it is worth determining whether this is worthwhile from a practical perspective. In other words, we wish to know how much of a difference it makes if we calculate the PPCI by estimating a NTPCI separately from the TCI and then combining these two separate estimates together for our PPCI, versus simply calculating the PPCI directly from the sample of most professional employees. We explore this question by going through the process of calculating the PPCI in each of the two ways and comparing the results.

The first method we used is to estimate *separate* hedonic models for each group. Based on the coefficients from these models we calculate a TCI and a NTPCI, then combine the two into a PPCI based on their relative share of expenditure on professional personnel.[52] Therefore, this PPCI is a weighted average of the TCI and NTPCI.

The second method we use is to estimate a *single* hedonic model for both teachers and non-teaching professionals, then use the coefficients from this model to calculate a PPCI directly. The coefficient estimates for the hedonic model for professional employees are reported below in Table 4-13. This model is exactly the same as the hedonic teacher model reported in Table 4-10, with the exception that the professional hedonic model includes dichotomous variables identifying principals, vice principals, counselors, and library and media specialists.[53]

The signs and magnitudes of the coefficients in Table 4-13 are, for the most part, qualitatively similar to those when we estimate the model for teachers only (Table 4-10). When we estimate the PPCI in these two distinct ways, we find that the correlation between the two methods is .9915. Given that there is virtually no difference between the two alternative methods of calculating the PPCI, ***we recommend using the model that includes both groups of employees to calculate the PPCI.***

The calculated PPCIs for each district in each year of our data, based on the model presented in Table 4-13 and actual district characteristics for cost factor variables, are reported below in Table 4-14.

[52] The shares we use, based on average budget shares from 1998 to 2001, are 67 percent for teachers and 13 percent for non-teaching professional. This results in weights of 0.8375 and 0.1625.
[53] A variable for one category of professional staff needs to be left out of the model to estimate the regression. In this case, a variable for teachers is excluded (teachers are the baseline occupation).

Table 4-13. Results of Preferred Professional Salary (PPCI) Model (Estimated with OLS)

Variable	Coefficient	t-statistic	Standardized Coefficient
Teacher Demographics			
Native American	-0.0237	-4.30	-0.0037
Black/ African- American	-0.0088	-12.57	-0.0130
Asian	-0.0193	-8.18	-0.0071
Male	-0.0046	-7.87	-0.0070
Teacher Credentials			
MA (and BA+30)	0.1469	225.78	0.2590
MA30	0.2151	233.28	0.2714
PhD	0.2132	82.68	0.0738
Years of Experience	0.0144	452.91	0.5522
Alternative	-0.0397	-5.70	-0.0049
Provisional	-0.0532	-50.75	-0.0516
NTE Communication Score	-9.23E-7	-0.01	-0.0010
NTE General Knowledge	1.32E4	2.32	0.1496
NTE Professional Knowledge Score	-8.719E-04	-13.07	-0.9813
Praxis Reading Score	-0.0022	-7.25	-0.2672
Praxis Math Score	-0.0006	-2.68	-0.0703
Praxis Writing Score	-0.0007	-2.00	-0.0870
Computer Based Praxis Reading Score	-0.0015	-4.17	-0.2702
Computer Based Praxis Math Score	-2.37E-04	-1.28	-0.0438
Computer Based Praxis Writing Score	-0.0012	-4.18	-0.2117
Principal	0.3642	217.32	0.1923
Vice Principal	0.2566	168.93	0.1480
Counselor	0.0113	8.37	0.0073
Library Media Specialist	-0.0032	-1.79	-0.0015
Year and Fiscal Capacity Variables			
Observation Year: 2000	0.0469	66.68	0.0713
Observation Year: 2001	0.0882	123.30	0.1358
Observation Year: 2002	0.1015	134.19	0.1570
Per Capita Income	6.71E06	93.58	0.1843
% of Designated Commercial Land	-0.1730	-13.77	-0.0278
Cost Factor Variables			
% of students receiving Free/Reduced Lunch (district level)	3.92E-04	10.52	0.0235
Measure of Violent Crime	1.52E05	17.14	0.0374
Proportion of Working Population that Commutes over 60 Minutes	0.1297	15.71	0.0196
Constructed Regional Average House Value	7.71E-07	31.41	0.0591
Adjusted R-Squared		0.8364	
Sample size		222,783	

Note: The model also includes dichotomous variables identifying missing values of the various test score variables.

Table 4-14. PPCI Estimates

	1999	2000	2001	2002
LEA 1, Allegany	0.973	0.970	0.965	0.960
LEA 2, Anne Arundel	1.007	1.010	1.016	1.019
LEA 3, Baltimore	1.008	1.008	1.008	1.009
LEA 4, Calvert	1.022	1.021	1.024	1.020
LEA 5, Caroline	0.999	1.002	1.002	0.997
LEA 6, Carroll	1.010	1.011	1.012	1.012
LEA 7, Cecil	0.991	0.990	0.987	0.990
LEA 8, Charles	1.023	1.023	1.024	1.020
LEA 9, Dorchester	0.991	0.990	0.988	0.985
LEA 10, Frederick	1.017	1.019	1.021	1.024
LEA 11, Garrett	0.961	0.957	0.953	0.948
LEA 12, Harford	0.992	0.993	0.991	0.989
LEA 13, Howard	1.005	1.006	1.009	1.011
LEA 14, Kent	0.999	0.999	1.002	1.007
LEA 15, Montgomery	1.019	1.020	1.024	1.028
LEA 16, Prince George’s	1.043	1.040	1.045	1.050
LEA 17, Queen Anne’s	1.000	0.998	1.000	1.005
LEA 18, St. Mary’s	1.002	0.999	1.003	0.999
LEA 19, Somerset	0.979	0.982	0.978	0.978
LEA 20, Talbot	0.986	0.984	0.985	0.984
LEA 21, Washington	0.979	0.976	0.974	0.971
LEA 22, Wicomico	0.968	0.971	0.968	0.972
LEA 23, Worcester	0.974	0.971	0.970	0.967
LEA 30, Baltimore City	1.054	1.060	1.052	1.055

The PPCIs are quite similar to the TCIs shown above in Table 4-12, which makes sense given that teachers represent the great majority of professional employees. Baltimore City (LEA 30) remains the district that appears to have the most difficulty attracting professional personnel (it is calculated to require salaries 5 percent above the average district to attract similar professional personnel), and Garrett (LEA 11) appears to have some of the least difficulty (it is estimated to require salaries 5 percent below the average district).

G. Testing for the Need for PCI Model Re-Calibration

Thus far all of our estimated models have assumed that the effects of the independent variables in the model (the coefficients) are constant across years.[54] It is possible, however, that this assumption does not hold. In this section we explore whether the coefficient estimates change across years. If they are found to change, it suggests the need to re-calibrate the model on a regular basis, and if they are not found to change, this re-calibration may not be necessary.

To formally determine whether it is necessary to re-calibrate the PPCI model, we estimate it separately for each year and test the coefficients to see if they differ by year. This test rejects the hypothesis that the model coefficients are the same across the four years of our data (1999-2002).[55] Thus, from a statistical standpoint it appears to be appropriate to regularly re-calibrate the model because the estimated effects of the various coefficients change significantly over time.

This may not be necessary, however, from a practical perspective. To test whether there is any substantive impact of re-estimating the model on an annual basis, we calculate PPCIs for each year using our model, which assumes the coefficients are "time invariant" or constant across years (from Table 4-13), and compare these to PPCIs that are estimated based on similar models (i.e. they include the same set of explanatory variables except the year dummy variables), which allow the coefficients in each year to be different (we do not report these for each year). Table 4-15 presents the correlations by year between these two methods of estimating yearly PPCIs. The correlations between time invariant and yearly PPCIs are very high, over 0.90. Thus, we have chosen to use the PPCIs based on one regression for 1999 to 2002.

---

[54] We treat our dataset as a pooled cross-section and account for inflation by including year dummy variables.
[55] This is tested with what is commonly called a Chow (1960) test. We also tested whether the coefficients on the cost variables differed across years (using a similar F-test) and are able to reject the null hypothesis that the cost variables are the same.

Table 4-15. Correlations of Time Invariant and Yearly PPCIs

1999	2000	2001	2002
0.9326	0.9792	0.9150	0.9792

H. Clustering of Data and District Fixed-Effects

As we described in Chapter 2, two issues arise when estimating hedonic models like those discussed in this chapter. The first issue is whether the coefficients estimated in the model are accurate (unbiased). One of the principal causes of biased coefficients is the omission of important variables from the model, which are correlated with variables in the model. In particular, we worry that our OLS models may fail to capture the preferences of districts for education, which may inappropriately influence our estimates of the effects of the cost variables.

The principal step we have taken to address this issue is to include as many important variables as possible. The fact that our professional salary models explain over 80 percent of the variation in the professional salaries suggests that we have included most of the important variables. Another approach that can be utilized to address this problem is to include district "fixed effects" in the model. District fixed effects are dichotomous (0-1) variables included in the model to capture any factor unique to the district that does not vary significantly across time. They serve as an insurance policy against important omitted district-level variables.

The second issue is whether the estimates of model precision (standard errors) are estimated accurately. Of particular concern is whether we can state with confidence that the cost factors affect teacher salaries. However, it is the measures of precision for district level variables (such as cost factors) that are the most apt to be estimated incorrectly, because of clustering of observations. In the absence of this correction, we inappropriately treat the district level data as if there are over 222,783 independent observations when in fact there are only 96 (24 districts across 4 years of data). We correct for this possible problem in several ways. Use of district level fixed effects removes any common factors for all teachers in a district that do not vary across the time period in our sample (e.g., district leadership).[56] To control for clustering at the teacher level (some teachers are in the sample over multiple years of data), we estimate a corrected set of precision measures ("robust" standard errors).

Table 4-16. Comparison of Cost Factor Coefficients in Fixed Effects and OLS Hedonic Models

Cost Factor	Fixed Effects	OLS Model	Fixed Effects As Percent of OLS
Professional Model:			
% of Students Receiving Free/Reduced Lunch (district level)	7.054E-04	3.924E-04	1.798
Constructed Regional Housing Price	1.120E-06	7.710E-07	1.453
Teacher Model:			
% of Students Receiving Free/Reduced Lunch (district level)	1.024E-03	5.822E-04	1.758
Constructed Regional Housing Price	1.220E-06	6.160E-07	1.981

Selected coefficient estimates, for teachers and all professionals, are reported in Table 4-16 for both the fixed effects and OLS models.[57] The fixed effects models are quite similar to those estimated with OLS (Tables 4-10 and 4-13) with two exceptions. First, we do not include the fiscal capacity variables since the fiscal capacity of districts are accounted for by the district fixed effects. Second, we were forced to drop two of the cost factor variables – the percentage of the population commuting over an hour to work and the violent crime rate – because either the coefficient for the variable was unstable (violent crime rate) or the variable did not change over time (commuting time). It is not surprising that this was necessary since the coefficients of the

[56] It is possible to test statistically whether another approach for addressing the second issue, "random effects," is adequate. The Hausman test confirms that fixed-effects is the preferred specification over random district effects.
[57] The full set of regression results for the fixed effects models for teachers and professional staff are reported in appendix Table B-6.

district level cost variables in the fixed effects model are based solely on variation over time, and with only four years of data there is relatively little variation.

For the two district variables, housing prices and subsidized lunch, the coefficients are substantially higher in the fixed effects regression model than OLS. To a certain extent this is not surprising, considering that the OLS model includes several additional cost variables. While the coefficients are higher in the fixed effects model, it is the relative relationship between these variables that will be important in the calculation of the PCI.

We use our estimates from the fixed effects model specifications to calculate TCIs and PPCIs, which are reported below in Table 4-17. In completing this calculation we had to make a decision as to whether it was appropriate to hold each district fixed effect constant or allow it to vary. There are plausible arguments for calculating the indices either way. In particular, one might argue for allowing the effects to vary because they capture aspects of school districts that influence their attractiveness as places of employment, implying they are outside of the control of each district and should therefore be considered a cost factor. On the other hand, it is quite likely that these effects capture the preferences of school districts for education as reflected in the salaries districts are willing to offer teachers. If this is the case, it is important to hold district fixed effects constant so that the value of our indices reflect only factors outside district control, which affect the preferences of teachers for various districts. In deciding which approach to take, we explored the correlation between the TCIs and PPCIs calculated from our OLS models and those calculated in each way from the district fixed effects models. The correlation between the PPCI based on the OLS and the calculation where fixed effects are held constant is far higher that when we allowed the fixed effects to vary.

Table 4-17. PPCIs Based on Models with Fixed Effects and Corrections for Clustering (Index Relative to Simple Statewide Average)

	TCI				PPCI			
District	**1999**	**2000**	**2001**	**2002**	**1999**	**2000**	**2001**	**2002**
Lea 1, Allegany	0.972	0.969	0.963	0.954	0.971	0.968	0.962	0.954
Lea 2, Anne Arundel	1.011	1.011	1.018	1.021	1.013	1.013	1.019	1.022
Lea 3, Baltimore	1.013	1.013	1.013	1.016	1.012	1.013	1.013	1.015
Lea 4, Calvert	1.005	1.004	1.008	1.002	1.008	1.008	1.011	1.006
Lea 5, Caroline	1.002	1.001	1.004	1.003	0.999	0.998	1.001	1.000
Lea 6, Carroll	1.007	1.009	1.010	1.011	1.012	1.013	1.014	1.015
Lea 7, Cecil	0.989	0.990	0.987	0.985	0.992	0.993	0.989	0.989
Lea 8, Charles	1.006	1.005	1.006	0.998	1.007	1.007	1.007	1.001
Lea 9, Dorchester	0.992	0.990	0.989	0.984	0.989	0.987	0.986	0.982
Lea 10, Frederick	1.015	1.017	1.017	1.022	1.017	1.020	1.020	1.024
Lea 11, Garrett	0.961	0.956	0.949	0.942	0.961	0.956	0.950	0.943
Lea 12, Harford	0.995	0.995	0.990	0.991	0.998	0.998	0.995	0.994
Lea 13, Howard	1.011	1.014	1.018	1.022	1.015	1.017	1.021	1.025
Lea 14, Kent	1.011	1.009	1.010	1.018	1.008	1.007	1.008	1.015
Lea 15, Montgomery	1.036	1.041	1.046	1.053	1.035	1.039	1.044	1.051
Lea 16, Prince George's	1.051	1.051	1.059	1.065	1.044	1.045	1.051	1.056
Lea 17, Queen Anne's	0.993	0.992	0.995	1.000	0.997	0.995	0.999	1.003
Lea 18, St. Mary's	1.005	1.001	1.004	0.998	1.006	1.003	1.005	1.000
Lea 19, Somerset	0.986	0.988	0.981	0.980	0.981	0.983	0.977	0.976
Lea 20, Talbot	0.986	0.986	0.991	0.992	0.988	0.987	0.992	0.992
Lea 21, Washington	0.977	0.973	0.969	0.964	0.979	0.976	0.972	0.968
Lea 22, Wicomico	0.966	0.971	0.964	0.963	0.968	0.972	0.966	0.965
Lea 23, Worcester	0.965	0.966	0.962	0.957	0.967	0.968	0.964	0.960
Lea 30, Baltimore City	1.047	1.047	1.048	1.058	1.034	1.034	1.034	1.043

As we did in sub-section 4.2.F, we test whether it makes sense to estimate the PPCI directly from the full sample of professions or to calculate the PPCI based on separate TCI and NPTCI indexes that are appropriately weighted by their budget shares. The correlation of the PPCI calculated in these two different ways are quite similar (the correlation is over .99), which again suggests that it makes sense to calculate the PPCIs directly from the sample of professionals rather than utilizing the more complex two-step process. Comparing the fixed effects PPCIs in Table 4-17 with those based on the OLS in Table 4-14, we observe that the two sets of indices are very similar. In fact, the correlations between these two estimates of PPCI are over 0.90 for all years. The absolute value of the difference between these indices is only about one percent. Less than 20 percent of districts have differences between the indices of over 2 percent. The high correlation between these two measures of PPCI raises the question of whether it is necessary from a practical perspective to estimate the more complex (fixed effects) models.

To sum up, in developing the PCI for professional personnel we have made a series of choices about what variables to include in the model, which statistical methodologies to use, and whether to include all professional personnel in an overall professional personnel cost index (PPCI). Our recommended choices include:

- Reducing district cost variables to only a few factors for student need (district level subsidized lunch rate), cost of living (constructed regional housing price), and amenities (violent crime, and percent of commuters traveling an hour or more).
- Combining the teacher salary model and other professional salary model into an overall professional staff salary model to estimate the PPCI.
- Using the simpler methodology (OLS) to estimate the hedonic models, because the resulting models include a broader set of cost factors and the calculated PPCIs are very similar to those calculated using the more complex methodology.

3. Non-Professional Salary Models and Index

The employees who fall in the non-professional personnel category are quite different from teachers or non-teaching professionals in several ways. First, they tend to be lower paid employee classes. They are therefore unlikely to have as much labor market power as professional employees, and they are less likely to have the economic wherewithal to search across the state for school district jobs that are in line with their job preferences. Second, many of these employees are unlikely to have regular full-day contact with students. This suggests that the characteristics of the students are less likely to influence their salaries. In fact, many of these employees are not linked to particular school buildings in the data. The types of occupations included in the nonprofessional category (clerical, custodial, craft and tradesmen, and service workers) are less specialized to education. For example, custodians may work for school systems or any number of private sector employers implying that these categories of employees are more influenced by the private labor market. Finally, the Maryland Staff Reporting System includes only a few personal characteristics of these employees (gender, ethnicity, age, and position) compared to professional staff. Experience is not a recorded field for this class of employees as a whole. For all of these reasons, we believe it is appropriate to estimate separate hedonic salary models for these employees.

A. Salary Model Results

Table 4-18 reports the statistical results from estimating a hedonic salary model for non-professional employees. While several specifications of this model were examined, for simplicity we are reporting only the preferred specification of the model. Cost variables in this model include calculated regional housing price, an overall unemployment rate, and the subsidized lunch rate (at the district-level). We have also tried models with the Census child poverty rate or an interaction between the subsidized lunch rate and population density. The indices resulting from the different student needs measures are very highly correlated (correlations above 0.90). We have chosen the subsidized lunch rate, because it is a stable variable that can be updated every year and is consistent with what is being used in the PPCI. Given the limited set of personnel characteristics, the model explains a reasonably high share of the variation in staff salary (53%). To ensure that the measures of precision (standard errors) estimated in the model are accurate, we have used "robust" standard errors (with clustering controlling for the 96 district and year combinations).

Discretionary variables: In terms of explanatory power (based on the standardized coefficient) the gender and age of the employee are important variables among the discretionary variables. The age variable is positively associated with salary levels, and serves as a rough proxy for experience. It is not clear why the gender variable has such a large effect on salaries, but this may partly be explained by the imperfect controls for experience and occupation. The occupation variables are, as expected, important control variables to include in the model. District wealth is included in the model to control for the fiscal capacity of the district, and is positively associated with staff salaries. The year variables indicate the percent growth in salaries since 1999.

Table 4-18. Results of Preferred Non-Professional Wage Model

Variable	Coefficient	Robust[1] t-statistic	Regular[1] t-statistic	Standardized Coefficient
Intercept	9.5553	90.38	568.12	
Discretionary (control) Variables:				
Staff characteristics:[2]				
Native American	-0.0103	-0.65	-0.57	-0.0012
African American	0.0321	1.73	12.64	0.0375
Hispanic	-0.0579	-4.62	-9.29	-0.0192
Male	0.3447	27.66	132.08	0.3997
Age[3]	0.0057	21.63	57.11	0.1385
Position:[4]				
Technical personnel	0.0468	1.67	9.74	0.0303
Crafts and trade personnel	-0.0246	-1.60	-6.20	-0.0162
Manual laborer	-0.2883	-12.39	-48.77	-0.1026
Service worker	-0.4732	-41.93	-184.88	-0.5698
District wealth (millions)	0.0000	6.08	51.01	0.1676
Year:				
2000	0.0083	0.33	2.84	0.0087
2001	0.0527	2.19	18.59	0.0553
2002	0.0650	2.85	21.88	0.0690
Cost Variables:				
Regional house price	1.3400E-06	2.37	15.79	0.0704
Share of students receiving subsidized lunch	1.6268E-03	1.67	11.63	0.0619
Unemployment rate	-0.0204	-1.99	-14.29	-0.0934
Adjusted r-square			0.53	
Sample size			84388	

[1]Dependent variable is logarithm of annual salary. Estimated with OLS with and without robust errors. Where robust standard errors are used, grouping by district and year is controlled for.

[2]For ethnicity and gender variables variable equals 1 if this characteristics applies, and 0 otherwise.

[3]Age has been limited to be between 18 and 79. Values outside this range are assigned the mean.

[4]For position variables the variable equals 1 if the person is in this position and 0 otherwise.

Cost variables: After reviewing a number of combinations of cost variables, we have selected three categories of variables that seem to fit the local labor market for non-professional employees. Employment decisions of these types of employees are likely to be strongly affected by cost-of-living in the region since they are generally lower paid occupations (compared to teachers and administrators). Given that these employees may commute into a high cost county to work, we are using a regional housing cost variable. We find that an increase in housing prices by $1,000 is associated with a 0.13 percent increase in non-professional salaries. The positive coefficient on the subsidized lunch rate indicates that poverty does affect working conditions for at least some of these employees. However, using robust t-statistics the coefficient is statistically significant from zero only at the 10 percent level. Finally, the coefficient on the unemployment rate indicates that a one-percentage point increase in the unemployment rate is associated with a .019 percent decrease in salaries. The higher the unemployment rate, the fewer job opportunities these employees have, and the more likely they will accept contracts with less salary growth. While the cost variables have the expected sign, none are among the most important variables explaining non-professional salary differences.

B. PCI for Nonprofessional Employees

Using the results of the hedonic salary model it is possible to develop the salary index for nonprofessional staff (NPCI). We predict salary levels assuming discretionary (control) variables are held at the state average, and only the cost variables are allowed to vary. The resulting predicted salaries are divided by salaries in the average district to produce the NPCI (Table 4-19).

The index values reflect the importance of housing prices among the cost variables. The districts with the highest NPCI are also districts with the highest housing prices (Montgomery, Howard, Anne Arundel, Prince George's, and Carroll Counties). The lowest index values are among the more rural districts in the state. The City of Baltimore has an average NPCI even though its housing prices are below average, because of a high poverty rate. We looked at the stability of this index across time and found that it is very stable (correlations above 0.95). The average fluctuation in the NPCI around the mean (coefficient of variation) is small (0.77%).

Table 4-19. Non-Professional Salary Index (NPCI)
(Index Relative to Simple Statewide Average)

District	1999	2000	2001	2002
Lea 1, Allegany	0.910	0.917	0.906	0.903
Lea 2, Anne Arundel	1.045	1.033	1.046	1.048
Lea 3, Baltimore	1.028	1.021	1.018	1.023
Lea 4, Calvert	1.035	1.029	1.040	1.037
Lea 5, Caroline	1.029	1.027	1.021	1.001
Lea 6, Carroll	1.044	1.034	1.036	1.039
Lea 7, Cecil	0.958	0.977	0.962	0.958
Lea 8, Charles	1.049	1.037	1.041	1.036
Lea 9, Dorchester	0.915	0.935	0.931	0.905
Lea 10, Frederick	1.061	1.053	1.059	1.057
Lea 11, Garrett	0.862	0.879	0.877	0.888
Lea 12, Harford	1.004	1.007	0.998	0.998
Lea 13, Howard	1.064	1.055	1.064	1.059
Lea 14, Kent	1.002	1.022	1.022	1.037
Lea 15, Montgomery	1.104	1.093	1.105	1.107
Lea 16, Prince George's	1.084	1.076	1.086	1.093
Lea 17, Queen Anne's	1.019	1.013	1.017	1.021
Lea 18, St. Mary's	1.031	1.019	1.029	1.034
Lea 19, Somerset	0.917	0.932	0.926	0.933
Lea 20, Talbot	1.014	1.011	1.020	1.025
Lea 21, Washington	0.996	0.984	0.993	0.970
Lea 22, Wicomico	0.965	0.964	0.955	0.953
Lea 23, Worcester	0.872	0.877	0.851	0.862
Lea 30, Baltimore City	0.992	1.006	0.997	1.015

4. Energy Cost Model and Index

As discussed in Chapter 2, energy expenditure is the only non-wage expenditure object for which we are estimating a separate cost index. While the process of determining energy costs is complex, especially with energy choice, several factors outside of district control do appear to affect energy costs. Small districts may face higher prices for several reasons. First, energy prices are often lower for higher volumes of energy use. Second, an energy manager, who can be hired to help a district negotiate lower energy rates, is a relatively fixed cost that could impose significantly higher burdens on smaller districts. The other external factor affecting energy costs is weather. In this section, we will present the results of the energy cost model, and present energy cost indices for Maryland counties.

A. Energy Cost Model

Based on data collected either directly from the districts or from available published data sources, we estimated an energy cost model for Maryland counties for 1999 to 2002 (Table 4-20). The dependent variable, energy expenditures per pupil, is expressed as a natural logarithm, and the coefficients in the regression can be interpreted as percent changes in energy costs. Several of the independent variables—square feet per pupil, wealth, enrollment, heating degree days, and cooling degree days—are also transformed into natural logs. Coefficients on these variables can be interpreted as elasticities (a 1 percent change in the explanatory variable is associated with the estimated percent change in energy costs). To indicate which variables have an important effect on energy costs, we also reported the standardized coefficients. The larger the standardized coefficient, the more important an explanatory variable is. The energy cost model only explains 35.4 percent of the variation in energy expenditures, even though the coefficients on most of the explanatory variables are estimated with precision. The relatively low explanatory power of the model is not surprising given the complex process for determining energy prices, and the limited set of explanatory variables available to us.

Table 4-20. Energy Cost Model (1999-2002)

Energy cost factor	Coefficient	t-statistic	Standardized Coefficients
Constant	-3.8375	-1.74	
Discretionary factors:			
Percent of cost in electric/gas	-0.4999	-2.11	-0.2214
Average square feet per pupil[1]	0.4836	2.67	0.3480
School building size (square feet)			
Under 10,000 square feet	1.7518	2.24	0.2518
Over 190,000 square feet	1.2316	2.35	0.3723
Adjusted age of school[2]			
Over 70 years old	-4.1259	-2.17	-0.2600
Between 50 and 70 years old	-0.1811	-0.20	-0.0213
School district wealth[1]	0.1453	2.72	0.2675
Non-discretionary factors			
District enrollment[1]	-0.0607	-2.25	-0.4001
Heating degree days (cold days)[1]	0.4910	2.72	0.4141
Cooling degree days (hot days)[1]	0.2024	2.29	0.3490
Adjusted R^2		0.3541	
Sample size		96	

Note: Dependent variable is the natural logarithm of total energy expenditure. Estimated with ordinary least squares regression.

[1]Expressed as natural logarithm. The coefficient can be interpreted as an elasticity.

[2]Expressed as natural logarithm. Adjusted age is calculated by taking into account the age and size of buiding during original construction and major renovations/additions.

Discretionary variables: To account for district decisions that can affect energy costs, we have included a range of "discretionary" variables. Districts that provide relatively more school facilities to their students should have higher energy costs. We measure space in school facilities by the square feet in district schools per pupil. Instead of using age at the time the building was first built, we construct an adjusted age measure (see Chapter 3), which captures renovations as well. Building size and age are available from the Maryland Public School Construction Program. As expected, the relative size of district facilities (square feet per pupil) is an important determinant in energy costs, with a one percent increase in size associated with a 0.48 percent increase in expenditures per pupil. As indicated by the standardized coefficient, this is a particularly important explanatory variable.

Instead of measuring school size and age directly, we have included variables to capture extreme observations. The coefficients on the variables for a very small and very large school are both positive. We would expect the former but not the latter, because large school buildings generally would have lower energy costs. We also found a strong negative coefficient on the variable for buildings over 70 years old, which goes against expectations. In discussions with some district business officials, they speculate that this result is due to the fact that very old buildings are less apt to have air conditioning. The wealth variable was included to account for the fact that wealthier districts may have more extensive heating and cooling systems (especially air conditioning). A one percent increase in wealth is associated with a 0.14 percent increase in energy spending per pupil.

Cost variables: The two cost factors included in the model are district size and weather. We would expect a negative coefficient on the enrollment variable (small districts have higher energy prices), and a positive coefficient on the weather variables (more very cold or hot days raises energy consumption). The results fit expectations, with a one percent increase in district enrollment associated with a 0.061 percent decline in energy costs per pupil. A one percent increase in the number of cold (hot) days is associated with a 0.49 (0.20) percent increase in energy costs. All three cost variables are among the most important explanatory variables in the energy cost model.

B. Energy Cost Index

The major output of the energy cost model is an adjusted energy cost that allows the cost factors to vary and holds the discretionary factors at the state mean. We did not include year variables in the model, because they affected the statistical significance of some of the discretionary variables (and not all the coefficients are statistically significant). Variation across years in the adjusted energy cost is due primarily to changes in the weather variables (enrollment is quite stable across years). To create the energy cost index we simply divided the adjusted energy cost in each district by the energy cost in the average district for each year (simple average of district adjusted energy costs).

Table 4-21 reports the adjusted energy cost indices from 1999 to 2002 and indices for the actual energy costs per pupil. Not surprisingly, the highest index values tend to be in the smaller counties (Allegany, Garrett, Kent, Somerset, Queen Anne's, and Talbot). The negative coefficient on the enrollment variable also leads to below average index values in the larger urban districts (Montgomery, Prince George's, Baltimore County, Baltimore City and Anne Arundel). The adjusted energy cost index in a particular year is only moderately correlated with actual energy prices per pupil in that year (correlations between 0.35 and 0.55). To examine the stability of the energy cost index across years we have taken several steps. First, we examined the inter-year correlations for the index. The correlations are quite high, typically above 0.80. To examine stability further, we estimated the coefficient of variation, which confirms the stability of the ECI. Index values typically only fluctuated 2 percent over time. While the energy cost model only explains a little over one-third of the variation in energy costs, the resulting ECI seems to be quite stable.

Table 4-21. Energy Cost Index (ECI)
(Index Relative to Simple Statewide Average)

	Adjusted Energy Costs				Actual Energy Costs			
District	**1999**	**2000**	**2001**	**2002**	**1999**	**2000**	**2001**	**2002**
Allegany	1.064	1.035	1.029	1.070	0.942	1.052	1.015	1.041
Anne Arundel	0.914	0.915	0.934	0.928	0.828	0.766	0.820	0.871
Baltimore	0.907	0.940	0.928	0.931	0.976	0.907	1.047	0.973
Calvert	1.031	1.059	0.960	1.021	0.949	0.849	0.868	0.724
Caroline	1.033	1.026	1.072	1.050	0.789	0.805	0.729	0.726
Carroll	0.975	0.970	0.999	0.991	0.851	0.846	0.857	0.906
Cecil	1.029	1.057	1.049	1.053	0.980	0.988	1.025	0.994
Charles	0.991	0.999	0.984	0.988	1.184	0.964	0.923	0.787
Dorchester	1.038	1.018	1.072	1.055	1.026	1.235	1.167	1.293
Frederick	0.963	0.953	0.981	0.959	0.951	0.946	0.848	0.981
Garrett	1.078	1.045	1.000	1.086	1.069	1.074	1.020	1.093
Harford	1.015	1.024	1.014	0.993	1.044	1.005	0.978	1.117
Howard	0.991	0.955	0.935	0.958	1.170	1.114	1.063	1.140
Kent	1.133	1.122	1.170	1.165	0.977	1.091	1.120	1.119
Montgomery	0.894	0.878	0.894	0.906	0.897	0.875	0.710	0.814
Prince George's	0.891	0.889	0.911	0.895	0.871	0.851	0.800	0.844
Queen Anne's	1.050	1.047	1.085	1.069	1.187	1.121	1.311	1.251
St. Mary's	0.974	0.973	0.992	0.992	0.790	0.841	0.881	0.768
Somerset	1.068	1.111	1.007	1.053	1.470	1.354	1.430	1.347
Talbot	1.048	1.054	1.095	1.067	1.091	1.058	1.071	1.054
Washington	1.003	0.994	1.032	1.011	0.970	1.060	0.890	0.920
Wicomico	0.983	0.981	0.968	0.837	0.780	0.912	0.948	0.929
Worcester	1.010	1.010	1.029	1.005	1.211	1.170	1.318	1.266
Baltimore City	0.916	0.945	0.860	0.919	0.997	1.114	1.160	1.040

Note: Based on a simple average of district energy costs per pupil for each year.

5. Calculation of the GCEI

The final stage in the process of calculating a geographic cost of education index (GCEI) for the state of Maryland is to combine the individual indices into an overall geographic cost index. The process of combining indices involves two steps. First, budget shares are developed for each category corresponding to a particular cost index. Second, calculation of the GCEI involves a weighted average of individual indices. We will briefly describe the process of developing budget shares before turning to the calculation of the GCEI.

A. Expenditure Data and "Budget Shares"

The approach we use to calculate the budget shares is a variant on the market basket concept. Instead of a market basket of consumer goods, for school districts we want to identify the major objects that districts spend their budget on. We used information on actual expenditures by object of expenditures and functional classifications to develop budget shares. The goal is to develop expenditure shares that match the cost indices that have been developed. Using data from MSDE (2003a), Table 4-22 reports expenditure shares.

Table 4-22. Expenditure Shares to Use in Calculating the GCEI

	1998	1999	2000	2001	Average
Instructional	67.40%	67.35%	67.18%	67.67%	67.40%
general ed, special ed, adult ed					
Wages and Salaries	53.92%	53.87%	53.63%	53.79%	53.80%
Fringe Benefits	11.42%	11.29%	11.52%	11.51%	11.44%
Contracts and Other Charges	2.05%	2.19%	2.03%	2.37%	2.16%
Nonteaching Professionals	12.57%	12.99%	13.48%	13.40%	13.11%
Administration, mid-level administration, health services, student services					
Wages and Salaries	9.65%	9.79%	9.94%	9.70%	9.77%
Fringe Benefits	1.99%	2.10%	2.17%	2.24%	2.12%
Contracts and Other Charges	0.94%	1.10%	1.37%	1.46%	1.22%
Nonprofessionals	10.82%	10.62%	10.26%	9.92%	10.41%
Maintenance, operations and food service					
Wages and Salaries	6.46%	6.36%	6.57%	6.22%	6.40%
Fringe Benefits	1.48%	1.40%	1.31%	1.30%	1.37%
Contracts and Other Charges	2.88%	2.86%	2.39%	2.40%	2.63%
Nonpersonnel Related					
Energy[1]	2.13%	2.03%	2.06%	2.13%	2.09%
Materials and Supplies	3.76%	4.00%	3.96%	3.82%	3.89%
Equipment	1.80%	1.63%	1.59%	1.52%	1.63%
Other	1.52%	1.38%	1.46%	1.54%	1.48%
All Nonpersonnel Except Energy	7.07%	7.01%	7.01%	6.88%	6.99%

Note: Budget shares used in the calculation of the GCEI are shaded.
[1]Subtracted from non-professional contracts and other charges.

We first divided expenditures into four broad categories: instructional personnel, nonteaching professionals, nonprofessional personnel, and nonpersonnel expenditures. Among instructional personnel expenditures we include general education, special education and adult education. Expenditures for administration, mid-level administrators, health services, and student services are grouped under nonteaching professionals. Expenditure categories of maintenance, operations, and food service best capture services provided by nonprofessional personnel. Finally, under nonpersonnel expenditures we included energy costs, materials and supplies, equipment, and miscellaneous other expenditures. Expenditures on transportation, capital, debt service, and community services are removed from the expenditures.

Under the three types of personnel expenditures, we developed budget shares for wages and salaries, fringe benefits, and contracts and other charges. As discussed in Chapter 2, contracted services and other charges is a composite of a number of types services provided to school districts, some of which could be provided by district personnel. If the district chose to provide these services in-house, then most of those costs would have been recorded as salary expenditures. We have assigned these expenditures to the three personnel categories: instruction, nonteaching professionals, and nonprofessional staff.

As expected the vast majority of expenditures (90 percent) are related to personnel (Table 4-22). Approximately two-thirds of expenditures are related to instructional personnel, 13 percent to nonteaching professionals, and 10 percent to nonprofessional expenditures. Energy expenditures represent only 2 percent of overall expenditures. Finally, roughly 7 percent of expenditures are for supplies, materials, equipment and miscellaneous, which are assumed not to vary across districts due to factors outside district control. The budget shares remained very stable over these four years.

B. Calculating the GCEI

The GCEI is simply a weighted average of the cost indices calculated for professional employees, nonprofessional employees, and energy costs. The weights are the budget shares for these categories. The construction of the GCEI can be represented as:

$$GECI = \lambda_1 PPCI + \lambda_2 \ NPCI + \lambda_3 \ ECI + \lambda_4 \ . \qquad (1)$$

The budget shares are for instructional and nonteaching professionals ($\lambda_1 \approx 80.5\%$), nonprofessional staff ($\lambda_2 \approx 10.5\%$), energy expenditures ($\lambda_2 \approx 2\%$), and other expenditures assumed not to vary across districts ($\lambda_2 \approx 7\%$). The budget shares are multiplied by the indices presented earlier in this chapter to produce the GCEI. Table 4-23 provides the calculated GCEI values for Maryland school districts from 1999 to 2002 (based on the OLS regression model for PPCI).[58]

Table 4-23. GCEI Results (Based on OLS Regression)
(Index Relative to Simple Statewide Average)

District	1999	2000	2001	2002
Lea 1, Allegany	0.969	0.967	0.962	0.959
Lea 2, Anne Arundel	1.008	1.009	1.015	1.018
Lea 3, Baltimore	1.011	1.007	1.006	1.008
Lea 4, Calvert	1.003	1.021	1.023	1.021
Lea 5, Caroline	1.018	1.005	1.005	1.000
Lea 6, Carroll	1.008	1.011	1.014	1.014
Lea 7, Cecil	0.997	0.992	0.989	0.989
Lea 8, Charles	1.007	1.023	1.023	1.020
Lea 9, Dorchester	0.999	0.982	0.982	0.978
Lea 10, Frederick	1.010	1.020	1.022	1.024
Lea 11, Garrett	0.964	0.953	0.949	0.948
Lea 12, Harford	0.993	0.996	0.994	0.992
Lea 13, Howard	1.011	1.011	1.013	1.015
Lea 14, Kent	1.003	1.002	1.005	1.010
Lea 15, Montgomery	1.024	1.026	1.030	1.034
Lea 16, Prince George's	1.037	1.039	1.044	1.048
Lea 17, Queen Anne's	1.004	1.003	1.007	1.011
Lea 18, St. Mary's	1.011	1.002	1.004	1.002
Lea 19, Somerset	0.981	0.978	0.972	0.973
Lea 20, Talbot	0.989	0.989	0.992	0.991
Lea 21, Washington	0.983	0.979	0.979	0.974
Lea 22, Wicomico	0.977	0.975	0.971	0.971
Lea 23, Worcester	0.963	0.963	0.960	0.959
Lea 30, Baltimore City	1.029	1.045	1.037	1.042

[58] The correlation of the GCEI based on the OLS is 0.94 or higher with the GCEI based on the fixed effects model. The GCEI based on the fixed effects models is available in appendix Table B-7.

As would be expected given the high budget share for professional personnel, the GCEI is very highly related to the PPCI (correlations above 0.96). The variation in index values for the GCEI is about the same as for the PPCI, ranging in 2002 from 0.948 in Garrett County to 1.048 in Prince George's County. Baltimore City has a GCEI that is 3 to 4 percent above the average district. When examining Table 4-23, it is clear that GCEI values changed little over this four-year period. The correlations between years are all above 0.94, and the average fluctuation in the index value across years is less than one-half of a percent.

6. Conclusions

The construction of the GCEI is both a science and an art. We have attempted to provide as much detail as possible in this chapter, so that the choices we made and the methodologies we used are transparent to policymakers, administrators, and researchers who have an interest in using the GCEI. We believe the GCEI, whose calculation is described in this chapter, represents the state of the art methodology as it now stands. Furthermore, as we describe here, although it was necessary to make some decisions that have consequential effects on the GCEI values for each district, for the most part the values are robust across a variety of different hedonic model specifications. Finally, it is again worth stressing that the GCEI we have calculated is quite stable over time. This is reassuring because it reflects the relative stability of the underlying conditions in each district that are likely to shape employee perceptions of a district's attractiveness as a place of employment, and because the GCEI, should it be implemented as a part of Maryland's State Aid formula, is unlikely to result in extreme year to year swings in resource allocations to school districts.

Chapter 5

External Tests of Validity

One alternative to the hedonic salary method for estimating geographic cost of education differences is to develop some type of competitive wage index (Goldhaber, 1999; Hanushek, 1999). One benchmark we might use to assess whether our hedonic results tend to reflect general trends in the labor market is to compare them to differences we observe in wages in each district. We describe this comparison in the first sub-section of this chapter.

As we described earlier, the underlying theory of the GCEI is that, all else equal, in order to attract employees of a given quality, districts that are less attractive places to work need to offer higher salaries. Thus, a measure of adjusted salary is serving as our measure of district attractiveness. An alternative way to judge the attractiveness of a given district is to examine whether the district is losing a disproportionate share of its teachers. If our measure of attractiveness does indeed represent the true attractiveness of various districts, we would expect a relationship between it and other measures of attractiveness, such as the percentage of teachers who leave the same districts. In other words, the relationship between the TCI (or the PPCI in the case of professionals) and district leavers provides a test of external validity for our measure of districts' attractiveness. We describe the results of this test in the second sub-section of this chapter.

1. Competitive Wage Index

A competitive wage index provides a measure of wages in one district relative to another. Some researchers have in fact suggested that this type of index may be a more appropriate measure of the impact of cost factors on wages than a hedonic model of teacher/school personnel salaries, due to the fact that salaries in education are not set in a perfectly competitive environment.[59] The states of Ohio and Massachusetts use a private wage index to measure cost of education differences. In Table 5-1 we show several wage indices for all counties in Maryland for 2002. These indices are created by taking the ratio of average wages in a county to the average of these county averages. We provide two different relative wage measures. The first is for all sectors of the economy, and the second is for those employed in business and professional services, which may serve as a better measure the type of employment school professionals (including teachers) would be engaged in were they not employed in school systems.[60]

One striking difference between the relative wage index and the PPCI is the extent that the index varies from one district to the next. For example, the average wage of the low wage district is less than half of that of the high wage district, whereas the differential between the lowest and highest PPCI values is closer to 10 percent.

One possible explanation for the significantly greater variation in the wage indices compared to the PPCI is that the private wage data is for average payroll by industry, not wages by occupations. Average payrolls are simply the total payroll divided by the total number of employees. Besides differences in the underlying wages for similar occupations (what we want to measure), there are three other reasons for variation in average payrolls across counties.

First, there may be a difference in the number of fulltime workers relative to part-time workers. If a county had a higher share of part-time jobs compared to another county, we would expect a lower average payroll, assuming all else is equal. Second, there may be a different mix of industries in one county compared to another. Even in the business and professional services

[59] This issue is discussed in greater detail in the next sub-section.
[60] For a discussion of the type of jobs teachers take upon leaving the teaching profession, see Goldhaber and Player (2003).

sector, one county may have relatively more employment in higher paying industry sub-sectors compared to another county.

Table 5.1. Relative Wage Index

LEA	County	All Sectors	Business and Professional Services
1	Allegany	0.808835	0.628143
2	Anne Arundel	1.224368	1.318665
3	Baltimore	1.193587	1.124275
4	Calvert	1.049947	1.320116
5	Caroline	0.803705	0.883462
6	Carroll	0.923406	0.805126
7	Cecil	1.012326	0.797872
8	Charles	0.916566	1.018375
9	Dorchester	0.834485	0.594778
10	Frederick	1.082437	1.090909
11	Garrett	0.718204	0.709381
12	Harford	0.949056	0.995164
13	Howard	1.383399	1.550774
14	Kent	0.808835	0.912476
15	Montgomery	1.492839	1.517408
16	Prince George's	1.214108	1.259188
17	Queen Anne's	0.807125	0.969052
19	Somerset	0.819095	0.773211
18	St. Mary's	1.108087	1.402805
20	Talbot	0.930246	0.809478
21	Washington	0.962736	0.794971
22	Wicomico	0.935376	0.905222
23	Worcester	0.663484	0.635397
30	Baltimore City	1.357748	1.183752

Finally, even within the same industrial sub-sector, industries can vary in the types of employees they hire. One manufacturing firm could choose, for example, to do all design work in-house with its own engineers, while another could contract these services out. The first business may have a higher average payroll than the second firm even if they pay the same salaries for the same occupations. Ideally, we would use fulltime salary information by occupational category, but this data is not available on a county level.

If there are factors in a district that make the district a relatively attractive or unattractive place to work for school personnel, we might expect them to also be related to the preferences of employees outside of the teaching profession. Thus, wages in other sectors outside of teaching should be related to our measure of districts' attractiveness, the PPCI. To test this, we correlate these two wage indices with our PPCI (based on the OLS specification reported in Table 4-13). The correlations are 0.67 and 0.63 for wages in all sectors and wages of business and professional services employees. These strong correlations provide good evidence that our hedonic salaries models do in fact reflect district characteristics that also affect wages of other sectors of the economy.

2. Comparison with Attrition Rates and Private Sector Wages

Table 5-2 reports the percentage of professionals who leave a particular district ("leavers") for any reason – that is, they are in a particular district in one year and not in the district in the next – as well as the percentage who leave a particular district to move to another district in the state ("movers"). The percentage of leavers and movers are both measures of attractiveness of a school and district. Research clearly shows that teachers are more likely to leave certain districts, particularly those with difficult working conditions (Hanushek et al, 2003; Lankford et al, 2002). Both, however, are imperfect measures. Leaver rates reflect the loss of teachers both to other districts and other states – a sensible measure of attractiveness – but they also reflect the loss of teachers for other reasons not related to a district's attractiveness, such as retirement. Mover rates provide a narrower measure of districts' attractiveness, however, they do not account for the loss of teachers to LEAs outside of Maryland. In practice, both measures appear to be picking up similar decisions since the correlations between them are moderate to strong (0.61, 0.38, and 0.52 in 1999-00, 2000-01, and 2001-02, respectively).

Table 5-2. Percentage of Movers and Leavers By Year and District

	1999-2000		2000-2001		2001-2002	
LEA	Leaver Rate	Mover Rate	Leaver Rate	Mover Rate	Leaver Rate	Mover Rate
1	9.30%	0.65%	10.28%	0.33%	11.11%	0.42%
2	11.58%	0.98%	12.93%	1.05%	11.48%	1.17%
3	13.23%	1.81%	15.61%	1.42%	12.22%	1.32%
4	8.82%	0.94%	14.26%	1.31%	9.16%	0.74%
5	9.56%	2.21%	23.27%	2.48%	10.96%	3.21%
6	8.79%	1.22%	15.04%	1.09%	10.23%	1.21%
7	9.81%	0.59%	12.85%	0.31%	10.63%	0.40%
8	15.49%	3.67%	16.83%	2.31%	17.21%	2.70%
9	11.17%	3.72%	13.95%	3.42%	13.72%	2.90%
10	11.06%	1.29%	19.00%	0.73%	11.09%	0.64%
11	2.87%	0.00%	8.44%	0.43%	5.69%	0.44%
12	9.02%	1.46%	13.05%	1.32%	9.74%	0.75%
13	10.45%	1.66%	13.83%	1.05%	11.60%	1.10%
14	9.21%	1.26%	10.74%	2.07%	11.86%	1.58%
15	11.38%	0.39%	15.99%	0.45%	10.84%	0.27%
16	16.04%	3.52%	15.05%	1.99%	14.19%	1.46%
17	15.72%	2.27%	16.73%	2.09%	11.35%	1.95%
18	11.49%	2.22%	13.67%	1.54%	10.41%	1.56%
19	10.00%	5.00%	24.50%	2.68%	15.36%	4.64%
20	18.67%	3.73%	29.40%	1.57%	25.50%	2.75%
21	7.98%	1.13%	10.67%	1.52%	8.80%	0.73%
22	11.31%	0.98%	13.44%	1.43%	10.29%	0.85%
23	13.81%	2.06%	10.58%	1.07%	6.60%	1.20%
30	14.41%	3.06%	16.08%	2.38%	18.89%	1.15%
State Average	11.30%	1.91%	15.25%	1.50%	12.04%	1.47%

We would expect a positive correlation between both the PPCI and leaver and mover rates given the assumption that both measure district attractiveness.[61] As we report in Table 5-3, which shows the correlation between the PPCI (based on the OLS specification reported in Table 4-13) and both leaver and mover rates, we do in fact see a positive relationship, however this relationship is not very strong.[62]

Table 5-3. Correlation between PPCI and Leaver/Mover Rates

	1999-2000	2000-2001	2001-2002
PPCI and Leaver Rate	0.3606	0.1919	0.3209
PPCI and Mover Rate	0.2720	0.2001	-0.0557

The correlation between the PPCI and leaver rates is in the 0.20 to 0.36 range, whereas the correlation between the PPCI and mover rates tends to be less strong, ranging from slightly less than zero to 0.27.[63] Though the positive correlations provide external validation that PPCI is in fact measuring differences in districts' attractiveness, we would have preferred to find an even stronger relationship. One possible explanation for the lack of a stronger relationship is that the hedonic model may fail to fully represent the dynamics of the teacher labor market. In particular, the hedonic model implicitly assumes a competitive labor market. While the setting of school salaries may have competitive elements (in the sense that school districts adjust their salaries in response to changes in the salaries of competing jurisdictions), these salaries are set in the public sector and therefore subject to political as well as economic forces. Consequently the

[61] We use the PPCI here since it is the component of the GCEI that measures districts' attractiveness to professional employees.
[62] We correlate the mover and leaver rates with the PPCI from the year before the move. Thus, for example, the 1999-2000 mover and leaver rates are correlated with the 1999 PPCI.
[63] We also correlated the leaver and mover rates with the PPCI calculated from the fixed-effects specification of the model. These correlations were similar but slightly less strong than the reported correlations with the OLS model.

setting of salaries in the teacher labor market may not be consistent with the setting of salaries in the private sector.

One potential problem is that of asymmetric information. Teachers are employed in particular school districts only when they wish to work in the district, and the district wishes to employ them. If a district sets salaries too low, some teachers will opt not to work in that district, and we can empirically observe this decision. However, we will not observe those cases when a district sets teacher salaries at a level above that required in order to attract a given set of teachers into the district, and the hedonic model implicitly assumes that salaries are set exactly at the level required to attract teachers.

As a check on this possibility, we included in Table 5-4 the correlation between district average free/reduced price lunch (FRPL) percentages and the leaver and mover rates. Although the correlations between FRPL and leaver rates are no stronger than are the correlations between the PPCI and leaver rates (shown in Table 5-3), the correlations between FRPL and mover rates are substantially stronger.

Table 5-4. Correlation between Free/Reduced Price Lunch & Leaver/Mover Rates

	1999-2000	2000-2001	2001-2002
FRPL and Leaver Rate	-0.0100	0.0778	0.2582
FRPL and Mover Rate	0.3990	0.4281	0.3087

Empirical evidence suggests the primary reason why teachers move from one school to another or one district to another is differences in working conditions, as represented by differences in student demographics (Hanushek et al, 2004; Lankford et al, 2002). In fact, recent research findings (Hanushek et al., 2004)) suggest that teachers must be paid substantial "compensating differentials" (also often referred to as "combat pay") to entice them to teach in high poverty urban areas; the estimate of the amount necessary is on the order of 25 to 40 percent of salary depending on their experience. These differentials are far higher than those that we calculate based on our PPCI. This discussion does not imply that the hedonic model is not currently the most appropriate methodology to use in order to make adjustments for differences in districts' attractiveness. Rather, it suggests that the state may wish to closely monitor this area of research so as to be aware of, and utilize, evolving state-of-the-art techniques to detect the influence of various cost factors on employee willingness to work in a particular location.

Chapter 6

Implementation Analysis for the Maryland GCEI

Once a measure of geographic cost of education differences across school districts in Maryland has been developed, decisions also need to be made on how this index will be updated and used in state aid formulas. The objective of this chapter is to discuss these implementation issues. Specifically, we will examine three areas: 1) inclusion of the GCEI in the foundation program; 2) inclusion of the GCEI in other education aid programs; and 3) updates of the GCEI. The objectives of this chapter are to recommend how the GCEI should be implemented within the existing aid system, and to recommend possible modifications of existing aid programs to be more consistent with the findings of education finance research.

1. Implementing the GCEI in the Foundation Program

With the implementation of the Bridge to Excellence in Public Schools Act of 2002 (Senate Bill 856), the financing system for public education in Maryland will change substantially between FY 2004 and FY 2008.[64] The legislation consolidates the large number of previously existing aid programs into four broad categories of programs: 1) the Foundation Program; 2) three programs for special needs students; 3) a general matching grant to encourage local tax effort; and 4) several other types of aid programs. Under the Bridge to Excellence Act, MSDE was required to hire a consultant to develop a method for calculating the GCEI as well as recommend how it should be included in the Foundation Program. The objective of this section is to examine the latter issue, inclusion of the GCEI in the Foundation Program. We will begin

[64] Our analysis of existing aid programs in Maryland is based heavily on Maryland Department of Legislative Services (2002), Volume I; and MSDE (2003d).

by examining the aid program in 2008 when the Foundation Program is fully implemented, and then turn to possible implementation options during the 2004 to 2008 time period.

A. Foundation Programs in Theory

The Maryland Foundation Program is similar in many respects to classic foundation programs implemented by most states in the country (NCES, 2001). A standard expenditure foundation program can be represented as:

> ***Expenditure Foundation:***
> *Total aid = (Foundation expenditure per pupil x Enrollment) –*
> *(Minimum local contribution rate x Local tax base).*

The state sets the minimum (foundation) level of spending per pupil and the minimum local contribution rate. If the required local revenue contribution is less than the required foundation spending level, then the school district receives the difference in state aid. If the required local contribution is greater than the foundation level, then a fully implemented formula would include "recapture" of the difference by the state for distribution to less wealthy districts. In reality, most states set state aid in this case to zero or possibly some minimum level of state aid (Yinger, forthcoming, appendix A).

While a classic foundation is easy to understand, it does not correspond well with an adequacy standard. Adequacy is usually defined as either an adequate level of resources in all districts or sufficient resources to provide students the opportunity to reach an adequate level of student achievement (Duncombe, Lukemeyer, Yinger, 2003). A resource adequacy standard implies that the foundation level is adjusted for differences in the cost of education across districts. A performance adequacy standard implies adjustment for not only education costs, but for differences in student needs. A classic foundation can be modified to match a resource adequacy standard by multiplying the foundation spending level by a geographic cost of education index (GCEI).

Resource Adequacy Foundation: *Total aid = (Foundation expenditure per pupil x GCEI x Enrollment) –* *(Minimum local contribution rate x Local tax base) .*

The resource adequacy foundation program will allow the foundation spending level to vary across districts according to differences in education costs. However, if the focus of the adequacy standard is student performance, then it is important to control for differences in student needs across districts as well.[65] To change the expenditure foundation to a performance adequacy foundation involves simply multiplying the foundation expenditure per pupil by the GCEI and the total weighted pupil count.[66] The weighted pupil count is distinguished from enrollment by the fact that it includes adjustments for students' needs.

Performance Adequacy Foundation: *Total aid = (Foundation expenditure per pupil x GCEI x Total weighted pupils) –* *(Minimum local contribution rate x Local tax base) .*

The foundation spending level per pupil would therefore vary across districts both because of geographic cost differences and the share of high need students.

---

[65] As we have described above in Chapters 2 and 4, these differences in student needs may also influence the GCEI.

[66] This approach is similar to that recommended by Duncombe and Yinger (1998), Reschovsky and Imazeki (1997), and Duncombe, Lukemeyer, and Yinger (2003). They used a comprehensive cost index that accounts for both resource cost differences and student needs rather than including the GCEI and the total weighted pupils separately. Total weighted pupils will be defined in the Maryland context later in this chapter. Their approach also incorporates an adjustment for economics of size (or sparsity).

B. Maryland Foundation Program with Full Implementation (FY 2008)

The Maryland Foundation Program is designed to achieve a resource adequacy standard by including a geographic cost of education index in the calculation of foundation aid. The higher aid required for special needs populations is dealt with in separate aid programs. The Maryland Foundation Aid Program in FY 2008 can be represented as (Department of Legislative Services, 2002):

> ***Maryland Foundation Program:***
> *Aid = [(Per Pupil Foundation amount x Enrollment) –*
> *(Local contribution rate x Local wealth)] x GCEI .*

Total aid will be determined by multiplying the per pupil foundation amount by enrollment to get the total foundation level. Total wealth in a district is calculated as the sum of 100 percent of the assessed value of the operating real property of public utilities, 40 percent of real property assessable base, 50 percent of personal property assessable base, and net taxable income. The state-set local contribution rate, which is the same for all districts, will be calculated based on a local share of 50 percent using the following formula:

> *Local contribution rate = (Foundation level x Total statewide enrollment x 50%) / Total statewide wealth.*

Aid provided to a district is not allowed to drop below a minimum aid level, which will be calculated in 2008 as 15 percent of the foundation level times enrollment in the district. In FY 2004, the minimum aid level is 25 percent of the foundation amount. In FY 2004, this minimum applies to three districts (Montogomery, Talbot, and Worcester), totaling an additional $14.2 million in State Aid (MSDE 2003c). While a minimum aid level may be a necessary political compromise, it essentially removes wealthy districts from the foundation formula. Assuming a limited amount of State Aid resources, the higher the minimum aid level is set, the more districts will be removed from the formula, and the less money will be available for distribution to low wealth and high cost districts.

C. Adding the GCEI to the Foundation Program

Presently, the cost of education adjustment (GCEI) is set at one for all but four districts (Anne Arundel, Baltimore City, Howard, and Montgomery) with cost adjustments ranging from 1 percent in Anne Arundel (index of 1.01) to 4 percent in Montgomery (index of 1.04). Assuming that these are the four districts with above average costs, the present index artificially truncates the index at one. Any GCEI below one is set to one, to prevent any district from losing money because of the cost adjustment. The cost adjustment is applied to the minimum aid level as well as regular foundation aid.

The GCEI developed in this study could simply be substituted for the present index. However, it must be decided what the base of the index will be, and whether the index should be truncated at one to guarantee that no district loses aid. The indices presented in Chapter 4 are all centered on the average district. If these are substituted into the Foundation Program, many districts would receive an adjustment down in their foundation aid, because they have below average costs. If reductions in state aid are not desirable, several approaches can be used to assure no district receives less aid due to the cost of education adjustment. One alternative is to use the present approach by setting any index values below one to equal one to prevent any reduction in aid. The second approach is to use as the base of the index the district with lowest cost; all other districts but this one will receive an increase in aid from the cost adjustment.

The first approach is simple and could be less costly to the state than the second approach, but it does not preserve the full range of the predicted differentials between districts in education costs. Thus, it essentially removes much of the variation in the index, and could significantly limit the impact of the cost of education cost adjustment. Furthermore, to the degree that education resources are limited, the setting of a lower bound of 1 disadvantages those districts with calculated costs that are higher than the average district cost because their GCEI adjustment relative to districts with actual GCEIs calculated to be less than one is diminished.

A second issue is whether there should be cost adjustment for districts receiving minimum aid. Given that minimum aid by definition removes districts from the foundation aid program, providing a cost adjustment for these districts does not appear justified under an adequacy standard. In addition, minimum aid has the same impact as above in diverting a limited state aid budget away from districts with less fiscal capacity.

The present approach for adjusting for cost of education differences is fundamentally different from a resource adequacy foundation program discussed previously. The present program adjusts aid for cost of education differences rather than the foundation level. In essence, the present approach is equivalent to multiplying both the foundation level and district wealth by the GCEI. While adjusting the foundation level for additional resource costs fits the adequacy goals of the program, multiplying wealth by the GCEI is not consistent with the design of a resource adequacy foundation program. The wealth of the district is included in the formula to capture the fiscal capacity of the district to raise local revenue to support schools. There is no reason to adjust it for geographic cost of education differences. By adjusting calculated aid by the GCEI rather than the foundation amount, more below average cost districts receive formula aid (as opposed to minimum aid). This provision along with the truncation of the cost adjustment at one both work to distribute more aid to low cost districts than they would receive under a similar resource foundation program.

D. Implementation of Maryland Foundation from FY 2004 to FY 2007

In the Senate Bill 856 phase-in period between FY 2004 and full implementation of the Maryland Foundation Program in FY 2008, the formula is to transition from the old formula to the new foundation program. The transition would occur in several ways. First, the per pupil foundation amount is to transition from the state-set foundation level in FY 2002 of $4,124 per pupil to the target per pupil amount established as part of Senate Bill 856. In FY 2004 the target amount is $5,730 and this is to increase over time due to inflation. In FY 2004, the Act provided that 40 percent of the difference would be funded, and this would gradually increase to 100 percent by FY 2008. Second, the state share for the historical "first tier" amount of $624 per pupil is to transition from 54 percent in FY 2004 to 50 percent by FY 2008. This latter transition affects the calculation of the local contribution rate.

Under the present formula, neither of these transition adjustments affects the application of the GCEI since it is applied to final calculated aid (or minimum aid). It is possible that the GCEI could be phased in over time by multiplying it by a phase-in adjustment. For example, the phase-in rate could be set the same as that used for funding the difference between the target foundation level and FY 02 foundation level (FY 04 is 40%, FY 05 52%, FY 06 71%, FY 07 83%, and FY 08 100%). The foundation formula with phase-in of the GCEI could be represented as:

Maryland Foundation Program (with phase-in from 2004-2007):
Total Aid = [(Foundation expenditure per pupil x Enrollment) –
(Local contribution rate x Local wealth)] x ((Phase-in rate x (GCEI -1))+1) .

If a resource adequacy foundation is used instead (where GCEI is multiplied by the foundation level), then the cost adjustment could be phased in as well. This could help reduce the cost of applying the GCEI, particularly if the GCEI is set at one for the district with the lowest cost. The following represents a possible transition formula:

Resource Adequacy Foundation (with phase-in from 2004-2007):
Total aid = [((Phase-in rate x (GCEI -1))+1) x (Foundation expenditure per pupil x Enrollment)] – (Minimum local contribution rate x Local tax base) .

E. Recommendations for Maryland Foundation Program

Existing aid formula: If the present foundation formula is used, then the application of the GCEI is straightforward since a placeholder is already in place in the formula. There are two modifications we would make to the present formula. First, ***the GCEI should not be applied to the minimum aid provision***. Minimum aid effectively removes a district from the Foundation Program by giving the district more aid then they would get under the program. In this case, the logic of using the GCEI really does not apply, because the district is off the formula anyway. Second, ***the GCEI should not be artificially truncated so that cost adjustments for districts with below average costs are set at zero***. If the GCEI is going to be included in the formula its full variation should be allowed to affect aid levels. Generally, the GCEI would be centered at the state average (average equals one). However, if the state did not want any district to receive reduced foundation aid because of the application of the GCEI, then the GCEI for the district with the lowest costs could be set at one. As demonstrated above, this cost adjustment could be phased in to reduce the financial implications of the GCEI.

Modifications of the existing formula: If modifications to the existing formula are possible, then we would recommend several changes to the formula so that it more closely matches the adequacy objectives of the Bridge to Excellence Act.

1. The GCEI should be multiplied by the foundation level (instead of final calculated aid), to provide an estimate of the adequate resources required in each district to support regular students.

2. The GCEI should be allowed to vary over its full range, rather than be truncated at one for districts with below average costs. If the state does not want a reduction in the required foundation level for districts with below average costs, then the GCEI for the district with minimum costs should be set at one.

3. If the impact of the GCEI needs to be phased in due to financial constraints, then we recommend that the GCEI be applied to only a part of the foundation initially, and then phased in to apply to the full foundation level by FY 08.

4. Minimum aid provisions should be eliminated, because they are inconsistent with the intent of an adequacy standard in the Bridge to Excellence Act. With minimum aid provisions, districts with high fiscal capacity receive more foundation aid than they are entitled to under a foundation formula, which effectively removes them from the foundation program. Given limited state financial resources, minimum aid removes state aid from districts with lower fiscal capacity and/or higher resource costs.

2. Implementing the GCEI in Other Aid Programs

The GCEI was originally intended to modify the Foundation Program to assure adequate resources in districts for regular education. However, there are several other aid formulas where the GCEI could be used to account for cost of education differences. Our objective in this section is to suggest modifications to other aid programs to use the GCEI (or one of its components) that appear consistent with the intent of the Bridge to Excellence in Public Schools Act.

A. Special Needs Programs

Existing programs: A key part of the Senate Bill 856 legislation was the creation or expansion of programs to provide aid to districts with special needs students. The three groups of students addressed in these programs are special education students, students at risk, and students with limited English proficiency (LEP). While programs for these populations existed prior to passage of Senate Bill 856, this legislation expanded the size of these programs and modified the distribution of aid.

All three programs have a similar design. The per-pupil funding level established in the Foundation Program is multiplied by the pupil weight for each type of special needs student. The result is the adjusted targeted per pupil amount, which is then multiplied by the state share to determine the special needs aid per pupil in the district with average wealth per pupil. The weights used in constructing the adjusted targeted per pupil amount are 0.74 for special education, 0.99 for at-risk students, and 0.97 for limited English proficient students.[67] The pupil weights are less than 1, but this still implies increases of aid to districts with more special needs students since these programs are supplemental to the funding that is received for regular education students.

The state share is the same as the state share established in the foundation program (50% in FY08). The final aid received by a district is wealth equalized as indicated in the following aid formula (Dept. of Legislative Services, 2002):

Maryland Special Needs Aid Programs: *Aid = [(Special needs aid per pupil x Enrollment of special needs students) / (Local wealth per pupil / Statewide wealth per pupil)] x Reducing factor .*

The "reducing factor" is used to adjust the aid received by the districts to the total aid budget for each program (reducing factor = total state aid budget/calculated state aid amount without adjustment). The reducing factor is simply multiplied by the calculated state aid for each district. The state guarantees that the district will receive special needs aid equal to 80 percent (in FY08) of the state aid per pupil in the district with average per pupil wealth (ratio of local wealth per pupil to state wealth per pupil equal to one). In essence, this minimum aid provision guarantees that even high wealth districts will receive substantial state aid per special needs pupil, which is further reinforced by the fact that the "reducing factor" does not apply to this minimum aid provision. Another key feature of these special needs programs is that districts are not required to contribute the difference between the target per pupil amount for special needs students, and the state share of aid.

[67] The target weights used as a benchmark were 1.17 for special education, 1.10 for at-risk children, and 1.00 for LEP students. These weights were reduced to reflect funding for special needs students from other federal or state aid programs (Dept. of Legislative Services, 2002).

Comparison with performance-based foundation formula: School finance research has examined different aid formulas to determine which formula best matches a performance adequacy standard (Ladd and Yinger, 1994, and Duncombe and Yinger, 1998). As presented in the first section of this chapter, a foundation formula can be modified to be a performance adequacy foundation by simply multiplying the foundation level per pupil by the GCEI and total weighted pupils.

If the total weighted pupil count is broken down into its basic components, then the aid formula would begin to look very much like a combination of the Foundation Program and special needs programs in Maryland. The foundation spending level is first multiplied by the GCEI to get the cost-adjusted foundation. The cost-adjusted foundation can then be multiplied separately by enrollment and the weighted pupil count for each type of special needs students. The result is the revised estimate of the required funding for a district to provide an opportunity for both regular education students and special needs students to reach the adequacy standard:

Performance Adequacy Foundation: *Total Aid = (Per pupil foundation amount x GCEI) x [(Enrollment + (Special education students x 0.74) + (At-risk students x 0.99) + (LEP students x 0.97)] – (Minimum local contribution rate x Local tax base) .*

While this formula is very similar to a combination of the present Foundation Program and special needs programs, there are some important differences. In a performance adequacy foundation, the per pupil foundation amount is multiplied by the GCEI for both the regular education students and the special needs students. If the objective is to provide districts with adequate resources to help all students reach state standards, then the resource levels for special needs students as well as regular education students should be adjusted for cost of education differences across the state. Second, a performance foundation applies the same local tax effort requirements to all types of students. Districts are not provided the option of whether to fully fund the local share of aid.

Recommendations for modifying special needs programs: Based on the differences between the present special needs programs and the performance-based foundation programs proposed in the education finance literature, it is possible to make several recommendations for modifying the present formula.

1. The GCEI should be multiplied by the per pupil foundation amount in calculating the target per pupil amount.

2. The state should either fund the full amount of the program (instead of half) or require a local contribution to assure local district appropriations for special needs students reaches the target per pupil amount. Otherwise, it is quite possible that poor districts in particular will not fully fund these programs. The result could be significant differences in the quality of services provided to special needs students across the state.

3. The minimum aid provisions should be dropped. Minimum aid provisions subsidize wealthy districts, thereby diverting funds from districts with less local fiscal capacity to fund programs for special needs students.

B. Guaranteed Tax Base (GTB)

Existing formula: Senate Bill 856 established for the first time in Maryland a wealth-equalized general purpose matching grant with the intent of encouraging tax effort in districts with below average wealth. The Guaranteed Tax Base program is a variant of one of the most common types of matching grants used in education. In the Maryland program, only districts with wealth per pupil below 80 percent of the state average will receive aid, and only for the local tax effort above that required in the Foundation Program. The GTB formula can be represented as (Dept. of Legislative Service, 2002):

Maryland Guaranteed Tax Base Program:
Aid = Local effort x (80% of statewide wealth per pupil – Local wealth per pupil) x Local enrollment .

Local effort = (Local education appropriations – Local share of foundation) / Local wealth .

The grant is technically a "closed-ended" matching grant, because it limits aid to no more than 20 percent of the per pupil foundation amount established in the Foundation Program. If this grant is successful in encouraging many low wealth districts to raise their tax effort to the ceiling level, it will become in effect another fixed grant supplementing the Foundation Program.

Adding the GCEI to the GTB: If the intention of the Guaranteed Tax Base program is to supplement the Foundation Program and encourage local tax effort, then the use of the GCEI to adjust local expenditures to reflect local costs is just as appropriate here as with the Foundation Program. The measure of local fiscal capacity used in this program is the local wealth base. However, the same level of wealth in districts with low education costs can buy more education resources than in a district with high education costs. A simple modification of the GTB program to account for education costs would be to divide the local wealth base by the GCEI (Duncombe and Yinger, 1998; Ladd and Yinger, 1994):

Maryland Guaranteed Tax Base Program (with GCEI):
Aid = Local effort x [80% of statewide wealth per pupil – (Local wealth per pupil / GCEI)] x Enrollment .

A district would receive aid if the local effort rate was positive, and the local wealth per pupil divided by the GCEI is less than 80 percent of the state average wealth per pupil. A district with a GCEI above one could receive aid if wealth was greater than 80 percent of the state average, while a district with GCEI below one would require local wealth less than 80 percent of the state average to receive aid. As with the foundation, if the State wanted to guarantee that no one lost aid because of the GCEI, it could set the GCEI at one for the district with the lowest costs.

Adjusting GTB for special needs students: Another modification to this program, which would be consistent with the focus on student performance in the Bridge to Excellence Act, would be to account for the share of special needs students in a district in allocating GTB aid. Low wealth districts do not all have the same share of special needs students. A modification to the GTB to account for differences in special needs student populations would be to divide the wealth per pupil in a district by a weighted pupil index, based on the number of total weighted pupils in a district. Total weighted pupils could be defined as:[68]

Total weighted pupils = Enrollment + (Special education students x 1.17) + (Free and reduced price meals students x 1.1) + (LEP students x 1.0) .

The total weighted pupil index can be calculated at the ratio of the local weighted pupils as a percent of enrollment and statewide weighted pupils as a percent of enrollment.

Weighted pupil index = (Local total weighted pupils / District enrollment) / (Statewide total weighted pupils / Statewide enrollment) .

The adjusted GTB formula would be:[69]

[68] The student need weights used in this formula correspond to the benchmark weights estimated in the adequacy study (Augenblick and Myers, 2001), but with some adjustments to the at-risk student weight (Department of Legislative Services, 2002).

[69] This approach is similar to that recommended by Ladd and Yinger (1994), and Duncombe and Yinger (1998). They used a comprehensive cost index that accounts for both resource cost differences and student needs rather than the product of the GCEI and the weighted pupil index. An alternative approach would be to substitute total weighted pupils for district enrollment in the GTB formula. While this approach would increase aid to low wealth districts that had high special needs populations, it would not help districts with average wealth but with high special needs populations. These districts may have as much difficulty financing an adequate education as a low wealth district with relatively low special needs populations. In addition, this approach could raise the cost of the GTB program considerably.

Maryland Guaranteed Tax Base Program (with GCEI and student needs): *Aid = Local effort x [80% of statewide wealth per pupil –* *(Local wealth per pupil / (GCEI x Weighted pupil index))] x Enrollment .*

A district would receive GTB aid if the local effort rate was positive and the local wealth per pupil divided by the product of the GCEI and weighted pupil index was less than 80 percent of the state average wealth per pupil.

C. Retirement Funding

Existing program: Under Senate Bill 856 the State of Maryland is required to pay the full retirement contribution for teachers and other eligible staff, whether their salary is funded by local revenue or by state aid.[70] However, the district must reimburse the State for the retirement benefits associated with federal aid. As pointed out in the publication by the Department of Legislative Services (2002, p. 99), "Because the State's contributions relate to employee salaries, this program directs more aid to wealthier counties (where school personnel are generally paid higher salaries) than to less wealthy counties." In addition, poor counties and those with high student needs may have difficulty recruiting senior teachers, and retaining good junior teachers. The result is a teacher workforce that is less experienced and less highly certified than in wealthy counties (Lankford et al., 2002; Hanushek et al, 2004). This program provides incentives to districts to hire more experienced or educated teachers, because of the state subsidy. Moreover, the State has little control over the cost of this program, which could become sizable.

[70] Eligible employees are those that have direct contact with children, which includes teachers, other professionals (e.g., librarians, counselors), and non-professional employees (e.g., teacher's aides, school lunch workers). This provision is covered in Maryland Code : STATE PERSONNEL AND PENSIONS : TITLE 22. EMPLOYEES' AND TEACHERS' RETIREMENT SYSTEMS : SUBTITLE 2. MEMBERSHIP : § 22-205. Membership in the Teachers' Retirement System - Scope.

Possible modifications: A more equitable and efficient solution would be for the State to add the total cost of this program to the Foundation Program, and distribute these funds through the foundation formula. Districts could pay for the state pension out of an expanded foundation grant. The State could require districts to make the retirement contribution, but would not subsidize those districts that choose to have expensive teacher payrolls.

If adding the pension funds to the Foundation Program is not feasible, there are modifications that can be made to the present pension program, which would limit its cost and be more equitable to less wealthy districts. Essentially, the State could define a standard salary per teacher, and agree to fund the pension contribution for this "standard" teacher. In addition, the TCI could be multiplied by the standard salary to adjust salary levels to the higher cost of living or tougher working conditions in some districts relative to others:

Pension aid (based on "standard" teacher):
Aid = FTE teachers x Standard teacher salary x TCI x Pension contribution percent .

The standard salary per teacher could be determined in a number of ways including: 1) estimating the average salary per teacher statewide, or 2) picking a certain teacher profile (in terms of level of experience and educational attainment) and then using a particular salary schedule to determine the standard salary per teacher. The salary schedule could come from a particular district, or could be a statewide average of district schedules. The cost of the program would clearly be affected by how the salary of the standard teacher is determined. It is possible that this type of program will provide an incentive for districts to hire inexperienced and less educated teachers, and to use the teacher pension subsidy for other purposes. The state could require that money only be spent on teacher pensions, and that unused funds be placed in a reserve account for future teacher pension costs.

D. Quality Teacher Incentives

This program was established to provide incentives for districts to hire high quality teachers. The State reimburses districts that provide a hiring bonus ($1,000 per teacher) for new teachers with a 3.5 or higher grade point average. These teachers must agree to teach in Maryland for three years. The State also provides a stipend of up to $2,000 for teachers who are certified by the National Board for Professional Teaching Standards and for teachers with Advanced Professional Certificates who teach in Challenge Schools or schools in the State School Improvement Process (which includes schools formerly designated as Reconstituted or Reconstitution-Eligible). Presently, teachers receive the same bonus regardless of their district of employment. Because some districts will have to pay more to attract high quality teachers than other districts, bonuses and stipends should be multiplied by the teacher cost index (TCI) to provide a more level playing field for districts to compete. This would effectively differentiate the bonuses so that teachers opting to teach in less attractive districts would receive larger bonuses than those opting to teach in more attractive districts.

3. Adjusting the GCEI Over Time

Besides making recommendations about where the GCEI could be used in school aid programs in Maryland, this report is also supposed to address how the GCEI should be adjusted over time. Specifically, how should the GCEI be adjusted on an annual basis to reflect changes in the underlying data used in its construction, and how frequently should the analysis used to construct the GCEI be redone?

A. *Updating the Data Used in the GCEI*

The GCEI developed in this report is based on data primarily from 2001 and 2002 (calendar or fiscal years). At the time the report was prepared, FY 02 data was the most recent information available on staff salaries and characteristics, housing information, expenditures, and school and district characteristics. Thus, there may be as much as a two-year lag between the data used to construct the GCEI and the fiscal year for which it will be applied. Below we address the implications of this lag for the accuracy of the GCEI, and whether the data used in the GCEI should be updated on an annual basis.

The GCEI as an index measures the relative difference in the cost of education resources across school districts in Maryland. The GCEI will change only if the costs of some resources increase faster in some districts than in others. In other words, a general increase in price levels (inflation) that affects all districts equally will not change the GCEI. In the short-run we would not expect there to be large differences in cost growth rates across school districts. This implies that GCEI should remain fairly stable over time, thus the GCEI created using data from 2002 is likely to be highly related to the GCEI using data from 2004. In other words, a GCEI created using FY 02 data is likely to be an accurate estimate of the GCEI using FY 04 data. This was demonstrated in Chapter 4, where the correlations between the GCEI calculated for 2002 (using 2001 data) had a correlation of over 0.90 with the GCEI calculated for 2000 (using 1999 data).

To update the GCEI index, only data for the factors outside district control need to be collected. The new data will be multiplied by the statistical weights in the existing hedonic salary models and the energy model. The result is a prediction of the salary or energy cost in districts with average characteristics for discretionary factors. For each cost category the predicted values for each district will be divided by the average district to construct a revised PCI or energy cost index. New budget shares for each index can be calculated with more recent expenditure data.

How frequently should the data used in the GCEI be updated? Given the stability of the GCEI, it is quite possible that the GCEI would need to be updated only every three to five years. One advantage of updating the data on an annual basis is precisely because there are likely to be very small changes in one year. The result would be slow transition in the index across time rather than a more sizeable change in the GCEI if the data were updated infrequently. The lack of dramatic changes in the GCEI would make it easier for districts to plan future budgets, and for the State to avoid the potential political backlash resulting from large changes.

B. Re-estimating the Staff Salary and Energy Models

On a less frequent basis the State should consider redoing the statistical analysis in the hedonic salary models and energy cost model. Given the general stability of the data, re-estimating these models on a frequent basis is not necessary. However, it is possible that sufficient enough changes will occur over time to necessitate the models being re-estimated every five years in order to maintain the validity of the GCEI measure. Re-estimation should involve not only rerunning the same models with new data, but also re-evaluating all the major assumptions used to construct these models. For example, should different measures (or additional measures) of cost-of-living and working conditions be tried in the model? Should salary models be estimated for different classes of employees? Should cost indices be calculated for other non-personnel expenditures besides energy? Finally, should a methodology other than a hedonic wage regression be used to estimate the salaries required to attract a given quality of teacher? Significant research is underway on teacher labor markets, which may yield better methods for determining personnel cost differences (Boyd, et. al., 2003).

Chapter 7

Summary and Recommendations

The purpose of this study has been to develop a geographic cost of education index (GCEI) for Maryland school districts, and recommend how it can be used in the Maryland Foundation Program (and other school aid formulas). In developing the GCEI, we have used a "market basket" approach, where cost indices are developed for the major resources used by school districts. The weight assigned to each cost index is based on the percent each category represents in the budget (budget shares). The primary resource used by school districts is personnel (largely teachers), therefore developing personnel cost indices (PCI) has been a major focus of our research.

The principal methodology we employ to construct the GCEI is a hedonic salary model, because it is designed specifically to capture those factors that affect the "attractiveness" of a school district to teachers and other personnel. This statistical methodology assigns "weights" to these factors representing their value to teachers expressed in terms of changes in salary. Factors included in the model are divided into discretionary factors (under the control of the district), and cost factors (outside district control). The cost factor results in hedonic salary models are used directly in constructing personnel cost indices (PCI) for each type of employee (discretionary factors are held constant in constructing the index).

Great care is taken to both collect a comprehensive a set of discretionary and cost factors, and to test these factors for reliability and validity (Chapter 3). Based on this analysis, a smaller set of factors is tested in teacher hedonic salary models (Chapter 4). In addition, we examine whether separate models should be estimated for teachers and other professional staff. Our determination is that from a practical standpoint, combining all professionals into one hedonic model for professional staff is preferable, because it is simpler and produces similar results. The heart of this report is the presentation of hedonic salary models, and the construction of personnel cost indices for professional staff (PPCI) and nonprofessional staff (NPCI). In addition, an energy cost model is used to develop an energy cost index (ECI). These three indices are combined into the GCEI using statewide expenditure shares.

The resulting GCEI has relatively little variation ranging from 0.95 to 1.05. Districts with above average costs tend to be larger urban counties with either high housing prices or high shares of students in poverty (percent of students receiving subsidized lunch). Districts with below average costs tend to be rural districts with below average housing prices. We test the stability of the GCEI and its component indices and find that they are quite stable.

To test the external validity of the GCEI (and PPCI), we have compared these indices to an index of average payroll for business and professional service sectors. The resulting wage index had significantly more variation than the PPCI, although they are strongly correlated. Another validity test is to examine how closely the PPCI matches the actual mobility rates of teachers. Do districts with a high PPCI also experience a greater share of teachers leaving the district and moving to another district? The correlations are positive but weak.

The lack of relationship between teacher mobility rates and the PPCI is particularly troubling, because the hedonic model in theory (and the resulting PPCI) is supposed to capture the value that teachers attach to certain job characteristics. A growing body of research indicates that teachers highly value working conditions (particularly the type of students they are teaching), and may require large pay differentials to work in certain schools. Yet, in the teacher hedonic models we estimated, working condition factors were of secondary importance compared to housing prices. Part of the explanation for these discrepancies may be related to limitations with the use of hedonic salary models in the public sector. Hedonic models are based on the assumption of perfectly competitive labor markets. Public personnel salary decisions, while certainly influenced by private labor markets, are ultimately set in a political process. We have made some adjustments to the hedonic model to reflect the influence of non-economic factors on the salary setting process, but these adjustments may not adequately capture the complexity of this process.

What recommendations do we make to the State of Maryland regarding adjustments for geographic differences in the cost of providing education services?

First, hedonic salary models are superior to either of the commonly used alternatives—private cost-of-living indices, and competitive wage indices—because they do attempt, albeit imperfectly, to capture the importance of working conditions on teacher decisions. Despite their limitations, hedonic salary models remain the state of the art methodology in geographic cost adjustments for education.

Second, we have made a range of recommendations about how the GCEI can be used in both the Foundation Program, and the other major school aid programs in Maryland. Including geographic cost adjustments in school aid programs is one important step towards assuring that adequate resources exist in districts so they can help their students reach academic standards.

Finally, it is important that Maryland revisit the estimation of geographic cost indices within 3 to 5 years. Significant research is underway on teacher labor markets, which is beginning to shed light on the importance that teachers attach to various characteristics of their jobs. Potential outcomes of this research are improvements to hedonic salary models, or entirely new methods for determining the salary differentials required to attract good teachers into challenging educational environments.

References

Alaska Department of Education and Early Development. 2001. *Alaska's Public School Funding Formula: A Report to the Alaska State Legislature*. Juneau, AK: author.

American Institutes for Research (AIR). 1999. *An Educator's Guide to Schoolwide Reform*. Arlington, VA: Education Research Service, http://www.aasa.org/issues_and_insights/config/Reform/index.htm.

Alexander, C. D., Gronberg, T. J., Jansen, D. W., Keller, H., Taylor, L. L., & Treisman, P. U. 2000. *A Study of Uncontrollable Variations in the Costs of Texas Public Education*. A summary report prepared for The 77th Texas Legislature. Austin, TX: Charles A. Dana Center, The University of Texas at Austin.

Augenblick & Myers, Inc. 2001. *Calculation of the Cost of an Adequate Education in Maryland in 1999-2000 Using Two Different Analytic Approaches*, Prepared for "Thornton Commission. Denver, CO: author, September.

Ballou, D. 1996. "Do Public Schools Hire the Best Applicants?" Quarterly *Journal of Economics* 111, 97-133.

Barro, S. M. 1994. *Cost-of-Education Differentials Across the States.* Washington, D.C.: U.S. Department of Education, National Center for Education Statistics, Working Paper No. 94-05.

Brazer, H. E., & Anderson, A. 1974. "A Cost Adjustment Index for Michigan School Districts." In E. Tron (ed.) *Selected Papers in School Finance, 1975*. Washington, DC: U.S. Department of Education.

Chambers, J. G. 1978. "Educational Cost Differentials and the Allocation of State Aid for Elementary/Secondary Education." *Journal of Human Resources* 13(4), 459-481.

Chambers, J. G. 1981. "The Hedonic Wage Technique as a Tool for Estimating the Costs of School Personnel: A Theoretical Exposition with Implications for Empirical Analysis." *Journal of Education Finance* 6(3), 330 - 354.

Chambers, J. G. 1997. *A Technical Report on the Measurement of Geographic and Inflationary Differences in Public School Costs*, Volume III. Washington, DC: National Center for Education Statistics.

Chambers, J., Taylor, L., & Robinson, J. *Alaska School District Cost Study: Volume I and II*. Report submitted to Legislative Budget and Audit Committee. January 2003.

Chow, G. 1960. "Tests of Equality Between Sets of Coefficients in Two Linear Regressions." Econometrica, 28, 591-605.

Clune, W. H. 1994. “The Shift from Equity to Adequacy in School Finance.” *Education Policy* 8(4), 376-394.

College Board. 2002. “2002 College Bound Seniors: A Profile of SAT Program Test Takers.” http://www.collegeboard.com/about/news_info/cbsenior/yr2002/html/2002reports.html.

Colorado Legislative Council Staff (CLCS). 2002. “2001 School District Cost-of-Living Study.” Memoradum from Deb Godshall, Assistant Director of CLCS to members of Colorado General Assembly, Feburary 25.

Department of Legislative Services (Maryland). 2002. “Maryland Legislator’s Handbook.” *Legislative Handbook Series*, Volume I. Baltimore, MD: author.

Dickey, K. & Logwood, B. 2001. “Virginia.” In National Center for Education Statistics (NCES). *Public School Finance Programs of the United States and Canada: 1998-99*. NCES 2001-309. Washington DC: U.S. Department of Education, Office of Educational Research and Improvement.

Duncombe, W., Lukemeyer, A. & Yinger, J. 2003. In J. W. Fowler (Ed.), *Developments In School Finance: 2001-02* (pp. 127-153). Washington, DC: National Center for Education Statistics.

Duncombe, W. & Yinger, J. 1998. “School Finance Reform: Aid Formulas and Equity Objectives.” *National Tax Journal* 51(2), 239-262.

Duncombe, W. & Yinger, J. 2000. “Financing Higher Student Performance Standards: The Case of New York State.” *Economics of Education Review* 19(5), 363-386.

Ferguson, R. F., & Ladd, H. F. 1996. “How and Why Money Matters: An Analysis of Alabama Schools.” In H. F. Ladd (Ed.), *Holding Schools Accountable: Performance-Based Reform in Education* (pp. 265-298). Washington, DC: The Brookings Institution.

Florida Department of Education. 2002. “2002 Florida Level Index.” Tallahassee, Fl: author, http://www.firn.edu/doe/fefp/pdf/fpli2001.pdf.

Fowler, W. J. and Monk, D. H. 2001. *A Primer for Making Cost Adjustments in Education*. NCES 2001-323. Washington, DC: U. S. Department of Education, Office of Educational Research and Improvement.

Garner, E. & Eckert, J. 2002. *Cost of Living Differentials in Colorado: 2002*. Fort Collins, CO: Colorado State University Cooperative Extension.

Goldhaber, D. D. 1999. “An Alternative Measure of Inflation in Teacher Salaries.” In J. William Fowler (Ed.), *Selected Papers in School Finance 1997-99* (pp. 29-54). Washington, DC: National Center for Education Statistics.

Goldhaber, D. & Callahan, K. 2001. “Impact of the Basic Education Program on Educational Spending and Equity in Tennessee.” *Journal of Education Finance*. 26, 415-436.

Goldhaber, D. D., & Player, D. 2003. “What Different Benchmarks Suggest About How Financially Attractive it is to Teach in Public Schools.” Working paper. University of Washington.

Greene, W. H. 2000. *Econometric Analysis*. Upper Saddle River, New Jersey: Prentice-Hall, Inc.

Greenberg, D., & McCall, J. 1974. “Teacher Mobility and Allocation.” *Journal of Human Resources* 9(4), 480-502.

Hanushek, E. A. 1999. “Adjusting for Differences in the Cost of Educational Inputs.” In J. William Fowler (Ed.), *Selected Papers in School Finance, 1997 - 99*. Washington, DC: National Center for Education Statistics.

Hanushek, E. A., Kain, J. F., & Rivkin, S. G. 2004. “The Revolving Door.” *Education Next, 4*(1), 76 - 82.

Hanushek, Eric A, Kain, John F., & Rivkin, Steven G. 2001. “Why Public Schools Lose Teachers.” National Bureau of Economic Research, Working Paper no. 8599, November.

Haveman, R. & Wolfe, B. 1994. *Succeeding Generations: On the Effects of Investments in Children*. New York: Russell Sage Foundation Jensen and Seltzer.

Heckman, James, Layne-Farrar, Anne, & Todd, Petra. (1996). "Human Capital Pricing Equations with an Application to Estimating the Effect of Schooling Quality on Earnings." Review of Economics and Statistics, 78(4), 562-610.

Jensen, B. & Seltzer, A. 2000. “Neighborhood and Family Effects in Education Progress.” *The Australian Economic Review* 33(1), 17-31.

Ladd, H.F. & Yinger, J.M. 1994. “The Case for Equalizing Aid.” *National Tax Journal*. 47(1), 211-224.

Lankford, H., Loeb, S., & Wyckoff, J. 2002. “Teacher Sorting and the Plight of Urban Schools: A Descriptive Analysis.” *Educational Evaluation and Policy Analysis, 24*(1), 37 - 62.

Levinson, A. 1988. “Reexamining Teacher Preferences and Compensating Wages.” *Economics of Education Review, 7*(3), 357-364.

Maryland State Department of Education (MSDE). 1996. *Financial Reporting Manual for Maryland Public Schools*. Baltimore, MD: MSDE.

Maryland State Department of Education. 1999. *Professional Salary Schedules, Maryland Public Schools 1999 – 2000*. Baltimore, MD: MSDE, Division of Planning, Results, and Information Management.

Maryland State Department of Education. 2002. *Professional Salary Schedules, Maryland Public Schools 2002 – 2003*. Baltimore, MD: MSDE, Division of Planning, Results, and Information Management.

Maryland State Department of Education. 2003a. *Selected Financial Data Maryland Public Schools 2000-2001, Part 2--Expenditures*. MSDE-DBS 01/03. Baltimore, MD: MSDE, Division of Business Services.

Maryland State Department of Education. 2003b. *Maryland Report Card, 2003 Performance Report: State, Systems, and Schools*. http://msp.msde.state.md.us/ Baltimore, MD: MSDE.

Maryland State Department of Education. 2003c. *Overview of General Fund State Aid Programs, FY 2005*. Baltimore, MD: MSDE, Division of Business Services, September 10.

Maryland State Department of Education. 2003d. "Final Calculations for the Major State Aid Programs for Fiscal Year 2004." Baltimore, MD: MSDE, Division of Business Services, Memorandum to local superintendents of schools, July 1.

Massachusetts Department of Education. 1999. *An Analysis of Geographic Differences in School Operating and Construction Cost*. http://finance1.doe.mass.edu/chapter70/formula01_wage0.pdf. Boston, MA: author, September 15.

Massachusetts Foundation Budget Review Commission. 2001. *Report of the Foundation Budget Review Commission.* Boston, MA: author.

McMahon, W. W. 1996. "Interstate Cost Adjustments." In J. William Fowler (Ed.), *Selected Papers in School Finance 1994* (pp. 89-114). Washington, DC: National Center for Education Statistics.

Mincer, Jacob. (1974). *Schooling, Experience, and Earnings*. New York: Columbia University Press.

Minorini, P. A. & Sugarman, S. D. 1999. "Educational Adequacy and the Courts: The Promise and Problems of Moving to a New Paradigm." In H. Ladd, R. Chalk, & J. Hansen. (Eds.) *Equity and Adequacy in Education Finance* (pp. 175-208). Washington, DC: National Academy Press.

Murnane, R. J., Singer, J. D. & Willet, J. B. 1989. The Influences of Salaries and "Opportunity Costs" on Teachers' Career Choices: Evidence from North Carolina. *Harvard Educational Review, 59*(3), 325-346.

National Center for Education Statistics (NCES). 2001. *Public School Finance Programs of the United States and Canada: 1998-99*. NCES 2001-309. Washington DC: U.S. Department of Education, Office of Educational Research and Improvement.

Nelson, F. H. 1991. "An Interstate Cost-of-Living Index." *Educational Evaluation and Policy Analysis* 13(1), 103-111

Peevely, G. & Dunbar, D. 2001. "Tennessee." In National Center for Education Statistics (NCES). *Public School Finance Programs of the United States and Canada: 1998-99*. NCES 2001-309. Washington DC: U.S. Department of Education, Office of Educational Research and Improvement.

Pollack, R. A. & Ginther, D. K. 2003. "Does Family Structure Affect Children's Educational Outcomes?" National Bureau of Economic Research, Working Paper no. 9628, April.

Reschovsky, A. & Imazeki, J. 1997. "The Development of School Finance Formulas to Guarantee the Provision of Adequate Education to Low-Income Students." In J. W. Fowler (Ed.), *Developments In School Finance: 1997* (pp. 123-147). Washington, DC: National Center for Education Statistics.

Rothstein, R. & Smith, J. 1997. *Adjusting Oregon Education Expenditures for Regional Cost Differences: A Feasibility Study.* Submitted to Confederation of Oregon School Administrators. Management Analysis & Planning Associates, L.L.C.

Shahrokh, F. 2002. *Regional Cost of Living Index*. Baltimore, MD: Maryland Department of Business & Economic Development, Business Research and Analysis, February.

Theobold, N.D. 1990. "An Examination of the Influences of Personal, Professional, and School District Characteristics on Public School Teacher Retention." *Economics of Education Review* 9(3), 241-250.

The Commission on Education Finance, Equity, and Excellence ("Thornton Commission"). 2002. *Final Report*. Annapolis, MD: Department of Legislative Services, Office of Policy Analysis, January.

U.S. Census Bureau. 2003. *Public Education Finance, 2001*. Washington, DC: U.S. Census Bureau, Governments Division, March.

U.S. Department of Education. 2003. http://nces.ed.gov/programs/digest/d02/tables/dt068.asp.

White, H. 1980. "A Heteroskedasticity –Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48, 817-830.

Wyoming Division of Economic Analysis. 1999. *The Wyoming Cost of Living Index: Policies & Procedures*. http://eadiv.state.wy.us/wcli/policies.pdf. Cheyenne, WY: Division of Economic Analysis, Department of Administration & Information, August.

Wyoming LSO School Finance Office. 2000. *School Finance Synopsis*. Cheyenne, WY: author.

Yinger, J. M. forthcoming. *Helping Children Left Behind: State Aid and the Pursuit of Educational Equity*. Cambridge, MA: MIT Press.

Appendix A

Geographic Cost Adjustments Used In Other States

One of the issues that states face when funding education is how to compensate for cost differences across geographic areas. The underlying philosophy is that a state's funding formula should account for the educational costs localities face so that schools are not advantaged or penalized by cost-related factors over which they have little or no control. Thus, a *geographic cost-of-education index* (GCEI) is designed to "level the playing field."

The objective of this appendix is to provide a brief description of the approaches that other states are using, at the time of writing, to adjust the aid systems for geographic cost differences. As discussed at the beginning of Chapter 2, there are three general approaches to geographic cost adjustment: cost-of-living indices, competitive wage indices, and hedonic salary models.[71] Table A-1 lists the states that use one of these three approaches.

Table A-1. Geographic Cost Adjustment Used by Other States

Type of Geographic Cost Index	States Using Geographic Cost Adjuments	States Adjusting for Teacher Education and Experience Levels
		Alabama
Cost of Living Index	Colorado	Georgia
	Florida	Minnesota
	Virginia	Mississippi
	Wyoming	New Mexico
Competitve Wage Index	Massachusetts	Oregon
	Ohio	Utah
	Tennessee	Washington
Hedonic Salary Index	Texas	West Virginia
Other Approaches	Alaska	Wyoming

Source: Thompson and Silvernail, 2001; Rothstein and Smith, 1997; Yinger, forthcoming, Appendix B.

[71] This appendix borrows heavily from Rothstein and Smith, 1997; and Thompson and Silvernail, 2001.

In addition, there are a number of states that adjust districts' funding levels for differences in the education and experience of their teacher corps. Typically, a standard salary schedule is selected for the state. District teachers are located on this salary schedule, and an estimate of the standard teacher salary costs per FTE teacher is developed for each district. Because the salary schedule is for the state as a whole, this is not a geographic cost adjustment. This adjustment methodology also does not distinguish between the costs over which districts have some control and those over which they do not, which means districts' decisions can affect the level of costs. For example, when districts make the decision to hire more senior teachers, their costs go up, but so too do the reimbursements from the state. That district decisions can affect costs violates a key principle of cost adjustments and provides an incentive for districts to add more experienced and educated teachers, which tends to favor wealthy districts where it is easier to recruit and retain the most experienced/educated teachers.

1. Cost of Living Indices

A. Colorado

In Colorado, the cost-of-living factor is based on a traditional market basket model that collects information from five main areas: 1) good and services including food at home, food away from home, medical care, recreation and other services; 2) housing including mortgage, insurance, property taxes, utilities, household operations and furnishings; 3) taxation including federal and state income taxes and local occupation taxes; 4) transportation; and 5) miscellaneous including savings, investments, charitable donations, and life insurance (Colorado Legislative Council Staff (CLCS), 2002). Data was collected through several methods including in-person sampling of retail outlets, personal interviews or telephone surveys of consumers, and data from the Public Utilities Commission (Garner and Eckert, 2002). The market basket was defined using the 2001 Consumer Expenditure Survey from the BLS for a three-person household with an annual income of $38,000.

To account for the differences in shopping patterns that might occur between urban and rural districts, a survey of shopping patterns was sent to households, and the results were used to identify which share of the shopping for particular items took place in the district and in neighboring areas. Cost of living is identified for the district and its "labor pool area" based on information on residence of teachers. The Legislative Council certifies a cost-of-living factor for each district every two years. Applied to the percentage determined by personnel costs, the factor can range anywhere from 1.008 in low-cost areas, to 1.638 in high-cost areas. It should be noted that the index provides a higher amount of funding to relatively affluent areas, such as school districts located in ski resort communities, and a lower amount to urban districts.

B. Florida:

The Florida Price Level Index (FPLI) was established by the legislature in Section 1011.62(2), of Florida Statute. The FPLI is a market basket model that is used to estimate educational cost differences across Florida counties. The FPLI is incorporated into the education finance system as a "district cost differential." The items included in the market basket are similar to those found in the CPI and include cost data on housing, transportation, health care, and food and other goods and services (Florida Department of Education, 2002). Data on prices is gathered from several sources including state agencies, telephone survey of retail outlets, and private consultants. Once prices for the items in the market basket are collected, the average prices of the items within each district are compared to the statewide average cost for each item, from which the district cost differential is computed. Prices are collected for 58 percent of the consumer market basket, with the other 42 percent assumed not to vary across geographic areas. The index uses 100 as the average, and districts varied from 88.3 to 113.6 in 2002. District cost differentials are computed annually by taking a three-year average of the FPLI.

C. Virginia

Virginia has a fairly traditional foundation-type aid program. A set of instructional and support positions is determined based on enrollment levels, and personnel costs are determined by multiplying this staffing level by statewide costs and salaries. Once the per pupil foundation level is determined for each district, an additional increment is added for instructional salaries and support salaries in Northern Virginia (near Washington D.C.), because of higher cost of living (Dickey and Logwood, 2001). It is not entirely clear how these increments were determined.

D. Wyoming

The Wyoming school finance formula includes adjustments for regional cost of living differences. The cost of living adjustment is based on a modified version of the Wyoming Cost of Living Index (WCLI), which "eliminates medical and shelter rental subcomponent of the housing component " (Wyoming LSO School Finance Office, 2000). The WCLI is constructed using a traditional market basket model comprised of price data from 27 communities across the state. The market basket contains 140 items which are divided into six categories including housing, food, recreation & personal care, apparel, and medical. Price collection is accomplished using local newspapers, price collection surveys, phone interviews, and in-person collection of price data (Wyoming Division of Economic Analysis, 1999). The six categories are weighted with respect to their importance in a consumer budget using weights similar to those used in calculating the Consumer Price Index (CPI-U). Not surprisingly, housing carries the largest weight in the index.

Albany and Laramie counties are used as the base point for the index with all remaining counties compared to these counties. Albany and Laramie counties are used as the base point, because of a larger supply of labor in these counties compared to the rest of the state. A multi-period average of the adjusted WCLI is used as the basis of cost adjustment to avoid instability in the index.

2. Competitive Wage Indices

A. Massachusetts

Massachusetts uses a geographic cost adjustment based on private sector wages from 21 labor markets across the state to estimate the relative cost differentials for staff in different areas of the state. Each district's wage adjustment is weighted at 80 percent of its labor market area, and 20 percent of the local district average (Massachusetts Department of Education, 1999). All wages in the area are factored into this weighting. The wage adjustment factor is multiplied by the foundation budget, which is the sum of six factors composing eighteen budget categories (Massachusetts Foundation Budget Review Commission, 2001).

B. Ohio

In Ohio, a district's adjusted cost of doing business factor (CODBF) is used to adjust the foundation level to reflect the relative cost of doing business in the county in which the district is located (Ohio Department of Education, 2003). The CODBF is calculated for each county based on wage information from the Ohio Department of Labor, Bureau of Employment Services (Rothstein and Smith, 1997). Wage information is collected from all major economic sectors for each county in Ohio. Average weekly wage data from these industries are aggregated at the county level using state employment shares by industry to produce an average weekly wage rate. Since personnel often work in one county and live in another, the cost of doing business factor is the average of weekly wages in this county and all of its neighbors. In summary, Ohio uses a regional competitive salary concept as the basis of its cost of doing business adjustment. As calculated, the CODBF measures a 41 percent difference in the cost of doing business between the (wages of the) highest and lowest paying counties. Despite the measured variation, the legislature has capped the amount of allowable variation at 7.5 percent, making the impact of the index much less dramatic.

C. Tennessee

Tennessee's school funding formula is the Basic Education Program (BEP), a foundation type formula, where the foundation level is built from student counts to required staffing levels, and unit costs for each component of the foundation (Peevely and Dunbar, 2001). The BEP funding level for each district is multiplied by a cost differential factor (CDF) to adjust for geographic cost differences (Goldhaber and Callahan, 2001). The cost differential factor is calculated using average payroll for nongovernmental employees based on place-of-work data (the ES-202 series). Similar to Ohio, average payroll is calculated for different industrial sectors, and the average wage is a weighted average of average payroll by sector using state employment weights (Eff and Eff, 2000). The average for each county is divided by the average payroll for the state. The ratio is artificially truncated at one, so that no district receives less aid as a result of this adjustment.

3. Hedonic Salary Index

Texas

Texas is the only state we are aware of that presently uses a variant of the hedonic salary approach in making geographic cost of education adjustments. The model is basically a teacher cost index that uses information from a variety of sources to identify the relative attractiveness of a given teaching opportunity and account for differences in resource costs that are beyond the control of the district (Alexander et al., 2000). The five components of the index are: (a) the average beginning salary of teachers in contiguous school districts, (b) the percent of economically disadvantaged students, (c) district size (in terms of average daily attendance), (d) location in a rural county (with a population of less than 40,000), and (e) whether the district is classified as an "independent town" or "rural." The CEI is based on a 1991 regression analysis of factors affecting variation in payroll costs among districts. It is applied to 71 percent of the Basic Allotment. The resulting weight varies from 1.02 to 1.20 of the base funding level.

In 2000, the Dana Center at the University Texas produced a study funded by the state legislature that looked at the potential impact of different approaches to making geographic cost adjustments in Texas (Alexander, et al., 2000). The final recommendations of the report suggested that the existing teacher cost index was the best way to adjust, and it called for an update of the data and methods used in the creation of the index. The recommendations were not acted on in the last legislative session due to budgetary considerations and the fact that there was a considerable amount of discussion surrounding a total overhaul of the finance formula. It is possible that the recommendations will be considered in the upcoming legislative session.

4. Other Methods

Alaska

Alaska uses a foundation formula, where the state sets a base amount per pupil, which is adjusted for enrollment size of the district, special needs students, and a "district cost factor." The district cost factor is multiplied by student counts, which includes adjustment(s) for district size and special needs students (Alaska Department of Education and Early Development, 2001). The district cost factor is calculated using information on actual district and school spending (operating costs), which is used in calculating "basic need" per student. The cost adjustment is based on the ratio of district basic need per pupil to the statewide basic need per pupil. Alaska is in the process of examining alternative cost adjustments, and just recently completed a cost study using the hedonic wage approach (Chambers, et al., 2003).

Appendix B Tables

Table B-1. Health and Retirement Benefits Provided Teachers

System	Monthly Health Allowance - Teachers	Retirement Allowance - Teachers
Allegany	$363.00	9.35%
Anne Arundel	$309.60	9.35%
Baltimore City	$160.10	9.35%
Baltimore County	$325.16	9.35%
Calvert	$333.39	9.35%
Caroline	n/a	9.35%
Carrol	$132.81	9.35%
Cecil	$336.20	9.35%
Charles	$295.08	9.35%
Dorchester	$389.42	9.35%
Frederick	$293.58	9.35%
Garrett	$437.18	9.35%
Harford	n/a	9.35%
Howard	$380.78	9.35%
Kent	$411.00	9.35%
Montgomery	$221.46	9.35%
Prince George's	$188.25	9.35%
Queen Anne's	$583.33	9.35%
St. Mary's	$205.26	9.35%
Somerset	$307.66	9.35%
Talbot	n/a	9.35%
Washington	$325.57	9.35%
Wicomico	$336.00	9.35%
Worcester	$206.00	9.35%

Source: Information gathered directly from districts by MSDE staff.

Table B-2. Results of Housing Price Model (2000)

Variable	Coefficient	t-statistic	Standardized Coefficient
Intercept	-$38,224	-22.52	
Age	-$623	-22.40	-0.1506
Age Squared	$4	16.33	0.0985
Size of Structure (square feet)	$92	201.30	0.6052
Height of House:			
1 Story	$10,167	14.41	0.0406
Over 2 Stories	-$33,965	-25.49	-0.0608
Detached House	$4,930	5.02	0.0130
Standard Housing Unit	$29,129	45.53	0.1409
Brick or Stone Construction	$22,975	35.49	0.0971
Housing Condition:			
Worse Than Average	-$14,426	-7.05	-0.0166
Better Than Average	$161,232	75.05	0.1758
County Variables:			
Allegany	-$45,355	-16.78	-0.0405
Anne Arundel	$65,571	50.09	0.2087
Baltimore	$32,477	26.83	0.1085
Calvert	$44,139	19.61	0.0516
Caroline	-$19,015	-5.18	-0.0122
Carroll	$40,348	22.93	0.0660
Cecil	$19,197	8.61	0.0226
Charles	$17,175	9.08	0.0256
Dorchester	-$13,977	-3.36	-0.0078
Frederick	$37,152	24.29	0.0819
Garrett	-$29,397	-4.82	-0.0111
Harford	$23,157	14.75	0.0473
Howard	$63,630	43.66	0.1512
Kent	-$1,836	-0.39	-0.0009
Montgomery	$99,089	83.71	0.3945
Prince George's	$39,960	30.94	0.1276
Queen Anne's	$49,211	17.92	0.0445
St. Mary's	$21,853	9.39	0.0246
Somerset	-$37,511	-6.44	-0.0147
Talbot	$32,080	10.96	0.0268
Washington	-$8,652	-4.47	-0.0118
Wicomico	-$18,231	-8.19	-0.0216
Worcester	$6,178	2.10	0.0052
Adjusted r-square		0.7073	
Sample size		58239	

Note: Dependent variable is housing sales price.
Estimated with ordinary least squares regression.

Table B-3. Results of Housing Price Model (1999)

Variable	Coefficient	t-statistic	Standardized Coefficient
Intercept	-$23,480	-18.31	
Age	-$633	-32.38	-0.16963
Age Squared	$3	19.53	0.09013
Size of Structure (square feet)	$81	237.60	0.61941
Height of House:			
1 Story	$8,573	15.17	0.03541
Over 2 Stories	-$35,004	-36.73	-0.07440
Detached House	$2,787	3.67	0.00797
Standard Housing Unit	$21,303	42.86	0.11123
Brick or Stone Construction	$20,856	39.59	0.09180
Housing Condition:			
Worse Than Average	-$19,060	-9.35	-0.01825
Better Than Average	$130,217	94.52	0.18762
County Variables:			
Allegany	-$32,645	-13.65	-0.02708
Anne Arundel	$62,137	62.35	0.22263
Baltimore	$35,964	38.54	0.13207
Calvert	$41,593	25.12	0.05665
Caroline	-$10,274	-3.43	-0.00677
Carroll	$43,216	32.66	0.08087
Cecil	$21,577	12.32	0.02694
Charles	$21,441	15.99	0.04057
Dorchester	-$4,614	-1.44	-0.00281
Frederick	$38,997	32.72	0.09043
Garrett	-$22,907	-5.54	-0.01076
Harford	$26,617	22.29	0.06081
Howard	$67,229	60.33	0.17774
Kent	$10,368	2.73	0.00526
Montgomery	$93,672	102.42	0.39338
Prince George's	$42,643	42.25	0.14431
Queen Anne's	$35,969	17.81	0.03745
St. Mary's	$23,993	13.86	0.03078
Somerset	-$31,706	-6.81	-0.01302
Talbot	$24,857	10.82	0.02222
Washington	$339	0.21	0.00047
Wicomico	-$9,171	-5.10	-0.01112
Worcester	$10,804	4.54	0.00926
Adjusted r-square		0.7425	
Sample size		72839	

Note: Dependent variable is housing sales price.
Estimated with ordinary least squares regression.

Table B-4. Results of Housing Price Model (1998)

Variable	Coefficient	t-statistic	Standardized Coefficient
Intercept	-$14,364	-10.68	
Age	-$623	-29.30	-0.1722
Age Squared	$3	15.30	0.0803
Size of Structure (square feet)	$75	215.00	0.6113
Height of House:			
1 Story	$7,341	12.79	0.0327
Over 2 Stories	-$31,333	-31.11	-0.0697
Detached House	$4,323	5.46	0.0131
Standard Housing Unit	$21,036	41.61	0.1175
Brick or Stone Construction	$19,508	35.88	0.0915
Housing Condition:			
Worse Than Average	-$20,948	-9.89	-0.0212
Better Than Average	$114,806	80.12	0.1762
County Variables:			
Allegany	-$32,101	-12.79	-0.0281
Anne Arundel	$55,330	52.31	0.2131
Baltimore	$31,916	32.06	0.1261
Calvert	$38,328	23.08	0.0589
Caroline	-$12,831	-3.97	-0.0086
Carroll	$37,524	27.65	0.0781
Cecil	$16,932	9.84	0.0244
Charles	$21,783	15.49	0.0442
Dorchester	-$11,998	-3.39	-0.0073
Frederick	$35,194	28.15	0.0876
Garrett	-$21,889	-4.43	-0.0094
Harford	$23,067	18.41	0.0567
Howard	$61,285	52.35	0.1780
Kent	$7,710	1.92	0.0041
Montgomery	$80,541	82.38	0.3646
Prince George's	$38,107	35.14	0.1308
Queen Anne's	$35,489	17.14	0.0402
St. Mary's	$20,904	12.14	0.0306
Somerset	-$32,440	-5.49	-0.0115
Talbot	$27,664	11.80	0.0270
Washington	-$1,218	-0.76	-0.0019
Wicomico	-$15,070	-8.10	-0.0196
Worcester	$4,294	1.84	0.0042
Adjusted r-square		0.7253	
Sample size		63946	

Note: Dependent variable is housing sales price.
Estimated with ordinary least squares regression.

Table B-5. Comparison of Adjacent County Averages of Adjusted Census House Price With and Without Neighboring Counties in Other States

County	Neighbor Counties In Other States	Old Average of County and its Neighbors	New Avarage with Other State Neighbors	Percent Difference
Allegany	5	$121,814	$115,485	-5.2%
Anne Arundel		$134,297	$134,297	0.0%
Baltimore	1	$132,985	$132,112	-0.7%
Calvert		$124,734	$124,734	0.0%
Caroline	2	$147,335	$139,883	-5.1%
Carroll	2	$133,974	$132,525	-1.1%
Cecil	3	$133,446	$130,780	-2.0%
Charles	3	$121,227	$119,322	-1.6%
Dorchester	1	$135,080	$138,114	2.2%
Frederick	2	$140,891	$138,108	-2.0%
Garrett	5	$111,687	$107,039	-4.2%
Harford	2	$133,888	$130,474	-2.5%
Howard		$138,160	$138,160	0.0%
Kent	2	$145,990	$137,586	-5.8%
Montgomery	2	$135,398	$139,347	2.9%
Prince George's	2	$131,621	$129,660	-1.5%
Queen Anne's	1	$146,855	$143,476	-2.3%
Somerset	1	$123,314	$123,678	0.3%
St. Mary's		$125,884	$125,884	0.0%
Talbot		$147,335	$147,335	0.0%
Washington	5	$128,717	$125,827	-2.2%
Wicomico	1	$128,586	$132,918	3.4%
Worcester	2	$125,884	$130,533	3.7%
Baltimore		$139,374	$139,374	0.0%

Note: Neighboring counties was defined as any county that shared a border with a Maryland county. For those Maryland counties, which are separated from Virginia counties by Potomac River, we included those Virginia Counties in reasonable driving distance of a bridge crossing the river.

Table B-6. Results of Teacher and Professional Staff Models (Estimated by Fixed Effects)

	Teachers Model		Professional Model	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	11.8214	79.12	12.0708	77.18
Teacher Demographics				
Native American	-0.0292	-3.64	-0.0267	-3.36
Black/ African- American	-0.0099	-8.49	-0.0101	-8.77
Asian	-0.0201	-5.43	-0.0199	-5.45
Male	-0.0077	-7.72	-0.0046	-4.67
Teacher Credentials				
MA (and BA+30)	0.1449	144.03	0.1511	148.84
MA30	0.2155	129.60	0.2139	134.52
PhD	0.2252	29.80	0.2119	36.34
Years of Teaching Experience	0.0015	231.43	0.0014	227.07
Alternative	-0.0375	-6.44	-0.0330	-5.76
Provisional	-0.0483	-39.38	-0.0508	-40.51
NTE Communication Score	-8.50E-05	-0.99	-2.24E-05	-0.26
NTE General Knowledge	0.0002	2.55	0.0001	1.49
NTE Professional Knowledge Score	-0.0008	-8.87	-0.0009	-9.42
Praxis Reading Score	-0.0019	-5.04	-0.0020	-5.34
Praxis Math Score	-0.0004	-1.42	-0.0006	-2.15
Praxis Writing Score	-0.0009	-2.09	-0.0009	-2.06
Computer Based Praxis Reading Score	-0.0014	-2.83	-0.0015	-2.90
Computer Based Praxis Math Score	-0.0001	-0.33	-0.0002	-0.87
Computer Based Praxis Writing Score	-0.0011	-2.63	-0.0011	-2.68
Principal			0.3656	92.58
Vice Principal			0.0107	4.31
Counselor			0.2553	73.81
Library Media Specialist			-0.0038	-1.23
Year and Fiscal Capacity Variables				
Observation Year: 2000	0.0547	104.63	0.0550	109.36
Observation Year: 2001	0.1102	177.12	0.1104	183.37
Observation Year: 2002	0.1239	91.59	0.1262	96.15
Cost Factor Variables				
% of students receiving Free/Reduced Lunch (district level)	0.0010	6.63	0.0007	4.75
Constructed Regional Average House Value	1.22E-06	17.72	1.12E-06	16.92
Adjusted r-square	0.8361		0.8455	
Sample size	199,578		222,783	

[1]Dependent variable is logarithm of annual salary. The models also includes dichotomous variables identifying missing values of the various test score variables.

Table B-7. GCEI Results (Based on Fixed Effects)
(Index Relative to Simple Statewide Average)

District	1999	2000	2001	2002
Lea 1, Allegany	0.968	0.966	0.960	0.954
Lea 2, Anne Arundel	1.013	1.012	1.019	1.021
Lea 3, Baltimore	1.011	1.011	1.011	1.013
Lea 4, Calvert	1.011	1.010	1.012	1.009
Lea 5, Caroline	1.003	1.002	1.005	1.001
Lea 6, Carroll	1.014	1.014	1.015	1.016
Lea 7, Cecil	0.989	0.993	0.989	0.988
Lea 8, Charles	1.011	1.009	1.010	1.004
Lea 9, Dorchester	0.983	0.983	0.983	0.977
Lea 10, Frederick	1.020	1.020	1.022	1.024
Lea 11, Garrett	0.955	0.953	0.947	0.944
Lea 12, Harford	0.999	1.000	0.996	0.995
Lea 13, Howard	1.019	1.019	1.022	1.025
Lea 14, Kent	1.009	1.010	1.012	1.019
Lea 15, Montgomery	1.037	1.039	1.044	1.050
Lea 16, Prince George's	1.042	1.042	1.048	1.053
Lea 17, Queen Anne's	1.000	0.998	1.002	1.006
Lea 18, St. Mary's	1.007	1.004	1.007	1.003
Lea 19, Somerset	0.977	0.981	0.974	0.975
Lea 20, Talbot	0.993	0.992	0.998	0.998
Lea 21, Washington	0.983	0.979	0.978	0.971
Lea 22, Wicomico	0.970	0.973	0.967	0.963
Lea 23, Worcester	0.960	0.962	0.956	0.954
Lea 30, Baltimore City	1.024	1.027	1.024	1.034