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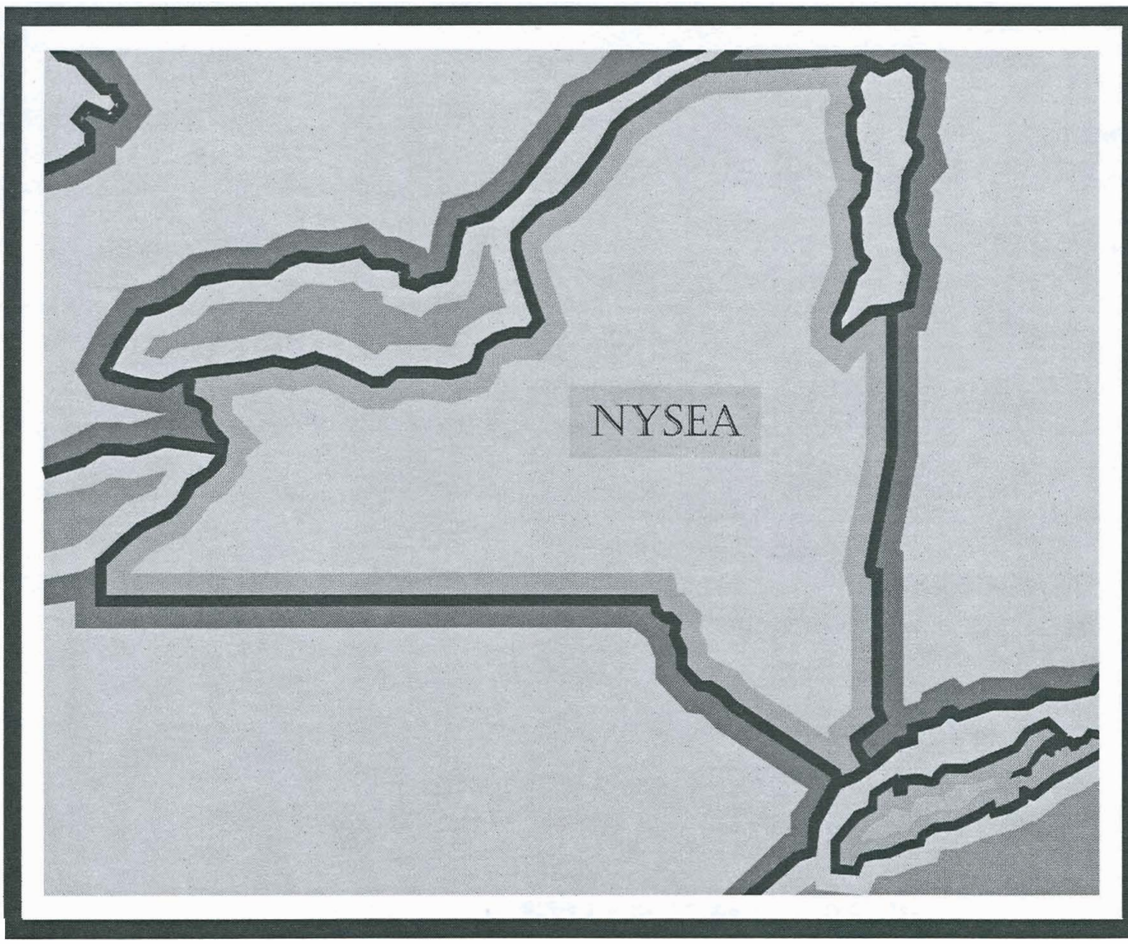

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CONTENTS

ARTICLES

EDITORIAL

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A Micro-Simulation Based Decomposition of the Health Status Gap Between US Blacks and Whites

Linda Dynan*

ABSTRACT

It is well established that health status differs across racial subpopulations within the United States. Specifically, African Americans (black) live lives that are substantially shorter, on average, than those of their white neighbors. Moreover, blacks generally experience worse health outcomes than whites throughout their lifetimes.

This paper examines the contributions of differences between blacks and whites in specific health-enhancing and health-deterring behaviors to the difference in self-reported health status (and a constructed health status measure) of these two groups. Micro-simulation based decomposition analysis using data from the 2005 Center for Disease Control Behavioral Risk Factor Surveillance System demonstrates that in particular, black/white differences in physical activity have relatively large impacts on the measured health status gap between the two groups, yet black/white differences in socioeconomic and demographic characteristics remain dominant sources in accounting for the observed health status gap.

INTRODUCTION

It is well established that there are underlying differences in health status across racial subpopulations within the United States (Link and Phelan, 1995; Williams and Collins, 1995; Hayward et al., 2000; Institute of Medicine, 2003; Sullivan Commission, 2004; Sequist et al., 2006). Specifically, members of the African-American (black) minority population experience worse health outcomes and live lives that are, on average, substantially shorter than those of their Caucasian (white) neighbors.

In 2001, for example, US life expectancy at birth was 80.2 years for white women and 75.5 years for black women, 75 years for white men and 68.6 years for black men (US Dept. of Commerce, 2004). Although per capita GDP in the US is the fourth highest in the world ($37,562) and per capita health care expenditure is the highest ($5,274 in 2002) (UN, 2005), black men in the United States, on average, live no longer than residents of poor countries with per capita GDPs of approximately $8,000. (Uruguay, for example, in 2002 had per capita income of $8,280, per capita health expenditure of $805, and life expectancy of 75.4 years (UN, 2005).)

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Expenditure on health services (intervention and treatment), however, is not sufficient to guarantee good health. In a comprehensive literature review, McGinnis, Williams-Russo and Knickman identify five "domains" that influence an individual's current and future health: genetic and gestational endowment, social circumstances, environmental conditions, behavioral choices, and medical care (McGinnis et al., 2002). Those authors further report:

> On a population basis, using the best available estimates, the impact of various domains on early deaths in the United States distribute roughly as follows: genetic predispositions, about 30 percent; social circumstances, 15 percent; environmental exposures, 5 percent; behavioral patterns, 40 percent; and shortfalls in medical care, 10 percent (McGinnis et al., 2002, p. 83).

Although all of these "domains," and their interactions, are essential to understanding racial variation in health status, this paper focuses in particular on the forty percent component represented by behavioral choices. Focusing on this component may in part develop understanding of the differences in health status between whites and blacks that may be attributable to racial (black/white) differences in participation in health-enhancing behaviors (such as exercise) or health-deterring behaviors (such as smoking). This component also reflects substantial differences for each group in the impact of particular behaviors on overall health status. This understanding of differences in health status (Fairlie, 2003)—difference on average in the participation in specific behaviors and difference in the impact of that behavior on health status—lends itself to an analysis of the health status gap using the decomposition methods first developed by Oaxaca (1973). This decomposition exercise stems from the labor economics literature. Oaxaca decomposition methods have been used to analyze gender and racial differences in wages (for example, Oaxaca, 1973; Blinder, 1973; Oaxaca and Ransom, 1994; Kim and Polachek, 1994; Fairlie and Sundstrom, 1999); and differences in computer ownership and small business ownership (Fairlie, 1999 and 2003). This methodology has also been applied in the health-related literature with respect to race and ethnicity (White-Means, 2000; Wenzlow et al., 2004; Charasse-Pouele and Fournier, 2006). It is particularly useful for identifying and quantifying group differences in measurable characteristics and categorical differences (Fairlie, 2003). In this paper, Oaxaca-Blinder decomposition methods, with recent advances in the technique as applied to nonlinear models developed by Fairlie (2003), are used to examine behavioral sources and their contribution to the white/black health status gap.

Better understanding of the contribution of specific behaviors, and the relative importance of these behaviors to health status, can inform policymakers as they attempt to prioritize among competing policies to narrow the health status gap between US blacks and whites. Such understanding can also inform health care providers and health educators regarding which particular behaviors to emphasize when advising and educating in order to achieve a larger positive impact. In pursuit of this understanding, the following are assessed:

1) Differences in the mean of the probability of health status predicted by the behaviors and characteristics according to racial group, and
2) The contributions of differences in specific behaviors across the two populations to the measured health-status gap.

These population characteristics and behavioral factors are cross-sectionally analyzed using data from the 2005 Center for Disease Control (CDC) Behavioral Risk Factor Surveillance System (BRFSS). This paper follows rules for inclusion in the Institute of Medicine's (2003 p. 41) review of unequal treatment. These rules exclude the impact of differential access and patient preferences on (in this case) perceived health status.

This analysis contributes to the literature by examining the contribution of differences in behavior to the black/white health status gap. The findings suggest that there are statistically significant differences in the distribution of characteristics and behaviors that contribute to measured health status. Differences across the two population groups in the "returns," or coefficients of the structural models associated with the observed behaviors and characteristics, are also found. These differences in returns have been characterized in the literature as the "direct effect of race." The measurement of the direct effect of race may include for example, unobserved influences through omitted variable biases, discrimination, and perhaps differential access or benefit from medical interventions. Consequently, it remains difficult to accurately disentangle and then interpret the findings related to the direct effects of race. Thus, the focus will be on the measured contributions of the black/white differences in behavior.

In particular, this analysis finds that differences in levels of physical activity dominate the behavioral contributions to the health status gap between whites and blacks in this data set. These results remain robust even when an alternative (constructed) measure of self-reported health status is analyzed. However, behavioral contributions as a whole remain a relatively small source of the black/white health status gap relative to the contribution of differences between blacks and whites in the distribution of socioeconomic and demographic characteristics.

The paper proceeds with a brief overview of the literature and discussions of the data and the methods of decomposition analysis. Presentation of the empirical results and a discussion of their implications follow. Finally, conclusions, potential policy issues, and areas for future research are considered.

II. HEALTH DISPARITIES LITERATURE REVIEW

A vast literature spanning numerous disciplines including medicine, health services research, sociology, and epidemiology has developed our understanding of health disparity across populations. A brief survey of the literature begins with McKeown's 1979 work that suggested that the role of medicine in producing health is quite limited. In response to McKeown, others have increasingly sought understanding of how health is achieved, and particularly to understand why health status varies across populations variously defined by: race, income, income inequality, or nation. For example, Sequist et al.'s (2006) work reinforces McKeown's finding that health is not created by medical care alone. In a study that focused on white and black diabetic patients between 1997 and 2001, Sequist and colleagues (2006) found that provision of better health care services for health-disadvantaged groups diminished, but did not eradicate, differences in health status across racial groups. The literature surveyed below identifies essential variables to include in estimating health status and health status differentials.

Link and Phelan (1995) propose that social conditions are fundamental causes of health status differentials. They argue that the racial health status gap persists primarily because socioeconomic resources offer (to those who possess them) access to a wide array of circumstances and environments that provide advantages in the production and maintenance of health. Their hypothesis is dynamic in predicting that advances in health information will be processed and implemented more quickly and fully by those possessing social advantage, thereby exacerbating existing gaps and allowing for persistence in the health status gap over time. Thus, Link and Phelan advocate the inclusion of socioeconomic resources such as income, education, and health insurance into models of health status. Hayward et al. (2000) also support the inclusion of educational attainment, but interpret it further as a marker of early access to resources. These variables are included in the estimation of health status and perform as expected.

Williams and Collins (1995) find that differences between socioeconomic groups in accessibility, utilization, and quality of care, or differences in the benefits derived from medical care, are contributing factors to the widening inequality in health status. However, they further find that the contribution of medical care is not sufficient to explain all of the observed health disparities. Williams and Collins note that:

> European mortality trends…document that a widening of mortality differences between [socioeconomic status] SES groups is partly due to differences in the decline of mortality from conditions amenable to medical intervention. However, the contribution of medical care is limited. The higher SES groups also experienced larger improvements in mortality than did their lower SES counterparts from those causes of death where medical care does not play a major role. (p. 352)

Like Williams and Collins, many authors have found differences across population subgroups in the magnitude of health benefits derived from medical care. Group differences in such benefits have been attributed, for example, to culturally appropriate/inappropriate interaction during medical encounters; race-matching between physicians and patients; or differences by race in patient compliance (for example, IOM, 2003; Sequist et al., 2006; Sullivan Report, 2004). Although important, the contributions of differences in medical care, or the benefits derived from medical care to the persistence of the health status gap, is not the focus of analysis in this paper.

Further complicating the discussion surrounding health disparities has been a debate about whether relative income inequality, rather than low "absolute" income alone, is bad for health. In response to this debate, Mellor and Milyo (2002) tested whether the statistical aggregates generally measured in studies that show income inequality is detrimental to health reflect causality when also controlling for individual income. Mellor and Milyo (2002) find no consistent evidence linking relative income inequality with health status. Accordingly, nominal individual income—rather than any measure of relative income inequality—is included in this study.

Although she does not focus on health status, White-Means (2000) decomposes medical use among the disabled elderly population by race. White-Means finds that differences in demographic characteristics such as wealth or educational level do not fully explain racial (black/white) differences in the use of physicians' services or prescription drugs.

Charasse-Pouele and Fournier (2006) study the impact of direct racial differences (i.e., when individuals with similar characteristics have different health outcomes indicating differing returns to those characteristics from the structural health equations) and indirect racial differences (i.e., when individuals with different characteristics have different health outcomes, after accounting for potential difference in the "returns") on self-reported health status among South Africans using nonlinear methods. They find that the racial health status gap in South Africa is largely attributable to the superior socioeconomic status (indirect racial effects) of whites, but the direct racial impact is complex, and linked to the indirect (socioeconomic) effects.

This paper uses similar methods to the Charasse-Pouele and Fournier (2006) study to explore and quantify the contribution of differences by groups in behavioral, socioeconomic and demographic characteristics (indirect racial effects) associated with health status on the health status gap between US blacks and whites. The purpose of the exercise is to draw attention to the role policy makers could take in reducing the indirect racial effect stemming, in particular, from differences in health-enhancing behaviors through support of appropriate educational interventions, or subsidization of programs targeted at promoting specific health-enhancing behaviors among blacks.

The literature discussed, although clearly not exhaustive, provides direction for the estimation of health status and insight into the potential sources of group differences in health status. The guidance thus provided is incorporated into the analysis that follows.

III. DATA AND METHODS

The data analyzed in this paper were obtained from the Center for Disease Control's (CDC) 2005 Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS, initiated in 1984, is a cross-sectional telephone survey conducted by the state governments with help from the CDC. Data from a random sample of civilian, non-institutionalized adults (people aged 18 or older) in households (one respondent per household) are collected. Phone numbers are randomly selected. Not included in “households” are vacation homes, group homes (such as fraternities or shelters), or institutions (such as nursing homes). Because the data and the findings from these data pertain only to the adult population who live in households, this sample is not representative of the whole adult US population, and may in particular under-represent black men who are disproportionately incarcerated and in the non-civilian population. However, health issues in those populations are likely to differ from the larger US population and require different policies to address their needs.

Further, non-coverage may be introduced by the telephone survey method employed while non-response may also introduce biases in the data. The CDC reports in the BRFSS documentation (2004) that, “Although overall approximately 95 percent of US households have telephones, coverage ranges from 87 to 98 percent across states and varies for subgroups as well.” The CDC technical notes advise that:

> No direct method of compensating for non-telephone coverage is employed by the BRFSS; however, post-stratification weights are used, which may partially correct for any bias caused by non-telephone coverage. These weights adjust for differences in probability of selection and nonresponse, as well as noncoverage, and must be used for deriving representative population-based estimates of risk behavior prevalence (CDC 2005, first page—no page numbering)

These sample selection issues were addressed by using post-stratification weights for all of the subsequent analyses, which address age, sex, and racial biases.

The 2005 BRFSS collected information on 356,112 adults from 50 states, the District of Columbia, Puerto Rico, and the U.S. Virgin Islands. The variables of particular interest for this analysis are race and health status. BRFSS identifies five categories of race or ethnicity: white, black, American Indian or Native Alaskan, Asian or Pacific Islander, and Hispanic. In this study, however, race or ethnicity is limited to those who self-identified as non-Hispanic white (278,672) and non-Hispanic black (27,735). BRFSS survey respondents reported their health status on a scale from one to five, one being excellent and five being poor.

The use of self-reported health status in an analysis such as this can be problematic if there are systematic differences in the “cutoffs” (that is the level of a characteristic that distinguishes one health level category from another) according to the racial subgroup to which the respondent belongs. To illustrate this issue, Table 1 identifies by race and health status category the mean number of days during the past month that physical health was self-reported by BRFSS respondents as “not good.” For the first three categories of health status, the number of days is fairly close across the racial categories. However, on average, it takes more days of “not good” health for a white respondent to report “fair” of “poor” health status that it does for a black respondent. Because whites may systematically rate themselves as being in better health than blacks when using self-reported “cutoff points,” it is possible that self-reported health status may overstate the size of the measured health status gap.

Table 1

Variables Used in the Constructed Health Measure

	Mean Number of Days in Past Month that Health was Not Good		**BMI Mean**	
Self-Reported Health	White	Black	White	Black
Excellent	0.869	1.144	25.03	27.39
Very Good	1.517	1.445	26.78	28.68
Good	3.262	2.882	28.72	29.95
Fair	11.342	8.959	30.13	31.91
Poor	23.77	20.66	30.35	32.81

To check the robustness of the self-reported health status decomposition results, an alternative dependent variable (health) was constructed that imposed the same cutoff points for both races. The measure was constructed using a combination of body mass index (an objective measure) and the number of days in the past month that the respondent's physical health was "not good" as follows: health=1 (excellent) if the respondent is neither overweight nor obese (BMI < 25) and had less than 2 bad health days in the past 30 days; health=2 (very good) if the respondent reported 2 bad health days and is not obese (BMI <30) or less than 2 bad days but is overweight; health =3 (good) if 3 days are in bad health and respondent is not obese; health=4 (fair) if 4-10 out of the past 30 days are in bad health at any BMI *or* the respondent is obese; and health =5 (poor) if health is not good for more than 10 days at any BMI. The cutoffs are based on the physical health days associated with the self-reported health status measure, but the same cutoffs are used regardless of race. When the BMI classification is included in defining health status, the self-reported health status gap understates this constructed health status gap measure.

A number or variables expected to affect the probability that a respondent self-reports a particular health status were used to estimate separate ordered probit models for each race (white and black) and to estimate pooled coefficients based on the literature survey above. The variables available in BRFSS from which the explanatory variables included in the probit models are constructed are presented in Table 2.

A potential endogeneity problem exists with respect to the explanatory variables associated with "physical activity": poor health status may reduce physical activity, while higher levels of physical activity may improve health status. However, differences in physical activity are quite large across the racial groups (see Table 3). To test the robustness of the analysis with respect to physical activity

Table 2
Explanatory Variables

Explanatory Variable Constructed from	Definition	Omitted Case
Partner	1 if married or member of a couple 0 otherwise	
Education	1=no school or only kindergarten 2=grades one through eight 3=grades nine through eleven 4=high school graduate or GED 5=one through three years of college 6=college graduate or more	no schooling
Emotional support*	1=always 2=usually 3=sometimes 4=rarely 5=never	never
Annual Household income	1=less than $10,000 2=$10,000 to less than $15,000 3=$15,000 to less than $20,000 4=$20,000 to less than $25,000 5=$25,000 to less than $35000 6=$35,000 to less than $50,000 7=$50,000 to less than $75,000 8=more than $75,000	<$10,000
Health plan	1 if insured 0 otherwise	
age	in years	
sex	0 if female 1 if male	
Census Region		northeast
northeast	1 if northeast 0 otherwise	
Midwest	1 if midwest 0 otherwise	
West	1 if west 0 otherwise	
South	1 if south 0 otherwise	
Islands	1 if US island 0 otherwise	
Body Mass Index**	4 digit, no decimal	
Current Smoker	1 if yes 0 otherwise	
Heavy Drinker***	1 if yes 0 otherwise	
High Risk****	1 if yes 0 otherwise	
Routine Checkup	1= within the past year 2=between 1 and 2 years ago 3=between 2 and 5 years ago 4=more than 5 years ago 5=never	never

Fruit Index	1= 0 to less than one serving per day 2=one to two servings 3=three or four servings 5= five or more servings	
Physical activity	1=meets moderate and vigorous 2=meets vigorous physical activity 3=meets moderate physical activity 4=insufficient activity to meet moderate or vigorous 5= no moderate or vigorous physical activity.	No moderate or vigorous

*Response to "How often does the respondent get the social and emotional support he or she needs?"

** Note BMI is an explanatory variable in the self-reported health status model, but not in the constructed health variable model.

*** A heavy drinker consumes more than 2 drinks daily if male or 1 drink daily if female ****high-risk indicates if the respondent has ever participated in behavior that elevates risk for HIV/AIDS.

levels, the analysis was conducted using all five possible health status outcomes, then repeated using only those respondents whose health was "good," "very good," or "excellent"; thus eliminating the group where health status may limit potentially health improving physical activity.

Table 3
Share of Respondents by Race and Health Category
Reporting Sufficient or Insufficient Physical Activity

	Insufficient	Sufficient	Insufficient	Sufficient
	Whites		Blacks	
Excellent	38.09	61.90	51.41	45.59
Very Good	44.61	55.34	53.89	46.11
Good	46.22	53.78	56.44	43.57
Fair	55.60	44.40	62.46	37.53
Poor	63.87	36.13	72.75	27.25
Overall Sample	47.93	52.05	59.78	40.22

An ordered probit model estimates the health statuses of each subpopulation using variables constructed from those identified in Table 2 that are believed to influence health status. The white-black health status gap is defined as the difference between the predicted health status of the white population and the predicted health status of the black population. Once having measured the levels of the characteristics associated with health status for each population (white, black), and how changes in these characteristics affect the probability of reporting a particular health status for each population, we can estimate what the health status of the black population would be if the characteristics or behaviors possessed by the black population were to yield the same returns to health status as they do to the white population (Ehrenberg and Smith, 2003). These estimates can then be decomposed into the share of each health status gap attributable to differences in behaviors and characteristics of the two groups, and the share attributable to differences in the different health status "returns" to those behaviors and characteristics. Both parts of the decomposition reflect the impact of race. The first part reflects the differences in *observed* characteristics and behaviors, while the second part reflects differences in the health generating process between two groups as well as *unobserved* influences such as discrimination and/or omitted variables. The former may be construed as indirect racial effects on health, and the latter a direct effect of race on health. A more formal description of the process, following Fairlie's (2003) extension of the Blinder-Oaxaca method in a nonlinear model (the probit) throughout the discussion, is presented below.

Health status is predicted from the ordered probit as the sum over all of the outcomes (in this case 1, 2, 3, 4 or 5) of the probability of an outcome multiplied by the value of the outcome. The average probability (not the probability of the average) is represented as $\overline{Y}_i$ where i takes on the values w=white and b=black.

The health status gap, $\overline{Y}w - \overline{Y}b$ can be decomposed into:

$$\bar{Y}_w - \bar{Y}_b = \left[\sum_{i=1}^{nw} F(X_{i,w}\hat{\beta}_w)/n_w - \sum_{i=1}^{nb} F(X_{i,b}\hat{\beta}_w)/n_b\right] + \left[\sum_{i=1}^{nb} F(X_{i,b}\hat{\beta}_w)/n_b - \sum_{i=1}^{nb} F(X_{i,b}\hat{\beta}_b)/n_b\right]$$

where F($\overline{X}$ β) is the cumulative distribution function from the standard normal distribution and n_j is the sample size for race j. The elements in the first bracket represent the part of the racial gap that is due to differences in the distribution of (all of) the X variables. Elements in the second bracket represent differences in the underlying group processes that generate the levels of Y observed, as well as unmeasured and unobserved characteristics and endowments. Given the more ambiguous interpretation of the second bracketed term, the focus of the analysis will be on the elements in the first bracket. The gap can also be measured using the black beta coefficients as weights in the first term and the white distribution X as weights in the second term. These alternative methods of calculating the gap can lead to different estimates (the indexing problem). For this reason, a range for the health status gap using both methods of weighting is reported.

When determining the contribution of specific variables to the health status gap, as is done here to assess the contribution of differences in the distribution of behavioral variable (high-risk for HIV/AIDS activity, level of physical activity, servings of fruits and vegetables, drinking, and smoking), the calculations are more complicated. The basic calculations (accounting again for the indexing problem by reversing the role of the white and black samples) determine the change in the average predicted probability using a ranked matching of the two samples and then replacing the black distribution for the white distribution *only for the variable of interest* while holding the rest of the white variables constant. The equation below is thus equal to the part of the racial gap that is due to the difference in the distribution of a specific X variable (corresponding to the first bracket in the previous equation):

$$1/n_b \sum_{i=1}^{nb} F(\hat{\alpha}^* + X_{1iw}\hat{\beta}^*_1 + X_{2iw}\hat{\beta}^*_2) - F(\hat{\alpha}^* + X_{1ib}\hat{\beta}^*_1 + X_{2iw}\hat{\beta}^*_2),$$

where X_{2i} represents the set of variables that remain constant.

However, because the sample sizes differ across racial subpopulations, Fairlie (2003) (2006) suggests the following solution. Use pooled (black and white samples combined) coefficient estimates to calculate predicted probabilities for each observation in the sample. (Note that the pooled estimates contain a race dummy that is then left out of the decomposition analysis because of the focus on differences in the group distribution of behaviors). Draw a random sample of the larger racial population to match the sample size of the smaller racial population. Rank each of the racial samples by their predicted probabilities and match them to each other. Perform the replacement decomposition exercise. Because the decomposition results depend on the random sample chosen, the exercise needs to be repeated a large number of times. (Relying on the central limit theorem, a large number of times will be 30). The mean of the estimates of the repeated samples is then calculated to approximate the true value of the decomposition.

IV. EMPIRICAL RESULTS AND DISCUSSION OF IMPLICATIONS

Mean values (or sample proportions) by racial group from the 2005 BRFSS for the dependent variables and the variables included in the ordered probit model are presented in Table 4. (Panel A of Table 4 presents difference in means for continuous and indicator variable; Panel B of Table 4 presents differences in sample proportions for categorical variables).

TABLE 4
PANEL A
Means (and 0/1 Indicator Variables) and Differences in Means
from the 2005 BRFSS

Variable	*White*	*Black*	*W-B*
Age	44.91	42.42	2.50* (0.00)
BMI	27.29	29.61	-2.32* (0.00)
Sex (Males)	0.414	0.319	0.095* (0.00)
Partner	0.660	0.363	0.297* (0.00)
Health Plan	0.877	0.807	0.070* (0.00)

Exercise	0.801	0.677	0.123* (0.00)
Smoker	0.228	0.228	0.000 (0.94)
Drinker	0.056	0.034	0.022* (0.00)
High Risk	0.025	0.055	-0.030* (0.00)
Northeast	0.202	0.148	0.055* (0.00)
Midwest	0.237	0.169	0.068* (0.00)
South	0.207	0.405	-0.197* (0.00)
West	0.265	0.045	0.219* (0.00)
Islands	0.002	0.054	-0.052* (0.00)

P-values are in parentheses.
* indicate significance at <1%

TABLE 4
PANEL B
Sample Proportions and Differences in Sample Proportions from the 2005 BRFSS

Variable	*Health Status (1=Excellent to 5=poor)*			
	White Self Report	*White Constructed*	*Black Self Report*	*Black Constructed*
Excellent	23.73	28.10	16.44	17.81
Very Good	37.94	30.76	28.87	28.11
Good	26.19	2.61	34.34	2.18
Sum	87.86%	61.47%	79.65%	48.10%
Fair	8.44	28.11	15.12	39.37
Poor	3.70	10.42	5.23	12.53
Sum	12.14%	38.53%	20.35%	51.9%
Mean Values	2.30	2.62	2.64	3.00

Pearson Chi2 4.8e+03
P (0.00)

	White	*Black*	*W-B*
Checkup			
Never	1.13	0.41	0.72
Past year	64.56	78.81	-14.25
1-2 years	15.07	11.46	3.61
2-5 years	9.48	5.51	3.97
5+ years	9.77	3.82	5.95

Pearson Chi2 2.3e+03
P (0.00)

Education			
None	0.04	0.04	0
grades 1-8	0.83	1.79	-0.96
grades 9-11	4.0	8.96	-4.96
HS/GED	27.03	34.20	-7.17
some college	28.34	29.18	-0.84
college grad or more	39.75	25.83	13.92
	Pearson Chi2 1.3e+04		
	P (0.00)		
Income			
>$10K	3.54	10.32	-6.78
$10K-<$15K	3.53	7.28	-3.75
$15K-<$20K	4.76	17.12	-12.36
$20K-<$25K	7.29	11.97	-4.68
$25K-<$35K	11.74	15.82	-4.08
$35K-<$50K	18.15	16.65	1.5
$50K-<$75K	21.37	13.03	8.34
> $75K	29.61	12.86	16.75
	Pearson Chi2 1.4e+04		
	P (0.00)		
Variable	*White*	*Black*	*W-B*
Emotional Support			
Always	45.05	45.18	-0.03
Usually	36.90	22.15	14.52
Sometimes	12.33	21.11	-8.78
Rarely	3.81	5.84	-2.03
Never	1.91	5.72	-3.81
	Pearson Chi2 4.7e+03		
	P (0.00)		
Fruits and Vegetables			
>1serving	4.24	6.62	-2.38
1-2servings	35.60	37.57	-1.97
3-4 servings	36.58	32.71	3.87
5+ servings	23.58	23.09	0.49
	Pearson Chi2 557.67		
	P (0.00)		
Physical Activity Level			
Moderate and Vigorous	18.00	10.31	7.69
Vigorous	11.46	12.66	-1.2
Moderate	22.52	17.15	5.37
insufficient	38.62	40.93	-2.31
none	9.40	18.96	-9.56
	Pearson Chi2 3.3e+03		
	P (0.00)		

From Table 4, it is clear that there are statistically significant differences in the mean values of the identified characteristics and behaviors across the populations examined. The statistical significance of the differences is practically uniform for the characteristics and behaviors under study, with the exception that the proportion of smokers in the white population is not statistically significantly different from the proportion of smokers in the black population. All of the other variables are significantly different across populations at levels of significance up to five percent. The mean health status gap between whites and blacks is 0.332203 in favor of whites (about 14.4 percent when divided by predicted white health status: 2.304).

The underlying structural equations of the health probability function also differ across the two racial groups. Because the variable to be estimated is an ordered qualitative variable, an ordered probit was used to estimate health status based on the other variables thought to underlie the respondent's self-reported (and constructed) health status. The results of the three (white, black and pooled) ordered probits are reported in Appendix Table A1 (self-reported health status) and Table A2 (constructed health status). The data are weighted using post-stratification weights to correct for non-response biases in the sample, and non-coverage of households without telephone services along race, sex, and age dimensions. Usable observation rates are 58 percent for whites and 60 percent for blacks.

It is important to remember, however, that the predicted health status here is merely an estimate of a probability function. The coefficients cannot be interpreted as marginal effects. The marginal impact of these variables on the probability of reporting a particular health status is calculated from the result of the ordered probit. The marginal impacts for each of the explanatory variables are available from the author.

Using the first decomposition method described above (and the reverse ordering to account for the indexing problem),

$$\bar{Y}_w - \bar{Y}_b = [\sum_{i=1}^{nw} F(X_{i,w}\hat{\beta}_w)/n_w - \sum_{i=1}^{nb} F(X_{i,b}\hat{\beta}_w)/n_b] + [\sum_{i=1}^{nb} F(X_{i,b}\hat{\beta}_w)/n_b - \sum_{i=1}^{nb} F(X_{i,b}\hat{\beta}_b)/n_b]$$

to estimate the health status gap between blacks and whites of the entire set of independent variables finds (see Table 5): the white-black gap is 0.332203 (favoring whites) and the contribution from group specific differences in the distribution of the independent variables ranges from 61.88 percent to 95.99 percent When the constructed health variable is used, the gap is 0.378498 favoring whites (a gap of about 14.6 percent=0.37849/2.62), and the contribution from group specific differences in the distribution of the independent variables ranges from 26.46 percent to 58.34 percent. This suggests that if all the measured characteristics and behaviors of blacks and whites (behavioral characteristics as well as socioeconomics and demographic characteristics) were identical, the health status gap between them would decline from 14.4 percent to between 0.7 percent and 5.6 percent (using self-reported values) but still not disappear. The same measures using the constructed measure show a similar decline, but failure to close, in the gap: from 14.6 percent to between 5.3 percent and 9.3 percent.

TABLE 5

All Variables Decomposition

Dependent Variable: Self-Reported Health Measure

Order	Gap	Group difference Distribution	Contribution Group Difference Distribution
White-Black	-0.332203	-0.318872	95.99%
Black-White	-0.332203	-0.205558	61.88%

Range of contribution of Group Differences in Distribution: 61.88%-95.99%

Dependent Variable: Constructed Health Measure

Order	Gap	Group difference Distribution	Contribution Group Difference Distribution
White-Black	-0.378498	-0.220821	58.34%
Black-White	-0.378498	-0.100151	26.46%

Range of contribution of Group Differences in Distribution: 26.46%-58.34%

Specific Variable Contributions: Self-Reported Dependent Variable

The results for the decomposition exercise identifying the contribution of differences across racial groups in the distribution of specific individual behaviors to the health status gap are presented in Table 6. Standard errors are calculated according to the delta method proposed by Fairlie (2003). Ranges are presented to account for the indexing problem noted above. These calculations of the health status gap use pooled coefficients with a racial dummy included in estimating the coefficients, but the racial dummy is then set equal to zero to assess the impact of difference by race in the distributions of characteristics and behaviors. The self-reported health status gap due to differences in distribution of the full set of characteristics using the pooled estimation is 0.304492 (91.66 percent of the gap), a figure within the range reported in Table 5 (61.88 percent to 95.99 percent).

The findings are as follows: black/white differences in the share of each subpopulation that has engaged in high risk behaviors contributes between 0.56 percent and 0.57 percent of the overall health status difference; physical activity contributes between 14.67 percent and 15.93 percent; diet contributes between 0.66 percent and 0.68 percent. Smoking differences yielded no significant differences by race (and as noted, the difference in means by race for smoking was also not significant as documented in Tables 4). Drinking behavior was not significant in the probit model, and although

TABLE 6

Specific Behavioral Variable Contribution To Health Status Gap Pooled Coefficient Method

Dependent Variable: Self-Reported
Pooled Estimates: White Health=2.299816
Black Health (race dummy=0)=2.604308
Distributional Gap=-0.304492/0.332203= 91.66%

	B Replaces W	W Replace B
High Risk	0.00186	0.0018894
	(0.00021)	(0.00022)
	0.56%	0.57%
Physical Activity (5 outcomes)	0.0529079	0.0487349
	(0.00038)	(0.00038)
	15.93%	14.67%
Physical Activity (3 outcomes--	0.0209485	0.0211616
gap=-0.139727/0.308333=45.32%)	(0.00049)	(0.0005)
	6.79%	6.86%
Fruits and Vegetables	0.0022899	0.00218431
	(0.0001)	(0.0001)
	0.69%	0.66%

Dependent Variable: Constructed
Pooled Estimates: White Health=2.629956
Black Health (race dummy=0)=2.835241
Distributional Gap=-0.205285/-0.378498= 54.24%

	B Replaces W	W Replaces B
High Risk	0.0033824	0.0033812
	(0.0002)	(0.0002)
	0.89%	0.89%
Physical Activity (5 outcomes)	0.0642087	0.0627651
	(0.0004)	(0.00037)
	16.96%	16.58%
Physical Activity (3 outcomes)	0.006833	0.0824342
Gap=0.009059/-0.087293=-10.37%	(0.0007)	(0.0007)
	7.83%	-94.43%
Fruits and Vegetables	0.000961	0.0009213
	(0.0001)	(0.0001)
	0.25%	0.24%
Drinking	0.0030162	0.0029071
	(0.0001)	(0.0001)
	0.79%	0.77%

Delta method SEs are reported in parentheses.

Dependent Variable: Constructed, No Smokers
Pooled Estimates: White Health=2.597028
Black Health (race dummy=0)=2.782873
Distributional Gap=-0.185845/0.388827=47.80%

	B Replaces W	W Replaces B
High Risk	0.0077996	0.0027536
	(0.0002)	(0.00024)
	2.01%	0.71%
Physical Activity	0.0681445	0.0654424
	(0.0004)	(0.00044)
	17.53%	16.83%
Fruits and Vegetables	0.002427	0.0024061
	(0.0002)	(0.00015)
	0.62%	0.62%
Drinking	0.0029708	0.0029021
	(0.0001)	(0.00015)
	0.76%	0.75%

Delta method SEs are reported in parentheses.

differences by drinking behavior were statistically significant, the magnitude of the contributions from drinking was less than 0.00 percent.

As noted above, differences in distribution of characteristics and behaviors account for approximately 91.66 percent of the health status gap, 15.89 percent-17.18 percent of which is due to behavioral differences and about 74.48 percent to 75.77 percent is due to differences in socioeconomic and demographic characteristics. Thus differences in "returns," or direct effects of race, account for approximately 8.34 percent of the health status gap. Although important, behavioral differences between blacks and whites contribute substantially less than socioeconomic and demographic characteristic differences to the health status gap between blacks and whites.

Because physical activity may influence health and health may influence physical activity, the analysis with respect to physical activity was conducted a second time, including only those respondents who reported good or better health as a sensitivity test. Although the contribution of differences in physical activity to the health status gap diminished in magnitude when respondents who reported less than good health were removed from the data set, these differences nonetheless remained the largest contributor to the health status gap (6.79 percent to 6.86 percent) from the behavioral variables tested.

Overall, differences in physical activity were found to make up the largest contribution to the health status gap when assessing the contribution of differences in the distribution of included behaviors to the racial health status gap based on self-reported health status in this data set. If blacks were to adopt the physical activity behaviors of whites, the health status gap would narrow from 14.4 percent to between 12.12 percent and 12.30 percent as measured from self-reported health status in the unrestricted (all five outcomes) data set.

Specific Variable Contributions: Constructed Dependent Variable

The health status gap using the constructed measure is 0.378498 (about 14.6 percent =

.378498/2.6). Following the same method as that used to conduct the analysis for self-reported health status, the constructed health status gap due to differences in distribution using the pooled estimation method is 0.205285 (54.24 percent of the gap) and is in the range reported in Table 5 (26.46 percent to 58.34 percent).

The findings are as follows: difference by race in the share of the subpopulation who have engaged in high-risk behaviors contributes 0.89 percent of the overall health status difference; physical activity contributes between 16.58 percent and 16.96 percent; diet contributes between 0.24 percent and 0.25 percent; and drinking behavior contributes between 0.77 percent and 0.79 percent. Smoking differences yielded no significant differences by race (the difference in means by race for smoking was also not significant as documented in Tables 4A).

The findings using the constructed health measure reinforce the self-reported health status findings. Again, black/white differences in physical activity are the largest measured behavioral contributor to the black/white health status gap. If blacks were to adopt the same physical activity levels reported by whites, the health status gap between them would narrow from 14.6 percent to between 11.99 percent and 12.05 percent.

The analysis using the constructed estimates of health faced the same endogeneity issues with physical activity as the self-reported measure. Therefore, a sensitivity test was conducted again with the dependent variables restricted to the three better health status outcomes (good, very good or excellent). The measured health status gap between whites and blacks in this group was much smaller (-0.087293) than in the full sample (-0.378498). This result suggests that the distributional differences across racial groups would favor blacks (reducing the gap by 0.009050, to -.078234), and is explained not by differences in the distributions of characteristics and behaviors, but rather by the health generating processes and unexplained elements that contribute to health status. However, when the two samples were restricted to “good or better” health, 61.47 percent of the white sample achieved “good or better” health status under the constructed measure while only 48.09 percent of the black sample did. This result suggests that the bulk of the distributional difference in behaviors may be among respondents in “fair” to “poor” health.

When the physical activity replacement exercise was simulated repeatedly in the restricted sample, the findings suggest that if whites had engaged in physical activity only to the same extent as blacks, their health status would worsen by 0.006833 or 7.8 percent of the gap. The health status of blacks if they engaged in physical activity at the same level as whites would improve by 0.0082342, or close about 94 percent of the remaining gap between blacks and whites.

Finally, the coefficient on smoking yielded a sign contrary to expectation in the probit model. Smoking was construed to be negatively associated with BMI that in part determines health status under the constructed measure. The analyses were again conducted using the constructed measure, but only including nonsmokers in the samples. These analyses are presented and, although differing in magnitudes, the relative importance of differences in physical activity across racial groups in the health status gap is underscored.

V. CONCLUSIONS, POLICY ISSUES, AND AREAS FOR FUTURE RESEARCH

Although the analyses presented here do not establish causation, the descriptive results reported can contribute to efforts to narrow the health status gap because they identify sources, and levels of contribution of the identified sources, to the observed health status gap. This analysis finds that 61.88 percent to 95.99 percent of the measured self-reported health status gap between blacks and whites can be attributed to differences in behaviors and other socioeconomic and demographic characteristics. (If self-reported health status is replaced by a constructed measure of health status based on self-reported days in poor health and BMI, then the percentage of the measured health status gap between blacks and whites that can be attributed to differences in behaviors and other socioeconomic and demographic characteristics is 26.46 percent to 58.34 percent). Yet even if all the measured characteristics and behaviors were identical across the two groups, the health status gap between them would decline to between 0.7 percent and 5.6 percent (using self-reported values) or to between 6.0 percent and 10.6 percent (using the constructed measure), but still not disappear.

Nonetheless, further efforts to understand which behaviors differ, and why, are likely to improve the health status of minority populations by giving rise to policies that promote specific health-enhancing behaviors. Such policies might involve expanding choice sets, or initiating behavioral change through strong promotion by health care providers, public health agencies and in public schools, towards specific health enhancing behaviors through education and advisement.

In particular, a relatively large share of the gap in terms of behavioral differences—ranging from 14.67 percent to 16.96 percent of the overall approximately 14 percent health status gap —was attributable to difference in physical activity in the unrestricted (five health status level, self-reported measure) samples. If the physical activity gap were to close, the health status gap favoring whites has the potential to narrow to between 11.99 percent and 12.30 percent. Policies designed to enhance physical activity among African American would thus seem to be a promising source of immediate action to reduce the health status gap. Such policies might include community recreation centers located in predominantly African American communities, tax waivers for health fitness facilities that locate in predominantly African American communities, or subsidies to Medicaid recipients for fitness facility memberships. Alternatively, efforts to create built communities to enhance physical activity (green spaces and walkability) can be supported and subsidized by government.

Although physical activity had a relatively large impact in the domain of behavior, behavioral aspects were dwarfed by the contribution of the other socioeconomic and demographic attributes to the health status gap consistent with what has been reported in the literature on health disparities. However, the present analysis suggests that emphasis on enhanced physical activity among blacks would be an appropriate strategy as it promises the relatively largest reduction in the health status between blacks and whites among the behaviors measured in the analysis. Yet, these efforts alone, as has been found in this analysis, will not be sufficient to close the health status gap between blacks and whites. There remain differences in socioeconomic and demographic characteristics of blacks and whites as well as in the underlying health-generating process and unobserved endowments that will need to be measured and addressed.

Research into specific health behaviors by race and ethnicity, sex, and health status will improve society's ability to target specific groups in ways that will help close the health status gap. Further research that investigates differences in improvements to health status for given behavioral investments (such as quitting smoking, increasing exercise—or engaging in other health-generating behavior) and other behavioral differences that were not captured in BRFSS data analyzed in this study (such as caloric intake, compliance with disease screening recommendations) may serve to improve our understanding, and our ability to reduce the health status gap that has persisted between U.S. blacks and whites for too long.

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Appendix

TABLE A1
Dependent Variable=Self-Reported Health Status (1=excellent to 5=poor)
Ordered Probit Coefficients

Variable	*White*	*Black*	*W/B Pooled*
Constant	0.676	1.315	0.704
Black			0.012
			(0.289)
Age	0.0001	-0.002	0.001
	(0.92)	(0.66)	(0.722)
Age^2	0.0001*	0.000*	0.000
	(0.00)	(0.00)	(0.00)
Health Plan	0.001	-0.21	-0.005
	(0.89)	(0.43)	(0.568)
Checkup (never)			
past year	0.116*	0.072**	0.110*
	(0.00)	(0.02)	(0.000)
past 2 years	0.013	-0.074	0.006
	(0.27)	(0.12)	(0.606)
past 5 years	0.034*	0.059	0.035*
	(0.01)	(0.33)	(0.007)
past	–0.103*	-0.210	-0.107*
	(0.00)	(0.23)	(0.00)
Partner	0.071*	0.034	0.061*
	(0.00)	(0.11)	(0.00)
Education (none)			
1-8^{th}	0.438*	-0.325	0.324**
	(0.00)	(0.41)	(0.021)
1-11^{th}	-0.150*	-0.045	-0.152*
	(0.00)	(0.59)	(0.00)
1-12/GED	-0.197*	-0.102*	-0.174*
	(0.00)	(0.01)	(0.00)
1-some college	-0.090*	-0.048**	-0.080*
	(0.00)	(0.05)	(0.00)
1-college +	-0.156*	-0.068*	-0.152*
	(0.00)	(0.01)	(0.00)
Income (low)			
10K or more	-0.073*	-0.190*	-0.080*
	(0.00)	(0.00)	(0.00)
15K or more	-0.201*	-0.018	-0.168*
	(0.00)	(0.70)	(0.00)
20K or more	-0.139*	-0.151*	-0.134*
	(0.00)	(0.00)	(0.00)
25K or more	-0.164*	-0.059***	-0.145*
	(0.00)	(0.10)	(0.00)
35K or more	-0.115*	-0.113*	-0.115*
	(0.00)	(0.00)	(0.00)
50K or more	–0.088*	-0.088*	-0.090*
	(0.00)	(0.01)	(0.00)
High Income	-0.145*	-0.154*	-0.150*
	(0.00)	(0.00)	(0.00)
Sex	0.038*	-0.030	0.034*
	(0.00)	(0.16)	(0.00)

Emotional Support (none)			
Rarely	0.284*	0.300*	0.301*
	(0.00)	(0.00)	(0.00)
Sometimes	0.075*	0.102**	0.094*
	(0.00)	(0.03)	(0.00)
Usually	-0.161*	0.006	-0.120*
	(0.00)	(0.91)	(0.00)
Always	-0.363*	-0.176*	-0.314*
	(0.00)	(0.00)	(0.00)
Smoker	0.328*	0.182*	0.315*
	(0.00)	(0.00)	(0.00)
Drinker	0.004	-0.027	-0.002
	(0.77)	(0.62)	(0.871)
BMI	0.0004*	0.0003 *	0.0004*
	(0.00)	(0.00)	(0.00)
Fruits/Veg	-0.036*	-0.038*	-0.037*
	(0.00)	(0.00)	(0.00)
Exercise (none)			
Insufficient	-0.368*	-0.249*	-0.341*
	(0.00)	(0.00)	(0.00)
Moderate	-0.458*	-0.253*	-0.425*
	(0.00)	(0.00)	(0.00)
Vigorous	-0.632*	-0.461	-0.597*
	(0.00)	(0.00)	(0.00)
Mod+Vig	-0.706*	-0.574*	-0.680*
	(0.00)	(0.00)	(0.00)
High Risk	0.088*	0.075***	0.073*
	(0.00)	(0.08)	(0.00)
Midwest	0.001	0.004	-0.001
	(0.93)	(0.88)	(0.944)
South	0.033*	-0.012	0.027*
	(0.00)	(0.57)	(0.001)
West	0.031*	-0.006	0.025*
	(0.00)	(0.90)	(0.001)
Islands	-0.125***	0.034	0.043
	(0.07)	(0.38)	(0.206)
Predicted Health Status	2.304044	2.636247	2.33551
Sample Size	161,794	16,780	178,574
Wald Chi2	35799.71	3033.66	37643.42
Prob >chi	0.00	0.00	0.00

Predicted health status is calculated as:
[1-Φ(βhatXbar)]*0 + [Φ(μ1- βhatXbar) - Φ(-βhatXbar)]*1 + [Φ(μ2- βhatXbar) - Φ(μ1- βhatXbar)]*2+[Φ(μ3- βhatXbar) - Φ(μ2-βhatXbar)]*3+ [Φ(μ4- βhatXbar) - Φ(μ3-βhatXbar)]*4 [1-Φ(μ5- βhatXbar)]*5
Φ is the normal CDF (Greene, 2003)
P-values are in parentheses: * indicates significance at 1%; ** at 5% and *** at 10%.

TABLE A2

Dependent Variable= Constructed Health Status (1=excellent to 5=poor)
Ordered Probit Coefficients

Variable	*White*	*Black*	*W/B Pooled*	*W/B Pooled No Smokers*
Constant	0.322	1.023	0.199	0.104
Black			0.095*	0.125*
			(0.00)	(0.00)
Age	0.042*	0.059*	0.045*	0.045*
	(0.00)	(0.00)	(0.00)	(0.00)
Age^2	-0.0004*	-0.0005*	-0.0004*	-0.0004*
	(0.00)	(0.00)	(0.00)	(0.00)
Health Plan	0.068*	0.053**	0.066*	0.044*
	(0.00)	(0.03)	(0.00)	(0.00)
Checkup (never)				
past year	0.119*	0.089*	0.116*	0.104*
	(0.00)	(0.00)	(0.00)	(0.00)
past 2 years	0.036*	-0.029	0.030*	0.027**
	(0.00)	(0.55)	(0.01)	(0.05)
past 5 years	0.040*	0.081	0.042*	0.039*
	(0.00)	(0.20)	(0.01)	(0.01)
past	–0.075*	-0.056	-0.073**	-0.054
	(0.01)	(0.71)	(0.02)	(0.14)
Partner	0.074*	0.050**	0.064*	0.052*
	(0.00)	(0.02)	(0.00)	(0.00)
Education (none)				
1-8th	0.374*	0.103	0.341**	0.355***
	(0.01)	(0.87)	(0.03)	(0.06)
1-11th	-0.112*	-0.107	-0.119*	-0.051
	(0.00)	(0.23)	(0.00)	(0.27)
1-12/GED	-0.099*	-0.036	-0.084*	-0.124*
	(0.00)	(0.36)	(0.00)	(0.00)
1-some college	0.008	0.026	0.015***	0.001
	(0.32)	(0.29)	(0.06)	(0.89)
1-college +	-0.181*	-0.167*	-0.180*	-0.199*
	(0.00)	(0.00)	(0.00)	(0.00)
Income (low)				
10K or more	-0.101*	-0.222*	-0.117*	-0.065**
	(0.00)	(0.00)	(0.00)	(0.03)
15K or more	-0.174*	-0.057	-0.154*	-0.148*
	(0.00)	(0.23)	(0.00)	(0.00)
20K or more	-0.133*	-0.085**	-0.156*	-0.099*
	(0.00)	(0.04)	(0.00)	(0.00)
25K or more	-0.138*	-0.109**	-0.132*	-0.120*
	(0.00)	(0.02)	(0.00)	(0.00)
35K or more	-0.046*	-0.047	-0.046*	-0.058*
	(0.00)	(0.15)	(0.00)	(0.00)
50K or more	–0.062*	-0.018	-0.059*	-0.047*
	(0.00)	(0.59)	(0.00)	(0.00)
High Income	-0.119*	-0.053	-0.119*	-0.133*
	(0.00)	(0.12)	(0.00)	(0.00)

Sex	0.174*	-0.073*	0.149*	0.181*
	(0.00)	(0.00)	(0.00)	(0.00)
Emotional Support (none)				
Rarely	0.265*	0.312*	0.289*	0.308*
	(0.00)	(0.00)	(0.00)	(0.00)
Sometimes	0.083*	0.092**	0.098*	0.129*
	(0.00)	(0.05)	(0.00)	(0.00)
Usually	-0.067*	0.069	-0.032	0.001
	(0.00)	(0.14)	(0.12)	(0.96)
Always	-0.115*	-0.013	-0.080*	-0.040
	(0.00)	(0.76)	(0.00)	(0.11)
Smoker	0.048*	-0.066*	-0.045*	
	(0.00)	(0.01)	(0.00)	
Drinker	0.119*	-0.074	-0.118*	-0.113*
	(0.00)	(0.16)	(0.00)	(0.00)
Fruits/Veg	-0.011*	-0.003	-0.011*	-0.022*
	(0.00)	(0.79)	(0.00)	(0.00)
Exercise (none)				
Insufficient	-0.360*	-0.119*	-0.309*	-0.308*
	(0.00)	(0.00)	(0.00)	(0.00)
Moderate	-0.476*	-0.181*	-0.422*	-0.430*
	(0.00)	(0.00)	(0.00)	(0.00)
Vigorous	-0.583*	-0.269	-0.523*	-0.547*
	(0.00)	(0.00)	(0.00)	(0.00)
Mod+Vig	-0.660*	-0.302*	-0.601*	-0.625*
	(0.00)	(0.00)	(0.00)	(0.00)
High Risk	0.108*	0.128*	0.098*	0.088*
	(0.00)	(0.00)	(0.00)	(0.00)
Midwest	-0.011	0.043	-0.005	0.004
	(0.17)	(0.13)	(0.544)	(0.67)
South	0.021*	0.018	-0.012	-0.011
	(0.01)	(0.40)	(0.13)	(0.22)
West	0.020*	0.052	0.022*	0.016***
	(0.01)	(0.25)	(0.01)	(0.07)
Islands	-0.203*	-0.183*	-0.188*	-0.218*
	(0.00)	(0.00)	(0.00)	(0.00)
Predicted Health Status	2.623016	3.001514	2.649246	2.628331
Sample Size	161,778	16,778	178,556	137,897
Wald Chi2	14089.72	1249.06	14844.61	11913.96
Prob >chi	0.00	0.00	0.00	0.00

Predicted health status is calculated as:

$$[1-\Phi(\beta\text{hatXbar})]*0 + [\Phi(\mu_1-\beta\text{hatXbar}) - \Phi(-\beta\text{hatXbar})]*1 + [\Phi(\mu_2-\beta\text{hatXbar}) - \Phi(\mu_1-\beta\text{hatXbar})]*2+[\Phi(\mu_3-\beta\text{hatXbar}) - \Phi(\mu_2-\beta\text{hatXbar})]*3+ [\Phi(\mu_4-\beta\text{hatXbar}) - \Phi(\mu_3-\beta\text{hatXbar})]*4 \quad [1-\Phi(\mu_5-\beta\text{hatXbar})]*5$$

Φ is the normal CDF (Greene, 2003)

P-values are in parentheses: * indicates significance at 1%; ** at 5% and *** at 10%.

Income Inequality And Educational Attainment Rates: The New York Story

Ali R. Cannoni and James J. Jozefowicz*

ABSTRACT

This paper examines the relationship between changes in income inequality and educational attainment rates in New York counties during the 1990s. The dependent variable is the change in the Gini coefficient over the decade. The independent variables include the Gini coefficient for 1990, educational attainment rates at the high school, bachelor's degree, and graduate/professional levels, the natural logarithm of population density in the county, real public educational expenditures in the county for several years preceding the 1990s, and an index of racial diversity in the county in 1990. Results of OLS regressions suggest that county population density, and educational attainment rates at the bachelor's and graduate degree levels are associated with increases in county income inequality over time. Alternatively, the initial level of income inequality and the high school attainment rate are associated with decreases in income inequality over time in New York counties.

1. INTRODUCTION

From job shortages in the early 1990s to labor shortages later in the decade, the face of New York changed over the last ten years of the 20^{th} century. New York experienced rising income inequality between 1980 and 2000, based on the changes in the Gini coefficient. The Gini coefficient based on household income data for New York was 0.419 in 1980, rose to 0.467 in 1990, and increased to 0.499 in 2000. This represents a 19.1 percent increase over that twenty year period.

Policymakers are often interested in finding ways to mitigate income inequality, but "should an increase in [income] inequality…be considered a favorable rather than an unfavorable development?" (Becker & Murphy 2007). According to Becker and Murphy (2007), "policies designed to deal with inequality must take account of its cause" since in some instances "the rise in inequality [comes] along with an acceleration of economic growth that [raises] the standard of living" (Becker & Murphy 2007). Therefore, this paper is an impartial examination of the factors associated with rising income inequality in an effort to understand its causes in New York counties.

Income inequality arises because citizens differ from one another in characteristics that have an impact on their incomes. According to Weil (2005), these differences across people exist in human capital (i.e., education and health), where they live (e.g., rural vs. urban), their ownership of physical

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capital, their specific skill sets, and their luck (374). The economic climate then translates these differences into differences in income for these individuals. DeFina (2007) cites technological change, immigration, and deunionization as additional contributing factors to income inequality. Becker and Murphy (2007) note that the U.S. has experienced rising income inequality primarily because of educational attainment differences triggered by changes in the returns to education. Thus, we have chosen to concentrate on the role of education in order to see if the recent experience of New York counties with income inequality is consistent with that of the nation.

This paper is organized into six sections: Section 2 presents past research. Section 3 discusses the data and their main characteristics. Section 4 discusses econometric issues and introduces the empirical model. Section 5 presents the empirical findings and section 6 provides a brief conclusion.

2. LITERATURE REVIEW

Schultz (1963) discusses increasing human capital as a way to decrease income inequality; focusing on support for public education as a potential way to decrease it. Ahluwalia (1976), and Papanek and Kyn (1986) suggest that education is associated with equality of income. Conversely, Ram (1989) does not strongly support the idea that increased education will decrease income inequality. It is evident that there is no clear answer as to whether or not investment in education will decrease income inequality over time (Sylwester 2002).

Sylwester (2002 & 2003) conducts two distinct studies using international samples of 50 countries; the first asks if educational expenditures will reduce income inequality, and the second looks at changes in income inequality and enrollment in higher education. Sylwester (2002) concluded that countries that increase the percentage of GDP devoted to education had lower income inequality in subsequent years. Sylwester (2003) could not determine if rising education levels cause the degree of income inequality across countries to converge. However, he does find that countries with larger enrollment rates in higher education saw their income inequality decrease, but only if people could afford not to work and attend school.

Chiswick and Chiswick (1987) explain how increased participation in higher education could change the composition of the labor force. However, they did not determine whether income dispersion would increase or decrease. Chiswick and Chiswick (1987) explain that if few are highly educated, the increased participation in education can temporarily raise income inequality because more individuals from the unskilled cohort move to the skilled cohort. However, over time increased enrollment in education might lower income inequality as more and more unskilled laborers become skilled, which lowers the wage premium for skilled workers (Chiswick & Chiswick 1987).

Alternatively, Jimenez (1986) emphasizes the roles of primary and secondary education in decreasing income inequality and suggests that higher education might actually lead to a more skewed income distribution. Behr et al. (2004) look at income distribution, educational dispersion, and public K-12 educational expenditures at the state-level during the period 1970-2000. They find that a decrease in educational dispersion leads to a decrease in income inequality during the study period. In addition, the results indicate that larger educational expenditures eventually reduce income inequality. Ahluwalia (1976), Marin and Psacharopoulos (1976), Ram (1984), Papanek and Kyn (1986), and Park (1996) all find that greater education levels correlate positively with income equality. However, as previously mentioned, Ram (1989) does not find a strong relationship between education levels and income inequality.

Park (1996) performs a cross-country study of the Kuznets inverted U-hypothesis with an emphasis on the role of education measures. The results indicate that the presence of education variables in the regression weakens the robustness of the Kuznets hypothesis and reduces the income variables' significance. More importantly, however, Park found that education measures alone accounted for 42 percent of the variation in income inequality, as measured by the adjusted R^2.

There have been many studies of income inequality and educational attainment conducted worldwide. However, very few of them have measured income inequality at the sub-unit level (e.g., state or county) of a highly developed economy. Exceptions include Behr et al. (2004), Jenkins and Jozefowicz (2006), and to some extent Sylwester (2002 & 2003). We believe that what is largely true of developing economies, as widely studied in the literature, also holds in certain sub-units of developed economies. Thus, like Jenkins and Jozefowicz (2006), our focus is the county level.

Jenkins and Jozefowicz (2006) study 67 counties across Pennsylvania during the 1990s and observe that an increase in educational attainment rates at the high school and bachelor's degree levels is associated with a reduction in income inequality. The initial level of income inequality in the county also reduces income disparity. Alternatively, they find that population density and educational attainment at the graduate level increase income inequality in a county.

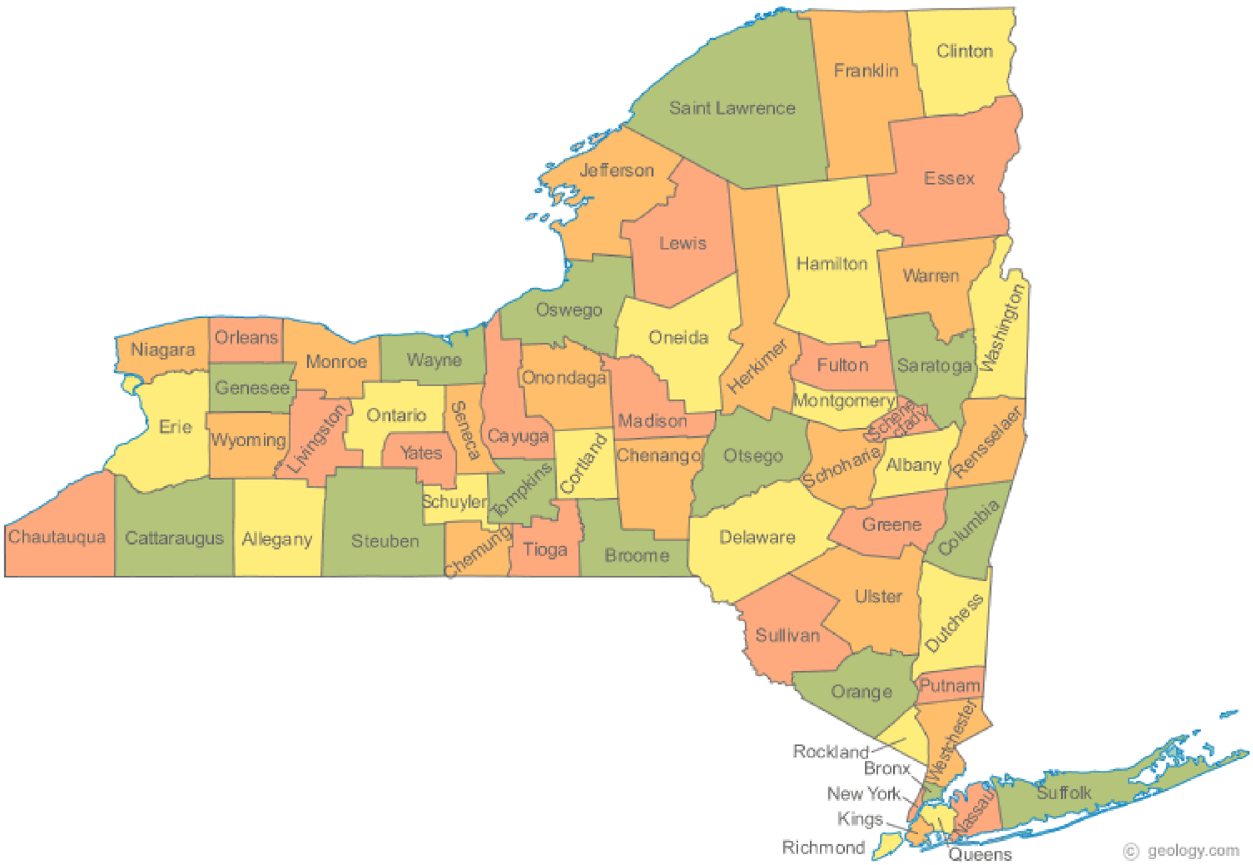
As Jenkins and Jozefowicz (2006) point out, a typical deficiency of cross-country studies is the rather small number of observations in the sample (e.g., Tinbergen (1972) n=3, Psacharopoulos (1977) n=49, Ram (1984) n=28). Another drawback, discussed by Jenkins and Jozefowicz (2006), is that Gini coefficients calculated at the national level mask state differences. In a similar fashion, state-level Gini coefficients mask county differences. Our sample consists of 62 counties in New York, which is large in comparison to many cross-country studies and focuses on the relationship between educational attainment and changes in the Gini coefficient in these counties.

3. DATA

The sample is a cross-section of the 62 counties in New York observed over the period from 1990 to 2000. It is comprised of data from the 1990 and 2000 Census reports, which were retrieved from the U.S. Census Bureau website. For a complete list of the counties please visit http://www.nysac.org/Counties/Member_County_Web_Sites.php . A map of New York State counties can be found in Figure 1.

Figure 1: Map of New York State

Counties



Source: http://geology.com/state-map/new-york.shtml

3.1 Dependent Variable

The change in the Gini coefficient between 1990 and 2000 is utilized as the dependent variable in this study, $\Delta GINI = GINI2000 - GINI1990$. This is consistent with Edwards (1997), Savvides (1998), Sylwester (2002 & 2003), and Jenkins and Jozefowicz (2006). We use the Gini coefficient as a measure of income inequality because of its widespread use in other studies and for comparison purposes. Furthermore, Clarke (1995) finds that the Gini coefficient is correlated with other income inequality measures.

Sylwester (2003) uses a twenty year period (i.e., 1970-1990) when analyzing changes in income inequality, but, like Jenkins and Jozefowicz (2006), this study only considers one decade for the calculation of the dependent variable because the breakdown of income brackets from the 1980 Census was incompatible with that of the 2000 Census for Gini creation. As discussed in Jenkins and Jozefowicz (2006), if the household income data used to formulate the Gini coefficients is not consistent, it would create skewed Gini coefficients. Although a longer time period would be preferred, the availability of appropriate Census data constrains this analysis to ten years.

As mentioned by Jenkins and Jozefowicz (2006) and Sylwester (2002 & 2003), using the change in the Gini coefficient as the dependent variable attempts to reduce reverse causality. Sylwester (2003) suggests, "…it is unlikely that changes in income inequality between periods *s* and *t* should affect…period *s*" (Sylwester 2003, 251). Other studies of the link between educational levels and income distribution, such as Ahluwalia (1976), Slama (1978), Papanek and Kyn (1986), and Ram (1989), have employed a measure of income inequality at one point in time as the dependent variable. However, this may result in reverse causality problems. Is the greater disparity in the educational attainment levels of the population caused by income inequality or do existing differences in educational attainment levels lead to increased income inequality? In contrast, using the current framework, the research question is, do New York counties with higher educational attainment rates at the high school, bachelor's, or graduate levels experience rising or declining levels of income inequality?

3.2 Construction of the Gini Coefficients

The individual Gini coefficients for 1990 and 2000 are calculated as follows:

$$GINI = 1 - \sum_{i=1}^{n} f_i (p_i + p_{i-1})$$

where f_i is the proportion of households in income bracket i and p_i is the proportion of total income received by households in income bracket i and all lower income brackets. The Census uses ten household income brackets (e.g., less than \$10,000; \$10,000 to \$12,999; \$15,000 to \$19,999; etc.).

We assume that each household in an income bracket earns the midpoint of that income range so the total income earned by households in an income bracket is obtained by multiplying the number of households in that bracket by the midpoint. These results are then added up across income brackets to obtain the total income earned by households in a county. The ratio of the total income earned by an income bracket to the total income earned in the county provides the proportion of income earned by households in each income bracket.

The feasibility of approximating the distributions by assigning each household in the income bracket to the midpoint of that bracket for the first nine income ranges (those less than \$200,000) was tested. The estimated aggregate household income for those households earning less than \$200,000 was calculated by multiplying the midpoint of each income bracket by the number of households in that income range and then summing the results. Then, the ratio of the estimated aggregate household income to the actual aggregate household income reported by the Census for those households earning less than \$200,000 was calculated for each county in New York. The majority of the ratios equaled 1.01 with a few 1.02 values. Thus, the validity of using the midpoints of the income brackets is confirmed.

The tenth income bracket published by the Census is $200,000 or more. This presents a problem in the calculation of the Gini coefficient since there is no midpoint for an income bracket that has no finite end. In order to address this difficulty, the average earnings for the $200,000 or more bracket were calculated by dividing the county-specific aggregate household income in that bracket by the number of households in that income bracket in that particular county as reported by the Census. The resulting average earnings for the tenth income bracket were used as its midpoint in the county-level Gini calculations. This approach of creating county-specific midpoints is better than assigning a fixed midpoint for the uppermost bracket to all of the counties in the sample because it yields greater variation in the resulting dependent variable. Since the independent variables are county-specific, it makes sense to have a corresponding county-specific midpoint for the $200,000 or more income bracket.

3.3 Independent Variables and Expected Signs

The independent variables used in this study are the initial level of income inequality, educational attainment rates, the population density, public education expenditures, and an index of racial diversity. This model is similar to both Jenkins and Jozefowicz (2006) and Behr et al. (2004).

The Gini coefficient for 1990 (GINI1990) is the initial level of income inequality in the county. As discussed in Sylwester (2003), it is important to control for potential non-linearities. It is conceivable that counties with more income inequality have rates of educational attainment that differ from those counties with lower income disparity. Sylwester (2003) mentions that observations with Gini coefficients near the extrema of the variable range will be less likely to get closer to those bounds. The expected sign for the GINI1990 coefficient is negative. As noted by Jenkins and Jozefowicz (2006), overall increases in employment levels, like those observed in New York during the late 1990s, may reduce the amount of income inequality.

The educational attainment rates for 1990 are divided into high school graduate or equivalent (HSATT), bachelor's degree (BADEGATT), and graduate degree, which includes doctoral and other professional degrees (GRADATT). Jenkins and Jozefowicz (2006) mention that educational attainment rates serve as proxies for levels of existing human capital at the beginning of the sample period. By calculating these attainment rates separately we can see the individual impact each has on changes in income inequality in New York counties between 1990 and 2000.

The expected sign for HSATT is negative. Based on the work of Jimenez (1986), as the fraction of the population holding a high school diploma increases, *ceteris paribus,* a decrease in income inequality is expected. Jimenez (1986) focused mainly on primary and secondary education in reducing income inequality.

Since college attainment rates are significantly lower than high school attainment rates in New York, it is expected that increasing BADEGATT will increase income inequality. According to Chiswick and Chiswick (1987), the wage premium for college graduates may worsen income equality over time.

GRADATT should raise income inequality. Because fewer people obtain a graduate or higher degree, the wage premium for that educational level is higher, at least initially, as discussed by Chiswick and Chiswick (1987). Clearly, any increases in attainment at the graduate and professional degree levels will contribute to more skewed income distributions, as mentioned by Jenkins and Jozefowicz (2006).

In an effort to control for the extent of urban/rural character of a county, the natural logarithm of its 1990 population density is used as an explanatory variable (LPOPDENS). This is consistent with the approach of Benzing et al. (2003). It is expected that counties with more densely populated areas (i.e., urban areas) will be characterized by increases in income inequality over the decade. Thus, a positive sign is anticipated for this variable.

To control for the racial/ethnic composition of a county, an index of racial diversity (RACE90) is included. RACE90 is based on Alesina et al. (1999), and it is calculated as follows:

$$RACE90 = 1 - \sum_i (Race_i)^2$$

where $Race_i$ represents the share of population self-identified as $i =$ (White, Black, Asian and Pacific Islander, American Indian, and Other). This variable measures the probability that two people randomly selected from a county will belong to different racial/ethnic groups. It is anticipated that RACE90 will have an ambiguous impact on the dependent variable.

Total real expenditures for public education (TOTEDEXP) within a county for the years 1962, 1977, and 1982 are included to reflect the allocation of resources to public education. Fields (1980), Jimenez (1986), Sylwester (2002), and Behr et al. (2004) have studied the role of public education expenditures in affecting the income distribution. Since it takes time for spending on education to affect income inequality, the sum of the lagged education expenditures is employed to smooth out fluctuations and more accurately represent the effect of education spending on the stock of human capital. While a longer consecutive time series of such expenditures would be desirable, data availability issues constrain it to just the three years mentioned, and data were unavailable for the five New York City counties. Sylwester (2002) uses ten years in his study because of similar data availability issues. As discussed by Behr et al. (2004) and De Gregorio and Lee (2002), we hypothesize that more money devoted to public education will reduce income inequality over time. Therefore, TOTEDEXP should have a negative impact on the dependent variable.

3.4 Descriptive Statistics

Descriptive statistics appear in Table 1. The mean of the county Gini coefficient rose 0.023135 over the ten year period from 0.420335 in 1990 to 0.457413 in 2000. The median Gini coefficient rose from 0.414 in Madison County to 0.458 in Rensselaer County in 2000. The maximum Gini in 1990 was 0.583 in New York County and 0.609 in New York County for 2000. The average change in the county Gini coefficient from 1990 to 2000 was 0.037078 with a standard deviation of 0.028105.

Table 1: Descriptive Statistics

VARIABLE	MEAN	ST.DEV	MAX	MIN
∆Gini	0.037078	0.028105	0.067272	-0.108138
Gini1990	0.420335	0.031944	0.583414	0.366794
HSATT	34.28856	4.826807	44.84964	15.88746
BADEGATT	10.67092	3.625878	22.12967	5.891397
GRADATT	7.705389	3.688004	23.47682	3.642311
RACE90	0.143436	0.148855	0.675181	0.011694
TOTEDEXP	4.80×10^8	8.52×10^8	4.30×10^9	16206737
LPOPDENS	5.334915	1.85904	10.86703	1.131402

The averages for the 1990 educational attainment variables are 34.28 percent for high school, 10.6 percent for bachelor's degree, and 7.70 percent for graduate degree or higher. The maximum high school attainment rate was 44.84 percent in Livingston County, while the minimum high school attainment level was 15.87 percent in New York County. The highest level of bachelor's degree holders was 22.12 percent in New York County, and the lowest was 5.89 percent in Lewis County. The highest level of graduate degree holders was 23.47 percent in Tompkins County, followed by New York County where 20 percent of the population held graduate degrees.

Mean population density in 1990 was 2,537 people per square mile. Maximum density was 52,419 people per square mile in New York County, while minimum was a mere 3.1 people per square mile in Hamilton County.

4. MODEL

4.1 Econometric Issues

The educational attainment rate variables (HSATT, BADEGATT, and GRADATT) are highly correlated with one another. Therefore, in order to avoid multicollinearity problems, only one educational attainment rate will be included at a time. Preliminary regressions were run using only two or all three educational attainment rates together, but multicollinearity was clearly evident.

In addition, there is concern that the New York City counties (i.e., Bronx, Kings, New York, Queens, and Richmond) are outliers in the sample. Therefore, regressions are run on both the full sample (n = 62) and a sub-sample, which excludes the New York City counties (n = 57).

Finally, the expectation that the stochastic error term will have a constant variance across observations is confirmed by the results of White tests for heteroskedasticity in some models, but not in others. As a result, where necessary, the standard errors are corrected using the White heteroskedasticity-consistent variance-covariance matrix.

4.2 Regression Models

Four different model specifications are estimated. The models vary by the number of counties used (i.e., full sample or sub-sample which omits New York City counties), whether RACE and/or TOTEDEXP are included, and by the choice of educational attainment variable (e.g., HSATT, BADEGATT, or GRADATT) used. The lack of available data for TOTEDEXP for New York City counties limits the number of regression models for the full sample. The models are summarized as follows:

$$\Delta GINI = \beta_0 + \beta_1(GINI1990) + \beta_2(LPOPDENS) + \beta_3(EDATT) + \varepsilon \quad \textbf{(1)}$$

$$\Delta GINI = \beta_0 + \beta_1(GINI1990) + \beta_2(LPOPDENS) + \beta_3(EDATT) + \beta_4(RACE90) + \varepsilon \quad \textbf{(2)}$$

$$\Delta GINI = \beta_0 + \beta_1(GINI1990) + \beta_2(LPOPDENS) + \beta_3(EDATT) + \beta_4(TOTEDEXP) + \varepsilon \quad \textbf{(3)}$$

$$\Delta GINI = \beta_0 + \beta_1(GINI1990) + \beta_2(LPOPDENS) + \beta_3(EDATT) + \beta_4(RACE90) + \beta_5(TOTEDEXP) + \varepsilon \quad \textbf{(4)}$$

5. RESULTS

5.1 Full Sample Findings

The results presented for Model 1 appear in Columns 1-3 of Table 2 and are based on the full sample. In Column 1, GINI1990, LPOPDENS, and HSATT show expected signs, but only GINI1990 is statistically significant. The negative and statistically significant estimated coefficient for GINI1990 indicates that high-income inequality counties are more apt to experience a decline in their income inequality over time. Jenkins and Jozefowicz (2006), Sylwester (2003), and Benabou (1996) obtain similar results. In addition, the high school attainment rate is associated with less income disparity over the decade, while greater population density leads to greater income inequality. Jimenez (1986) also finds that secondary educational attainment leads to reduced income inequality.

The results presented in Column 2 replace HSATT with BADEGATT. In this regression, both GINI1990 and LPOPDENS are statistically significant with the expected signs. Although BADEGATT is not statistically significant, it appears that increasing bachelor’s degree attainment rates leads to an increase in income inequality over time. A positive and significant coefficient on LPOPDENS was also obtained by Jenkins and Jozefowicz (2006).

Table 2: Ordinary Least Squares Regression Results
(Full Sample)

Dependent Variable: $\Delta GINI$

	MODEL 1			MODEL 2		
Independent Variable	**Column 1**	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**
Constant	0.2344 (2.714)	0.1205 (2.400)	0.1441 (2.807)	0.2077 (2.240)	0.1075 (1.726)	0.1309 (2.017)
GINI1990	-0.3725** (-2.554)	-0.2943** (-2.180)	-0.3529** (-2.522)	-0.3244** (-2.054)	-0.2694* (-1.765)	-0.3275** (-2.050)
LPOPDENS	0.0037 (1.365)	0.0045* (1.768)	0.0050** (2.117)	0.0061 (1.512)	0.0058 (1.301)	0.0061 (1.494)
HSATT	-0.0017 (-1.593)			-0.0017 (-1.600)		
BADEGATT		0.0014 (1.294)			0.0013 (1.085)	
GRADATT			0.0018* (1.707)			0.0017 (1.539)
RACE90				-0.0423 (-0.808)	-0.0201 (-0.357)	-0.0184 (-0.338)
Adjusted R^2	0.101	0.088	0.151	0.096	0.074	0.093
N	62	62	62	62	62	62

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Note: The t-statistics appear in parentheses below the estimated coefficients.

In Column 3 in Table 2, GRADATT is used in place of HSATT and BADEGATT. In this case, all three variables are statistically significant with the expected signs. Educational attainment at the graduate/professional level is associated with an increase in income inequality during the 1990s in New York counties. In their analysis of Pennsylvania counties, Jenkins and Jozefowicz (2006) also found a positive sign on GRADATT.

The findings obtained after adding RACE90 as an independent variable in Model 2 appear in Columns 4-6 of Table 2. In Column 4, the results are unchanged in terms of signs and significance. The same is true in Column 5, except LPOPDENS becomes insignificant. In the case of Column 6, both LPOPDENS and GRADATT lose their statistical significance. RACE90 is not statistically significant in any model, but it carries a negative sign throughout. This suggests that greater racial diversity in a county fosters reductions in income disparity over time.

5.2 Sub-sample Findings

In Table 3, the results are based on the sub-sample, which excludes the five New York City counties, and Model 1 appears in Columns 1-3. The findings in Column 1 reveal expected signs for GINI1990, LPOPDENS, and HSATT, and statistically significant coefficients for GINI1990 and HSATT. This is in contrast to the full sample results in Table 2, where HSATT was not significant, but still retained a negative sign. The findings for Column 2 are similar to Column 1 in that GINI1990 and the educational attainment variable are significant. However, in this regression, BADEGATT is used as the measure of educational attainment, and it has a positive sign. In Column 3, GINI1990 and GRADATT are both significant. GINI1990 continues to have a negative sign, while GRADATT has a positive coefficient. These signs are consistent with Jenkins and Jozefowicz (2006). LPOPDENS is not statistically significant in any of these models, but it maintains a positive sign.

Table 3: Ordinary Least Squares Regression Results
(Sample excluding New York City Counties)

Dependent Variable: $\Delta GINI$

	MODEL 1			**MODEL 2**		
Independent Variable	**Column 1**	**Column 2**	**Column 3[a]**	**Column 4**	**Column 5**	**Column 6[a]**
Constant	0.2969 (2.637)	0.1608 (2.1752)	0.2062 (1.901)	0.2837 (2.569)	0.1186 (1.462)	0.1632 (1.704)
GINI1990	-0.4522** (-2.306)	-0.3817** (-2.058)	-0.4890* (-1.943)	-0.3638* (-1.838)	-0.2997 (-1.528)	-0.4069* (-1.817)
LPOPDENS	0.0014 (0.360)	0.0004 (0.107)	0.0019 (0.382)	0.0053 (1.193)	0.0037 (0.755)	0.0055 (1.039)
HSATT	-0.0023* (-1.791)			-0.003** (-2.328)		
BADEGATT		0.0029* (1.916)			0.0031** (2.002)	
GRADATT			0.0030* (1.934)			0.0032* (1.940)
RACE90				-0.1360* (-1.822)	-0.0880 (-1.231)	-0.0964 (-1.294)
Adjusted R^2	0.094	0.102	0.123	0.132	0.110	0.137
N	57	57	57	57	57	57

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
[a] Standard errors are White heteroskedasticity-consistent.
Note: The t-statistics appear in parentheses below the estimated coefficients.

By omitting the New York City counties, the signs on the coefficients in Table 3 are unchanged from Table 2, but there are increases in significance for the HSATT and BADEGATT educational attainment variables. LPOPDENS loses what significance it had once the New York City counties are removed in Table 3.

In Model 2, RACE90 is added as an independent variable in Columns 4-6 of Table 3. In Column 4, the results are robust in sign across the board. GINI1990 loses some significance and becomes insignificant in Column 5. In all three columns, RACE90 retains its negative sign, but it is only statistically different from zero in Column 4 in the presence of HSATT.

Real total expenditures on public education in the county for the years 1962, 1977, and 1982 are added in Model 3, which appears in Columns 1-3 of Table 4. In Column 1, the signs on the estimated coefficients are unchanged. The significance levels of the existing variables remain largely the same, but HSATT increases in significance in Column 1 and GINI1990 loses some significance in Column 2. While the estimate on the education expenditures variable is not statistically significant, it does have the expected negative sign indicating that higher spending on public education will lead to less income inequality over time. Jenkins and Jozefowicz (2006) and Behr et al. (2004) also find that educational expenditures reduce income inequality.

Table 4: Ordinary Least Squares Regression Results
(Sample excluding New York City Counties)

Dependent Variable: $\Delta GINI$

	MODEL 3			MODEL 4		
Independent Variable	**Column 1[a]**	**Column 2[a]**	**Column 3[a]**	**Column 4[a]**	**Column 5[a]**	**Column 6[a]**
Constant	0.2584 (2.107)	0.1331 (1.678)	0.1783 (1.847)	0.2581 (2.059)	0.1007 (1.376)	0.1451 (1.670)
GINI1990	-0.4167** (-2.007)	-0.3533* (-1.765)	-0.4583* (-1.922)	-0.3478* (-1.768)	-0.2874 (-1.594)	-0.3917* (-1.781)
LPOPDENS	0.0054 (0.910)	0.0046 (0.847)	0.0059 (1.239)	0.0077 (1.231)	0.0069 (1.129)	0.0085 (1.500)
HSATT	-0.0021** (-2.019)			-0.0029** (-2.454)		
BADEGATT		0.0030* (1.938)			0.0031* (1.906)	
GRADATT			0.0030* (1.857)			0.0032* (1.871)
RACE90				-0.1225 (-1.616)	-0.0743 (-1.075)	-0.0832 (-1.194)
TOTEDEXP	-7.36×10^{-12} (-1.092)	-8.66×10^{-12} (-1.288)	-8.29×10^{-12} (-1.331)	-5.15×10^{-12} (-0.899)	-7.66×10^{-12} (-1.244)	-7.15×10^{-12} (-1.281)
Adjusted R^2	0.101	0.118	0.137	0.127	0.119	0.169
N	57	57	57	57	57	57

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
[a] Standard errors are White heteroskedasticity-consistent.
Note: The t-statistics appear in parentheses below the estimated coefficients.

We suspect that the lack of statistical significance for the educational expenditures variable has more to do with data limitations than its lack of relevance to the study. In particular, only three years of data were available to construct this variable while other studies have used much longer consecutive time series to measure similar effects. As pointed out by Sylwester (2002), improvements in income inequality due to educational expenditures occur only very slowly, and three years is probably not enough time for such effects to become evident.

Columns 4-6 in Table 4 represent Model 4 and include both RACE90 and TOTEDEXP. In all cases, the signs of the variables remain the same and the significance levels are roughly consistent with previous findings. GINI1990 loses some significance in Column 4 and becomes insignificant in Column 5. RACE90 and TOTEDEXP exhibit the negative signs that they have in other models when analyzed separately, but neither variable is statistically significant. RACE90 was significant at the 10 percent level in Column 4 of Table 3 and barely misses that level of significance in Column 4 of Table 4.

There is an issue concerning whether TOTEDEXP is capturing a quantity or a quality effect of education on income inequality. In an effort to address this concern, the 1990 enrollment rates for primary/secondary school and college from the Census were included in Models 3 and 4. The addition of these variables has no impact on the signs of the original independent variables and little to no effect on the significance levels of these variables. In the case of Model 3, neither of the enrollment rate variables is statistically different from zero. In the case of Model 4, only the college enrollment rate variable is significant at the 10 percent level. TOTEDEXP remains insignificant throughout these regressions. Sylwester (2002) points out that the educational expenditure variable will have an impact on income inequality changes independent of enrollment rates (as a measure of the quantity dimension) if the educational expenditures are improving educational quality, which is affecting income inequality. Based on these findings, the quantity aspect receives some support because only the college enrollment rate is significant and only in some of the regressions.[2]

5.3 Summary of Findings

Overall, GINI1990 has a negative and statistically significant estimated coefficient in all but two regressions. The sign for this variable agrees with expectations and the findings of Jenkins and Jozefowicz (2006), Benabou (1996), and Sylwester (2003).

Although the significance of the educational attainment variables is not consistent across the samples, their signs are remarkably robust. These findings suggest that increases in educational attainment rates at the high school level in New York counties, *ceteris paribus*, result in reductions in income inequality over time. However, the opposite is true at the college and graduate education levels. As noted by Chiswick and Chiswick (1987), this may suggest that the wage premium for workers with bachelor's degrees or graduate degrees had not yet declined appreciably in New York counties during the 1990s.

6. CONCLUSIONS

The signs of the estimated coefficients in the analysis are robust. It appears that the initial level of income inequality and high school attainment rates in a county are both associated with decreases in income inequality during the 1990s for New York. Policymakers seeking to understand the behavior of income inequality within the state of New York will find these results of interest.

The importance of educational attainment rates in reducing income inequality in New York counties demonstrated by the findings of this study supports the findings of other researchers. While Ram (1989) concludes that there is not strong support for the notion that increasing education leads to less income inequality, studies by Ahluwalia (1976) and Papanek and Kyn (1986) find that educational achievement promotes income equality. More specifically, the negative sign on HSATT and the positive signs on BADEGATT and GRADATT confirm the suggestion by Jimenez (1986) that educational attainment at the secondary school level will reduce income disparity while higher educational attainment will yield more skewed income distributions.

6.1 Future Research

Educational attainment rates at various levels are not accidental. Decomposing the reasons behind them was beyond the scope of this study, but the significance of educational attainment rates in explaining income inequality demonstrated by this analysis indicate that further investigation is warranted.

Another issue outside the purview of this study, but worthy of further inquiry is the extent to which in-migration and out-migration of educated individuals across New York counties occurs. Clearly, the movements of these individuals will affect the educational attainment rates measured within counties by the Census and provide a reflection of the economic base of the counties.

ENDNOTES

1. We are grateful for helpful suggestions from Stephanie Brewer Jozefowicz, Elizabeth Hall, Shannon Stare, and participants at the annual conference of the Eastern Economic Association, New York, NY, February 2007. Comments from William P. O'Dea and an anonymous reviewer were especially valuable.
2. These regression results are available from the authors upon request.

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Unemployment Index: A Multidimensional Measure Of Labor Market Efficiency

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ABSTRACT

The unemployment rate, which is measured by the Bureau of Labor Statistics as the proportion of labor force participants who are classified as being unemployed, is a traditional statistic that is used to evaluate labor market conditions. This conventional measure of unemployment considers incidence of unemployment and is a one-dimensional view of the unemployment experience. This analysis develops an alternative measure for evaluating labor market conditions that incorporates duration of unemployment. By aggregating the time that an individual is unemployed across the labor force, a measure of the gap between actual weeks of labor and potential weeks of labor is created. This ratio is then decomposed into familiar components of unemployment, incidence and duration. Incidence refers to the likelihood of experiencing unemployment and duration refers to the length of time spent unemployed. This framework provides a basis for creating an “unemployment index” in which the different components of unemployment are highlighted and used together as an indicator of labor market efficiency. Such an index can be useful for policy purposes when both incidence and duration are relevant in assessing economic conditions as well as in comparing the unemployment experience between different groups, identified by gender, race, age, state/regional residence, industry classification, or occupational classification.

INTRODUCTION

Unemployment refers to the labor force state in which a person does not have a job but is actively seeking employment. Because resources are scarce, it is a concern when labor is not being used in productive activities. Unemployment is observed continually and the desire is that unemployment be low.

There are several ways to measure unemployment. The standard measure in the United States is the unemployment rate, which is measured as the proportion of labor force participants who are classified as being unemployed based on the monthly Current Population Survey, and is announced by the Bureau of Labor Statistics:

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unemployment rate		= U / (U+E)
		= U / LF
where U	= number of labor force participants who are unemployed	
E	= number of labor force participants who are employed	
LF	= number of labor force participants.	

This measure is an "instantaneous" unemployment rate since it is an indicator of unemployment at a single point in time. The focus is on the incidence of unemployment. A limitation of this measure is that it does not take duration of unemployment or the number of spells of unemployment into consideration. Consequently, it reveals little about the burden of unemployment. Policies designed to combat the unemployment problem could differ according to whether a relatively large number of workers share the burden of unemployment and are unemployed for a brief time or whether a few individuals bear the brunt of the problem and are either unemployed for a long time or are chronically unemployed.

Furthermore, because this measure of unemployment is a time-specific ratio between two "stock" concepts, it does not capture the flow of individuals between different labor force classifications. For instance, if one is comparing unemployment rates for different time periods, a higher unemployment rate in one time period could reflect either a greater number of unemployed or fewer labor force participants. This is particularly relevant for groups whose members are not continuously in the labor force because those individuals who temporarily leave the labor force might have a higher or lower probability of being unemployed if they remained in the labor force than those who stay in the labor force continuously. Additionally, when the average labor force participation for a group is sufficiently less than one hundred percent, there is more room for variability in who actually experiences unemployment and how many individuals of the group experience unemployment.

Thus, although the unemployment rate has become the conventional standard measure of unemployment in the economy, it is limited in scope, ignoring other dimensions of the unemployment experience such as duration of unemployment or the number of unemployment spells experienced. A multidimensional measure of unemployment is developed in this paper. Applications of the index are explored briefly and potential areas for future consideration are suggested at the end.

LITERATURE REVIEW

Over time there have been a plethora of studies focusing on the dimensions of unemployment: incidence, duration, and number of spells. Labor force transition models provide a framework for analyzing incidence of unemployment, leading to possible explanations of differences in unemployment rates between different groups. Early studies include a study by Mincer (1966) who expressed unemployment rates in relation to labor force participation rates and another study by

Barrett and Morgenstern (1974) who addressed the higher observed incidence of unemployment among blacks and women. Other studies [Barron and Mellow (1981), DeBoer and Seeborg (1989), Fields (1976), Flinn and Heckman (1983), and Niemi (1975)] followed their lead in analyzing the incidence of unemployment within the context of a labor force transition. The notion underlying these studies is that unemployment is a temporary phase experienced by some people as part of the job search process. Many unemployed are changing jobs while others have entered (or re-entered) the labor force. They are unemployed until they either obtain employment or opt to leave the labor force. These studies focused on the likelihood that unemployment is experienced and on differential probabilities between groups. More recently, Shimer (2005) measured the probability that an employed worker will move from employment into unemployment (separation probability) and the probability that an unemployed worker will find a job (job finding probability). He found that the job finding probability is strongly procyclical but the separation probability is acyclical, especially over the past 20 years. As Shimer points out, “These findings sharply contradict the conventional wisdom that fluctuations in the separation probability (or in job destruction) are the key to understanding the business cycle” (p. 24).

Unemployment duration was initially modeled as part of the job search process in pioneering studies by Barron and Mellow (1979) and Sandell (1980). Alternative measures of the duration of unemployment and accompanying issues were explored in Akerlof and Main (1981, 1983), Carlson and Horrigan (1983), and Sider (1985). More recently the focus on the length of unemployment has shifted to the observed phenomena that unemployment duration has been gradually increasing over time [Groshen and Potter (2003), Mukoyama and Sahin (2004), and Valletta (1998, 2002)].

Although it is recognized that unemployment is experienced unevenly, with some people never experiencing unemployment while others experience repeated spells of unemployment, the frequency or number of unemployment spells has not been the subject of many analyses. Early studies that considered the number of spells of unemployment experienced by an individual include the studies by Akerlof and Main (1980) in which they compared the average duration of unemployment for those who experienced one spell of unemployment with those individuals who experienced multiple spells of unemployment, by Leighton and Mincer (1982) who identified repeated spells of unemployment as characteristic among teenagers, and by Corcoran and Hill (1985) who looked at the reoccurrence of the unemployment experience among adult men.

Attention to unemployment is usually focused on one dimension of the unemployment experience, primarily the unemployment rate. The contribution of the present study is that it develops a measure of aggregate unemployment that incorporates more than one dimension of unemployment, specifically, incidence and duration. Similarly, Carlson and Horrigan (1983) and Sider (1985) estimated the total number of unemployed people in a given time period to be the product of incidence and duration. Incidence is the inflow into unemployment and duration is the expected average duration of a completed spell of unemployment. The validity and applicability of this formula depends upon a steady-state assumption and whether spells refer to completed spells of unemployment or in-progress spells. If the assumption holds that flows into and out of unemployment are constant over time, then unemployment can be measured as the product of incidence and average completed spell duration without being concerned that duration and incidence are interdependent. Both studies addressed potential biases in estimating mean completed spell length when the restrictive steady-state condition of constant unemployment flows is relaxed. In Sider's analysis, the observed biases were consistent with the expected biases.

In considering the relationship between incidence and duration, both incidence and duration are expected to fluctuate counter-cyclically but not necessarily independently. When the business cycle is in an economic downturn, both incidence and duration are expected to increase. During an economic recovery, both incidence and duration are expected to decrease. However, the implication behind interdependency between incidence and duration is that longer duration implies a higher incidence at any point in time. If the unemployed are experiencing longer duration, the unemployment rate will be higher. Baker (1992) found that the countercyclical movement in duration applies uniformly to all individuals irrespective of expected duration but that those with a longer expected duration of unemployment are more likely to become unemployed during a downturn. This supports my hypothesis that a link between incidence and duration might exist but that the observed increase in duration over time might not systematically affect the pattern of incidence over time.

Looking over the long run, Valletta (1998) attributed the positive relationship between incidence and duration to permanent job loss. In the U.S. from 1967 to 1998, there has been an increase in the incidence of permanent job loss, which occurs when firms downsize, plants are closed, or firms declare bankruptcy. Permanent job loss is associated with longer unemployment duration, which in turn explains the observed lengthening of the national average duration of unemployment. This suggests that the countercyclical pattern of both incidence and duration reflects a structural change in the type of unemployment that has been occurring instead of a systematic cause-and-effect relationship between incidence and duration. Valletta's findings are consistent with those of Baker (1992).

Some studies debate the relative roles of duration and incidence in the unemployment rate. Blanchard and Diamond (1990) concluded that incidence plays a stronger role whereas Baker (1992) maintains that changes in duration have the predominant influence on the unemployment rate. Barrow (2004) assesses the use of the monthly reported unemployment rate as an indicator of the strength or weakness of the labor market over the business cycle. As a result of data availability, ease of conceptual understanding, and media coverage, the traditionally reported unemployment rate plays a major role in assessing the condition of the labor market, and hence the overall economy, among both professionals and the general public. Barrow focuses on changes in the labor market since 1990 that suggest that the reported unemployment rate is artificially low, conveying the impression that the labor market is stronger than it really is. Some of the factors that contribute to declines in the unemployment rate are decreases in the size of the labor force because a higher proportion of the population is either institutionalized, on disability insurance, or has ceased to actively look for employment because they are discouraged or are engaged in an alternative activity until they perceive that the economy improves. She considers trends in alternative measures of the unemployment rate and labor market strength: percentage of marginally attached and part-time workers, labor force participation rates, employment-to-population ratios, and real average hourly earnings. By comparing the trends in these statistics between different business cycles, she concludes that there are no signs of labor market weakness that are not indicated by the unemployment rate. The recent low unemployment rates are consistent with a decreasing natural rate of unemployment or non-accelerating inflation rate of unemployment (NAIRU) since inflation rates have also remained low.

My study does not intend to challenge previous works or dispute the validity of the natural rate of unemployment. Rather, it seeks to augment our assessment of the condition of the labor market by developing a statistical measure of unemployment that is multidimensional. In summary, past studies of unemployment generally focus on only one dimension of unemployment, on the interplay between dimensions, or on the relative strength of the influence of individual dimensions. This analysis develops an alternative view of unemployment by extending a conventional measure of unemployment into an aggregated proportion of time in the labor force that is lost to unemployment. This ratio is then decomposed into its components, incidence and duration. The objective is to provide a formula for measuring unemployment that includes multiple dimensions of the unemployment experience and establish a framework for evaluating labor market conditions that incorporates duration of unemployment as part of the unemployment experience.

FRAMEWORK

Unemployment is a multidimensional experience. However, the conventional unemployment rate focuses only on the incidence of unemployment, ignoring duration. If we lengthen the period of the analysis beyond the survey week, another measure of unemployment is the proportion of time (in the labor force) that an individual spends in unemployment.

$$P_i = (S_i \cdot \bar{t}_{ui}) / t_{Li} = t_{ui} / t_{Li}$$

where
- P_i = proportion of time unemployed by the i^{th} individual; i=1,2,…,N
- S_i = number of spells of unemployment by the i^{th} individual; i=1,2,…,N
- $\bar{t}_{ui}$ = average duration (per spell of unemployment) by the i^{th} individual; i=1,2,…,N
- t_{ui} = number of weeks in the period spent in unemployment by the i^{th} individual; i=1,2,…,N
- t_{Li} = number of weeks in the period spent in the labor force by the i^{th} individual; i=1,2,…,N.

Leighton and Mincer (1982) measured unemployment as time in the labor force that is lost to unemployment in their analysis of unemployment experiences among teenagers. Leighton (1978) used a similar derivation in an analysis of unemployment as experienced by males in the labor force and Sue (1996) augmented the analysis by incorporating observed labor force discontinuities in an analysis of female unemployment experiences. If we apply this concept of unemployment to the entire labor force as time that is lost in the economy to unemployment, we can measure unemployment as a ratio of the total time that labor force participants spend in unemployment to their total time in the labor force. Aggregating across the labor force, this ratio represents a gap between actual weeks of labor and potential weeks of labor. The larger is the gap, the less efficient is the market. We can then decompose this measure of labor market efficiency into structural components, incidence and duration of unemployment, according to the following formula:

Proportion of time in the labor force lost to unemployment $= \sum t_{ui} / \sum t_{Li}$

$$= (N/L) \cdot (\bar{t}_u / \bar{t}_L)$$

where N = number of people unemployed sometime during the period

L = number of people in the labor force sometime during the period

N/L = incidence of unemployment during the period

$\bar{t}_u$ = average number of time units spent in unemployment by the unemployed during the time period

$\bar{t}_L$ = average number of time units spent in the labor force by the labor force participants during the time period.

With this formula, a measure of aggregate unemployment has been developed as the fraction of time that is lost by the labor force to unemployment by labor force participants within a specified period of time, which provides an alternative assessment of labor market conditions. This measure of unemployment can be used as an index formed by the product of incidence of unemployment and the duration of unemployment, weighted by time spent in the labor force. In Appendix A, the index is expressed using time units that are measured as fractional proportions of the time period under consideration in the analysis.

This index highlights the factors that compose the structure of unemployment. Incidence refers to the likelihood of experiencing unemployment and duration refers to the length of time spent in unemployment. Weighting by the extent of labor force participation adjusts for variations in time spent in the labor force among labor force participants. The relevance of this unemployment measure is underscored by Valletta (1998): “Although the unemployment rate by itself is our key indicator of labor market conditions, the underlying distribution of unemployment spell durations provides important additional information” (p. 30).

Algebraically, numerical values of the index will range between zero and one. If nobody is unemployed during the specified period, the unemployment index will be zero. If everybody spends his or her entire labor force time in unemployment, the index will have a value of one. A larger value of the index implies that more time was lost to unemployment and that the labor market was less efficient, because either more individuals experienced unemployment during the specified time period or the participants spent more time unemployed. Thus, the index reflects both incidence and duration of unemployment. Appendix B provides a refinement of the unemployment index as time that is lost to unemployment in terms that have been developed in labor turnover models for incidence and job search models for duration.

Because the formula includes duration of unemployment and time spent in the labor force into the calculation, this index is conceptually different from the natural rate of unemployment, the non-accelerating inflation rate of unemployment (NAIRU), or the full-employment rate of unemployment. The idea behind these concepts is that the unemployment rate would never be zero due to frictional unemployment but that there is a rate towards which the actual unemployment rate gravitates. These are theoretical concepts that have been developed to augment our understanding of the macroeconomy. Any numerical values assigned to these concepts are subject to academic perspective, specific circumstances reflecting the time period or economy (country), and political predisposition. It is acknowledged that the unemployment rate would not be zero and most economists speculate that a range of 3 percent to 6 percent is reasonable for the natural rate of unemployment. Therefore, the index developed here would not take on a value of zero. Rather, a value of zero is a mathematical lower limit for the index, which it would approach if both the incidence and duration of unemployment were very low. Similar to the comfort level that economists feel when the unemployment rate is low (or lower than a subjective rate), a low value for the index could also be established as a comfort threshold that reflects a combined tolerance of incidence, duration of unemployment, and time spent in the labor force.

Measuring unemployment as time in the labor force that is lost to unemployment, in terms of its components, incidence and duration, extends the conventional view of unemployment beyond the unemployment rate, which is limited to incidence. Therefore, the index is a direct indicator of economic inefficiency. A higher value will occur if either more people in the labor force are unemployed (incidence) or the unemployed are experiencing a longer spell in unemployment (duration). This would indicate a larger gap between actual weeks of labor and potential weeks of labor and consequently a less efficient labor market. The index refers to current (“in-progress”) spells of unemployment, not completed spells of unemployment. By using “in-progress” spells, there are two potential biases. During an economic downturn, spells are likely to be longer which will increase incidence. On the other hand, the increase in the incidence of unemployment will include newly unemployed individuals which will lower the average duration of “in-progress” spells of unemployment. These biases have opposite effects on the index and potentially cancel each other. However, the objective is not to correct for the biases. On the contrary, the point is to develop a measure of unemployment that incorporates different dimensions of the unemployment experience.

By using the average duration of unemployment spells sampled while in-progress at the time of the survey, rather than the expected duration of completed spells, the index reflects the actual proportion of labor force time that is lost to unemployment.

APPLYING THE DATA

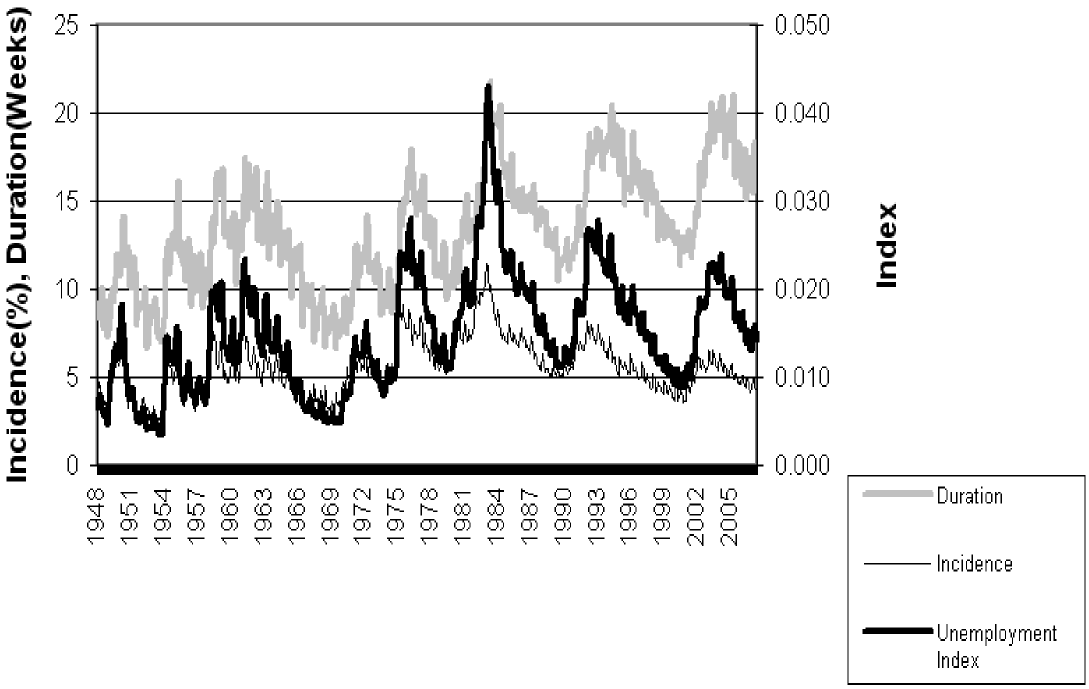
The next step is to calculate the unemployment index using data. Labor force data were obtained for the period from January 1948 to May 2007 from the Bureau of Labor Statistics using the Current Population Survey for individuals who were 16 years of age and older. The unemployment rate was used to measure incidence and the average weeks unemployed was used as a measure of duration. The average duration pertains to current (in-progress) spells of unemployment rather than completed spells. Data on the number of weeks spent in the labor force during the time period were unavailable. As a preliminary measure, it is assumed that the time period is 1 year (or 52 weeks) and that all labor force participants were in the labor force during the entire time period. This assumption is highly restrictive but it is made in the absence of information on the number of weeks spent in the labor force.[1] The unemployment index is calculated by obtaining the multiplicative product between incidence and duration for each month of the 713-month time period.

Figure 1 shows graphs of incidence, duration, and the index over the entire time period. This allows a comparison of time trends between incidence, duration, and an index of unemployment. Although both incidence and duration exhibit a similar cyclic pattern, the movement between the two components of unemployment appears to have been closer before mid-1981 than after that time. Since mid-1981, duration has been trending upward and is less consistent with incidence. For the period from November 1948 to June 1981, the correlation coefficient between the unemployment rate and average duration is 0.60. For the period from July 1981 to November 2006, the correlation coefficient is 0.32. The decrease in the correlation between incidence and duration strengthens the benefits of the index since it incorporates the trends in both components. Notably, since the early 1990s the pattern of the index is more similar to the pattern of duration. The conventional unemployment rate, which focuses on incidence of unemployment, ignores this aspect of unemployment.

Figures 2 (A through J) provide a more detailed view. Each figure highlights a graph of incidence, duration, and the unemployment index during one of the 10 business cycles as identified by the National Bureau of Economic Research (NBER, 2007) that have occurred since January 1948. Each cycle is measured from the peak of one cycle to the peak of the following cycle such that each period as graphed begins with an economic downturn followed by the time until the start of the next

FIGURE 1: Incidence, Duration, and the Unemployment Index

[Period: 1/1949-5/2007]

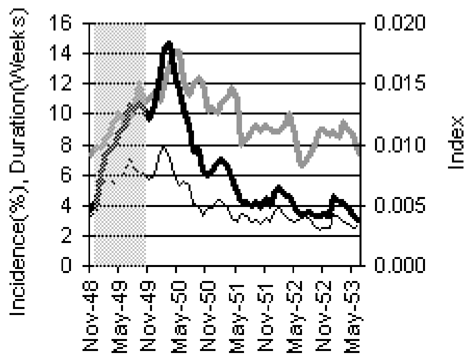


economic downturn. The shaded region in the graphs represents the economic downturn at the start of the business cycle. When economic conditions improve, the increase in economic activity leads to an increase in employment opportunities. Theoretically, the expectation is that the unemployment rate should decline after a downturn is over. Empirically, this does not necessarily occur. In general, the unemployment rate tends to decrease after the downturn ends, although not necessarily as soon as the economy starts to improve. The pattern for duration of unemployment usually continues to rise even after incidence decreases and then it eventually diminishes.

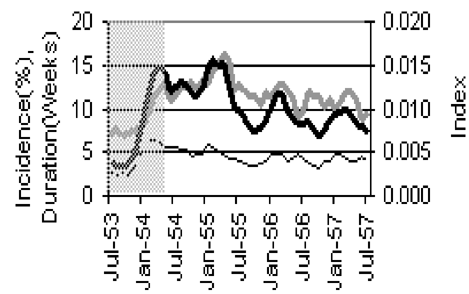
In particular, for the period from March 2001 through November 2006 in graph J, the unemployment rate (incidence) fluctuated modestly after the official end of the economic recession in November 2001 and did not trend downward until a year and a half later. However, for those who were unemployed for 27 weeks or more, the unemployment rate did not decline until early 2004, more than two years after the recession ended (U.S. Bureau of Labor Statistics, 2006). A plausible interpretation is that, as the economy improved, those who had been unemployed for a shorter term found jobs sooner than the longer-term unemployed. This would cause an increase in the average duration of all currently unemployed workers. As the longer-term unemployed found jobs, the average duration of

FIGURE 2: Incidence, Duration, and the Unemployment Index

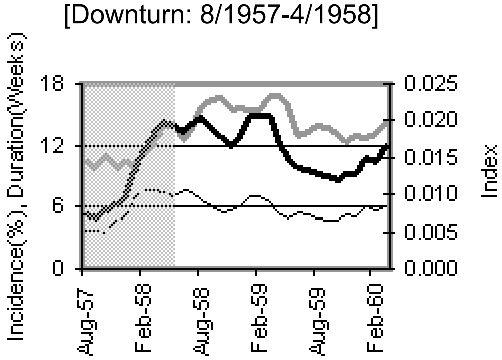
A. Business Cycle: 1/1949-6/1953
[Downturn: 11/1948-10/1949]



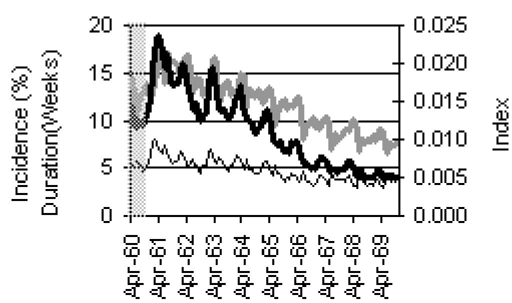
B. Business Cycle: 7/1953-7/1957
[Downturn: 7/1953-5/1954]



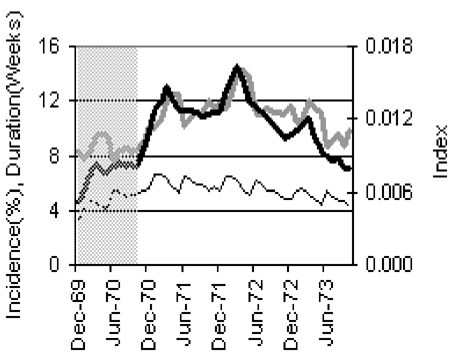
C. Business Cycle: 8/1957-3/1960
[Downturn: 8/1957-4/1958]



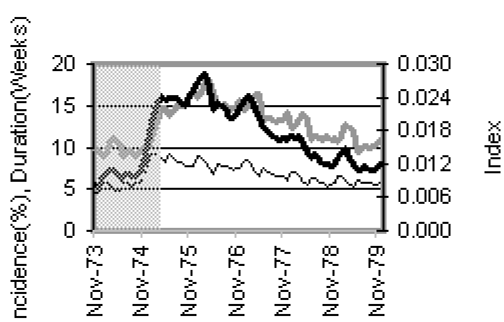
D. Business Cycle: 4/1960-11/1969
[Downturn: 4/1960-2/1961]



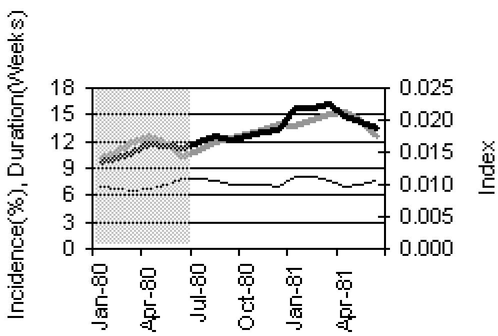
E. Business Cycle: 12/1969-10/1973
[Downturn: 12/1969-11/1970]



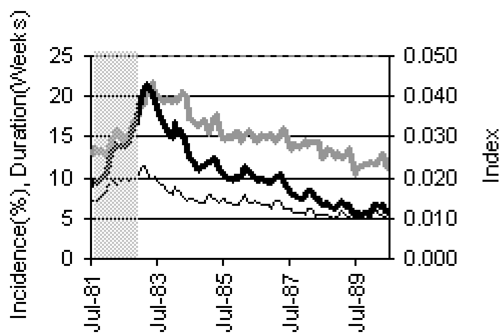
F. Business Cycle: 11/1973-12/1979
[Downturn: 11/1973-3/1975]



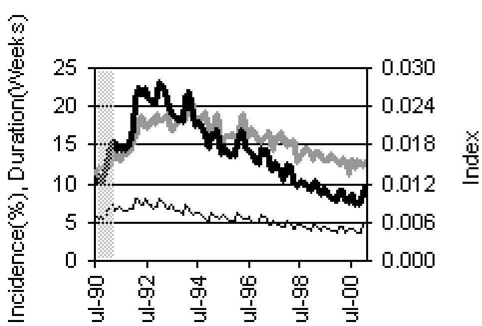
G. Business Cycle: 1/1980-6/1981
[Downturn: 1/1980-7/1980]



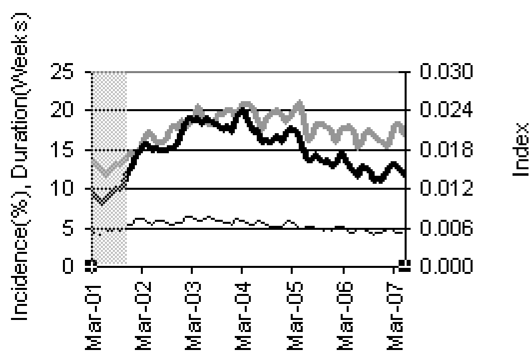
H. Business Cycle: 7/1981-6/1990
[Downturn: 7/1981-11/1982]



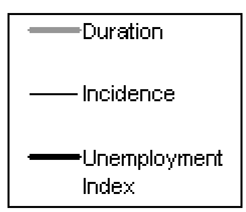
I. Business Cycle: 7/1990-2/2001
[Downturn: 7/1990-3/1991]



J. Business Cycle: 3/2001-5/2007
[Downturn: 3/2001-11/2001]



Legend:

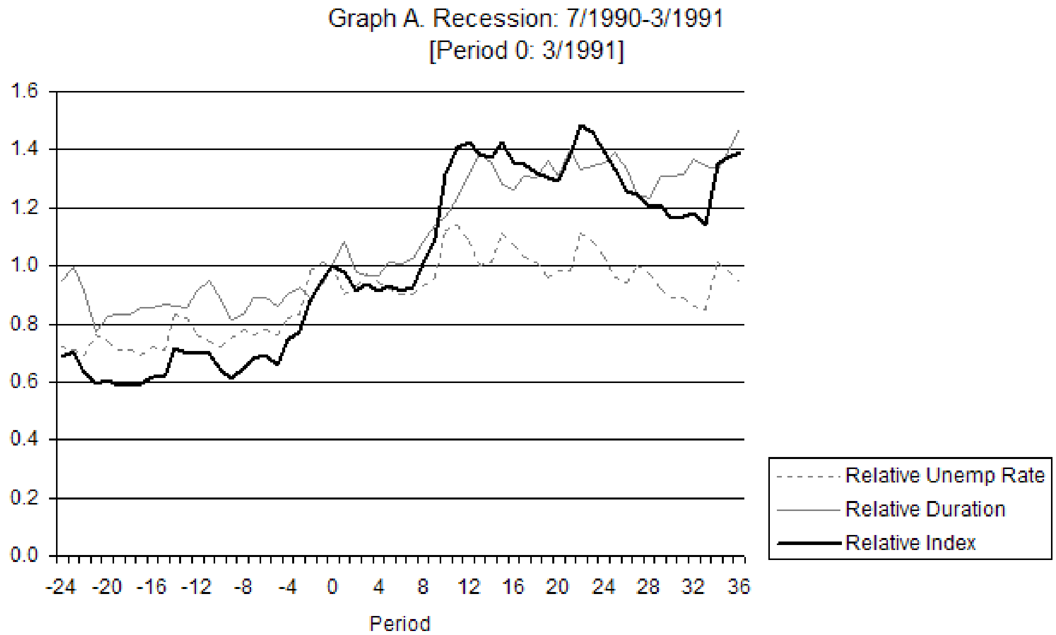


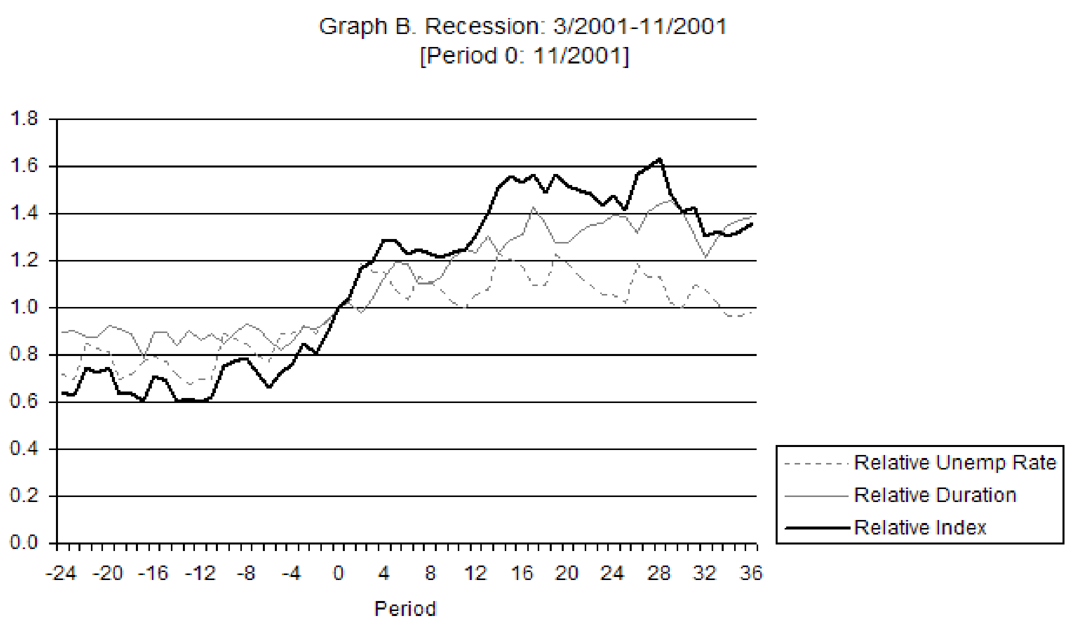
NOTE: The shaded area in each graph represents an economic downturn as defined by the National Bureau of Economic Research.

unemployment eventually decreased. In the graph, duration continued to trend upward until mid-2004, and although there subsequently appears to be a downward trend, average duration still remains above the level that prevailed at the beginning of the business cycle. The conventional unemployment rate (incidence) does not provide information on whether the shorter-term or longer-term unemployed are finding jobs. But since this affects the duration of unemployment, the trend in the unemployment index, which includes duration, makes it a better indicator of the aggregate unemployment situation.

This addresses Barrow's concern (2004) that the official unemployment rate is misleading in representing labor market conditions during the most recent economic recovery. Historically, the number of nonfarm jobs in the economy exhibits rapid growth after the end of a recession. This was not observed in the recovery period after the last two recessions, even though the unemployment rate did not indicate a weak labor market. While she found that "there is little evidence in other labor market statistics that the labor market in this economic recovery is much weaker than in previous recovery periods of the past 30 years" (p. 33), I have adapted a technique used in her analysis and applied it to the unemployment index developed in this study in order to demonstrate the applicability of the index in evaluating the condition of the labor market. Figure 3 shows a graph of the relative unemployment index, computed as a ratio between the index in a particular month and the index at the time of the cycle trough. The month of the trough is identified as Period 0. In Period 0, the relative index is 1. The graph tracks the relative index for 24 months preceding the trough and 36 months following the trough. During months when the relative index is larger than 1, the index in that month exceeds the value of the index at the trough. When the relative index is less than 1, the index in that month is lower than the value of the index at the trough. A value of 1.2 indicates that the index in that month is 20 percent above the index at the time of the trough, and a value of .95 indicates that the index in that month is 5 percent below the index at the time of the trough. Relative measures were also calculated for the incidence of unemployment (unemployment rate) and duration of unemployment. Graph A pertains to the 1990-1991 recession in which the trough occurred in March 1991 and graph B pertains to the 2001 recession in which the trough occurred in November 2001, as dated by the National Bureau of Economic Research (NBER, 2007). For both recessions, during the 24-month period preceding the trough, the relative index was always less than 1 and increased dramatically in the months leading to the trough. During the recovery periods, the trends in the relative index differ. In graph A, the relative index was below 1 in the eight months following the trough and then fluctuates dramatically with values greater than 1. Comparing the relative index with the relative unemployment rate and the relative duration, the magnitude of the relative index reflects the magnitude of relative duration whereas the trend pattern follows that of the relative unemployment rate. In graph B, the relative index continually exceeds 1, and exhibits a pronounced upward trend for 28 months after the trough. The relative unemployment rate index varies between 1 and 1.2 with a downward trend at the end whereas the relative duration index is gradually increasing. Following this recession, the pattern of the relative index is dominated by the relative duration. With respect to post-recession labor market conditions, the steady movement of the relative unemployment rate is consistent with Barrow's conclusion that the suggested labor market weakness after the most recent recession is not detected in either the standard unemployment rate or other labor market measures. On the other hand, the elevated

FIGURE 3: Relative Unemployment Index





magnitude and indiscernible pattern of the relative index lend credence to the suspected weakness of the labor market during the recovery.

Another potentially useful application of the unemployment index is in the area of program policy, such as extended unemployment benefits. Unemployment insurance benefits, which are intended as temporary financial assistance to qualifying unemployed workers, are administered at the state level. The amount of time during which a qualified unemployed person can collect unemployment insurance benefits is usually a maximum of 26 weeks. At the end of this time, if an individual is still unemployed when unemployment benefits are exhausted, the unemployed person might be eligible for additional weeks of benefits through an extended benefits program. Extended benefits, available during periods of high unemployment, are intended to relieve the longer-term unemployed from economic hardship (Franco, 2003). But how is a period of high unemployment determined? Under the Federally legislated Temporary Extended Unemployment Compensation (TEUC) program that was enacted in 2002, a high unemployment state was defined as one in which the insured unemployment rate is at least 4 percent and 120 percent of the rate over the prior 2 years or the total unemployment rate is at least 6.5 percent and 110 percent of either or both of the prior 2 years (Lake, 2002). That is, the criterion is based exclusively on the unemployment rate even though the intent is to relieve the hardship of those who are experiencing longer unemployment duration. As an alternative to basing the criterion for extended benefits solely on the unemployment rate, a threshold level for the index could be determined which would thereby define high unemployment or hardship in terms of a combination of both incidence and duration. Albeit subjective in choice, a possible threshold could be calculated as the product of a minimum tolerance-level unemployment rate and a minimum tolerance-level average duration, weighted by average duration of labor force participation. For example, suppose 4 percent is chosen as a minimum tolerance-level unemployment rate and 30 weeks is chosen as a minimum-tolerance-level average duration. The threshold index is then 1.2. For any month, if the current index were greater than 1.2, then the region would be identified as being in hardship or high unemployment whereas a current value that is less than 1.2 would not identify a high unemployment situation. If the unemployment rate increases dramatically at the same time that average duration decreases dramatically, the index could fall below the threshold level during a time of high incidence. However, since the unemployment rate and average duration tend to move together, this situation is unlikely to happen. A more likely occurrence is a decrease in the unemployment rate accompanied with a continual increase in duration. Under the current definition of high unemployment, eligibility for extended unemployment benefits could decline although hardship in terms of lengthy unemployment spells would still be pervasive. The formula for the index allows for a decrease (increase) in the unemployment rate along with an increase (decrease) in the average duration without reducing the functionality of the index in identifying high unemployment or hardship situations. For instance, if the unemployment rate were to decrease to 3 percent while average duration decreased to 14 weeks, the index would still be 1.2. Since the index incorporates both incidence and duration of unemployment, a threshold level as an indicator of hardship or high unemployment is fundamentally appealing since the burden of unemployment increases when unemployment benefits are exhausted and a job seeker has yet to find a job. The importance of including duration in assessment labor market conditions is underscored by the observed upward trend in duration [Groshen and Potter (2003), Mukoyama and Sahin (2004), and Valletta (1998, 2002)]. While the existing criterion for an extended benefits program could be modified to include duration, the specification of a threshold level for the index as an indicator of hardship is a more inclusive alternative to the current measure of hardship, which is based solely on the unemployment rate (incidence).

Because the formula for the index incorporates both incidence and duration, it would be of interest to those analysts who consider both incidence and duration to be relevant. For example, Valletta (2003) compares labor market conditions in California to the U.S. as a whole as well as to two major regions within the state, the San Francisco Bay Area and Southern California. He considers the impact of the federally legislated extension of unemployment insurance benefits on unemployed workers whose regular UI benefits have been exhausted. Valletta uses both the unemployment rate (incidence) and average duration of unemployment to assess labor market conditions, which highlights the relevance of using both aspects of unemployment. The countercyclical tendencies of average duration and the unemployment rate imply that they will move together but not necessarily identically. Valletta observed that duration and incidence were higher for the state of California than for the nation in the 1990s but differences tended to dissipate towards the end of the 1990s and the first few years of the new millennium. Although the state compares similarly with the nation in the early 2000s, Valetta highlights regional differences within the state, with the San Francisco Bay Area experiencing both higher incidence and longer unemployment duration than Southern California. Significantly, Valletta looks at the unemployment rate and average duration of unemployment separately. An alternative would be to use the unemployment index developed in this paper. In Valletta's analysis, instead of tracking the trends in both incidence and duration, he could compare the trends in the indexes for California and the United States.

CONCLUSION

By looking at unemployment as time in the labor force that is lost in the economy to unemployment, an unemployment index is created as the product of its structural components, incidence and duration of unemployment, weighted by time spent in the labor force. As a measure of the gap between actual weeks of labor and potential weeks of labor, the index can be used as an indicator of economic efficiency, providing a simple yet insightful view of unemployment in a broader examination that extends beyond any one particular dimension of unemployment.

The focus of the current study was to develop the index, use available data to compute the index, and discuss useful applications of the index. The index appears to be particularly useful as an indicator in assessing the strength of the labor market during the recent 2001 recession. A low unemployment rate was seemingly inconsistent with the slow employment growth that characterized the recovery phase, suggesting that the unemployment rate could be misleading as an indicator of labor market weakness. In comparison to its level at the end of the recession, the relative index did not suggest a strong labor market in the months after the business cycle reached its trough. The Conference Board produces a composite index of lagging indicators as a summary of the U.S. economy. Average duration of unemployment is the last of the seven statistical measures included in the weighted average (The Conference Board, 2001). As an alternative to duration, the unemployment index developed in this paper could be a suitable measure as a lagging indicator. Further exploration is warranted.

There are other avenues for future research that are beyond the scope of this paper. There is a body of literature on the full-employment (or natural) rate of unemployment, including discussions by Juhn, Murphy, and Topel (2002), Blanchard and Katz (1997), and Stiglitz (1997). Similarly, there is extensive literature on the Phillips Curve. The conventional unemployment rate is at the center of these areas. A potential path of research is whether substituting the unemployment index for the unemployment rate augments our understanding of either the natural rate of unemployment or the Phillips Curve and, if so, what insights can be gleaned.

DeFina (2002) explores the impact of unemployment on alternative poverty measures. His intent is to estimate the effect of aggregate unemployment on poverty. His findings conclude “whether and how aggregate unemployment affects poverty depend critically on the methods used to gauge poverty” (page 20). It is possible that the relationship between unemployment and poverty depends on the method used to gauge unemployment, offering a question for future research.

This preliminary analysis assumed that all labor force participants were in the labor force during the entire period from year to year. While this is a highly restrictive assumption, it does not prevent the theoretical development and initial exploration of the index as a valuable tool. In the current study, a time series analysis was implemented to provide an initial demonstration of the use and validity of the index. The availability of data on the number of weeks spent in the labor force would allow a refinement to the calculations of the index. This more complete construction could be useful in comparing the unemployment experience between different groups, identified by gender, race, age, state/regional residence, industry classification, or occupational classification.

ENDNOTES

1. Although data on the number of weeks spent in the labor force during the time period were not readily available using the Current Population Survey (CPS), there are other datasets such as the National Longitudinal Studies (NLS) as well as specific project datasets that contain information on time spent in the labor force that could be suitable in future research.

Fall 2008

2. In this analysis, (re-) entering the labor force is a type of job separation.

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APPENDIX A

The unemployment measure is modified to express the time units as fractional time units in terms of the proportion of time in the period under consideration in the analysis.

time in the labor force lost to unemployment

$$= \sum t_{ui} / \sum t_{Li}$$

$$= (N/L) \cdot (\bar{t}_u / \bar{t}_L)$$

$$= (N/L) \cdot \{(\bar{t}_u/T)/(\bar{t}_L/T)\}$$

$$= (N/L) \cdot \{T_u/T_L\}$$

$$= (N/L) \cdot (T_u) \cdot 1/(1-T_o)$$

where N = the number of people unemployed sometime during the period

L = the number of people in the labor force sometime during the period

N/L = the incidence of unemployment during the period

$\bar{t}_u$ = the average number of time units spent in unemployment by the unemployed during the time period

$\bar{t}_L$ = the average number of time units spent in the labor force by the labor force participants during the time period

T = the number of time units in the period

T_u = the average fraction of the period spent in unemployment by the unemployed

T_L = the average fraction of the period spent in the labor force by the labor force participants

$T_o = (1- T_L)$ = the average fraction of the period spent out of the labor force by the labor force participants.

APPENDIX B

Unemployment as time that is lost to unemployment can be further refined, in terms of labor turnover models for incidence and job search models for duration.

Incidence of unemployment can be decomposed into the probability of making a labor force transition and the conditional probability of being unemployed, given that a transition is made. For an individual, incidence of unemployment refers to the occurrence of at least one spell of unemployment in a given period of time. For a group of labor force participants, incidence denotes the extent to which members of the group experience unemployment. It is measured by the proportion of labor force participants who experience unemployment and represents the average probability of being unemployed in a given time period for the group.

Unemployment is a transitory state in which a person is not working and is looking for a job. Unemployment originates by leaving a job or (re-) entering the labor force. A spell of unemployment can end with either employment or exiting from the labor force. Among those who exit from the labor force, they may stay out either temporarily or permanently. The transitional nature of unemployment makes the turnover model appropriate for analyzing the incidence of unemployment. Unemployment is related to labor turnover to the extent that a "job separation"[i] may lead to a spell of unemployment. Probabilistically, the probability of unemployment equals the probability of separating from a job multiplied by the conditional probability of being unemployed, given that a separation has occurred.

$$\begin{aligned} \text{incidence of unemployment} \quad &= N/L \\ &= P_u \\ &= P_s \cdot P_{u|s} \end{aligned}$$

where N = number of people unemployed sometime during the period

L = number of people in the labor force sometime during the period

N/L = incidence of unemployment during the period

P_u = probability of being unemployed

P_s = probability of separating from a job

$P_{u|s}$ = conditional probability of being unemployed, given that a separation has occurred.

The model used in this analysis differs from the stock-flow model of the labor market that is used in Clark and Summers (1980), Blau and Robins (1986), and DeBoer and Seeborg (1989). The stock-flow model looks at flows of individuals between the various labor market states (employment, unemployment, and non-participation in the labor force). Empirically, the flows are monthly transitions.

[See Ehrenberg and Smith (2006, chapter 15) for a description of the stock-flow model.] In my analysis, labor force transitions refer to changes in employment and movements between labor force participation and non-participation, which is measured by the first component, P_s. Experiencing unemployment is accounted for in the second component, $P_{u|s}$, which is the probability of being unemployed, conditional on having made a labor force transition.

Duration can be defined as the length of time an unemployed person spends looking for a job. Job search models have been developed to analyze decisions such as whether or not to look for a job, setting realistic wage expectations, or when to stop searching. Job search activity can be pursued by either the unemployed or the employed. Since the job search model is used here in relation to duration of unemployment, the duration of job search is equivalent to the duration of unemployment.

The premise behind the job search model is that the job seeker is faced with a distribution of wage offers. The objective of the individual is to receive a job offer in which the wage is at least equal to the reservation (or acceptance) wage. The reservation wage is determined by equalizing the expected marginal benefit of an additional period of search with the marginal cost of searching one more period. It is the lowest wage acceptable to the job seeker. Although the job seeker knows his reservation wage, the seeker does not know which employers would offer him a job that meets his requirement nor does he know how many employers would do so. Generally, the higher the reservation wage, the smaller the probability that an acceptable job offer will be obtained in the next period. Moreover, the lower is the probability of obtaining an acceptable job offer, the longer will be the expected duration of job search. Hence, the duration of unemployment is inversely related to the probability of receiving an acceptable job when unemployed. Because it is possible that no jobs may be offered in the next search period, this probability can be further refined as the product of the probability of receiving any job offer (p) and the probability of receiving an acceptable job offer, given that a job offer has been received, (P_a):

$$\text{duration of unemployment} = \bar{t}_u = 1 / (p \cdot P_a)$$

where $\bar{t}_u$ = average number of time units spent in unemployment by the unemployed during the time period

p = probability of receiving a job offer

P_a = probability of receiving an acceptable job offer, given that a job offer has been received.

In this context, duration of unemployment can be decomposed into the inverse of the product of the probability of receiving a job offer and the probability of receiving an acceptable job offer, given that a job offer has been received.

The resulting specification for the measure of unemployment is:

time in the labor force lost to unemployment

$$= (N/L) \cdot (\bar{t}_u / \bar{t}_L)$$
$$= P_u \cdot \bar{t}_u \cdot (1/\bar{t}_L)$$
$$= P_s \cdot P_{u|s} \cdot \bar{t}_u \cdot (1/\bar{t}_L)$$
$$= (P_s \cdot P_{u|s}) \cdot (1 / (p \cdot P_a)) \cdot (1/\bar{t}_L)$$
$$= (P_s \cdot P_{u|s}) / (p \cdot P_a \cdot \bar{t}_L)$$

where $\bar{t}_L$ = average number of time units spent in the labor force by the labor force participants during the time period

The attractiveness of this decomposition of the unemployment rate is that it identifies components that affect the unemployment rate, and provides a specification that allows us to empirically measure the contribution of each component to the unemployment rate. Because the formula is weighted by time spent in the labor force (i.e., rather than by time spent in employment), this derivation for the index is a general formula that can be applied to both continuous labor force participants and those who have spent some time out of the labor force.

i. In this analysis, (re-) entering the labor force is a type of job separation.

APPENDIX C
Source of Data

The source of the data used in this analysis is from the Current Population Survey (CPS), Bureau of Labor Statistics, U.S. Department of Labor. Data were obtained for the period from January 1948 to May 2007 for the U.S. civilian population who were 16 years of age and older.

The table on the following page is a sample of the raw data for the time period January 2000 through May 2007, which includes the most recent business cycle as dated by the National Bureau of Economic Research (NBER, 2007).

a. The unemployment rate was used to measure incidence (UR):
   Units: percent; not seasonally adjusted
   Series ID: LNU04000000
b. The average weeks unemployed was used as a measure of duration (Duration):
   Units: Number of weeks; not seasonally adjusted
   Series ID: LNU03008275
c. The number of weeks spent in the labor force during the time period was unavailable.
d. The unemployment index is calculated for each month of the 713-month time period, using the f following mathematical specification:

$$\text{Index} = \text{UR} * \text{Duration} / (100 * 52).$$

Sample of Raw Data (1/2000 – 5/2007)

DA TE	R	Durati on	IN DEX	DA TE	R	Durati on	IN DEX	DA TE	R	Durati on	IN DEX
Jan-	4		0.0	Jan	6		0.0	Jan	5		0.0
00	.5	12.6	109	-03	.5	17.8	223	-06	.1	16	157
Feb	4		0.0	Feb	6		0.0	Feb	5		0.0
-00	.4	12.6	107	-03	.4	18.6	229	-06	.1	17.9	176
Mar	4		0.0	Mar	6		0.0	Mar	4		0.0
-00	.3	13.3	110	-03	.2	18.9	225	-06	.8	17.8	164
Apr-	3		0.0	Apr-	5		0.0	Apr-	4		0.0
00	.7	13.1	093	03	.8	20.6	230	06	.5	18	156
May	3		0.0	May	5		0.0	May	4		0.0
-00	.8	12.8	094	-03	.8	19.6	219	-06	.4	17.5	148
Jun-	4		0.0	Jun	6		0.0	Jun	4		0.0
00	.1	11.3	089	-03	.5	18.4	230	-06	.8	15.1	139
Jul-	4		0.0	Jul-	6		0.0	Jul-			0.0
00	.2	12.9	104	03	.3	18.4	223	06	5	16.1	155
Aug	4		0.0	Aug			0.0	Aug	4		0.0
-00	.1	12.9	102	-03	6	19.1	220	-06	.6	17.2	152
Sep	3		0.0	Sep	5		0.0	Sep	4		0.0
-00	.8	12.1	088	-03	.8	19.5	218	-06	.4	17.5	148
Oct-	3		0.0	Oct-	5		0.0	Oct-	4		0.0
00	.6	13	090	03	.6	19.6	211	06	.1	16.7	132
Nov	3		0.0	Nov	5		0.0	Nov	4		0.0
-00	.7	12.4	088	-03	.6	20.1	216	-06	.3	16.6	137
Dec	3		0.0	Dec	5		0.0	Dec	4		0.0
-00	.7	12.8	091	-03	.4	20	208	-06	.3	15.9	131
Jan-	4		0.0	Jan	6		0.0	Jan			0.0
01	.7	12.2	110	-04	.3	19	230	-07	5	15.5	149
Feb	4		0.0	Feb			0.0	Feb	4		0.0
-01	.6	12.8	113	-04	6	20.3	234	-07	.9	16.7	157
Mar	4		0.0	Mar			0.0	Mar	4		0.0
-01	.5	13.4	116	-04	6	20.8	240	-07	.5	18.4	159
Apr-	4		0.0	Apr-	5		0.0	Apr-	4		0.0
01	.2	13.1	106	04	.4	21	218	07	.3	18.3	151
May	4		0.0	May	5		0.0	May	4		0.0
-01	.1	12.4	098	-04	.3	20.3	207	-07	.3	17.1	141
Jun-	4		0.0	Jun	5		0.0				
01	.7	11.8	107	-04	.8	18.8	210				
Jul-	4		0.0	Jul-	5		0.0				
01	.7	12.3	111	04	.7	17.5	192				
Aug	4		0.0	Aug	5		0.0				
-01	.9	13.2	124	-04	.4	18.7	194				
Sep	4		0.0	Sep	5		0.0				
-01	.7	13.1	118	-04	.1	19.5	191				

Oct-			0.0	Oct-	5		0.0
01	5	13.5	130	04	.1	19.8	194
Nov	5		0.0	Nov	5		0.0
-01	.3	14.4	147	-04	.2	20	200
Dec	5		0.0	Dec	5		0.0
-01	.4	14.7	153	-04	.1	19.5	191
Jan-	6		0.0	Jan	5		0.0
02	.3	14.1	171	-05	.7	18.5	203
Feb	6		0.0	Feb	5		0.0
-02	.1	15	176	-05	.8	19.2	214
Mar	6		0.0	Mar	5		0.0
-02	.1	16.2	190	-05	.4	20.4	212
Apr-	5		0.0	Apr-	4		0.0
02	.7	17.2	189	05	.9	21.1	199
May	5		0.0	May	4		0.0
-02	.5	17.1	181	-05	.9	19.1	180
Jun-			0.0	Jun	5		0.0
02	6	15.9	183	-05	.2	16.3	163
Jul-	5		0.0	Jul-	5		0.0
02	.9	15.9	180	05	.2	16.5	165
Aug	5		0.0	Aug	4		0.0
-02	.7	16.3	179	-05	.9	18.4	173
Sep	5		0.0	Sep	4		0.0
-02	.4	17.5	182	-05	.8	18.2	168
Oct-	5		0.0	Oct-	4		0.0
02	.3	18	183	05	.6	18.3	162
Nov	5		0.0	Nov	4		0.0
-02	.6	17.8	192	-05	.8	17.8	164
Dec	5		0.0	Dec	4		0.0
-02	.7	18.8	206	-05	.6	17.5	155

Source: Current Population Survey (CPS), Bureau of Labor Statistics, U.S. Department of Labor
Key: UR – Unemployment Rate, percent, U.S. civilian population 16 years and over; not seasonally adjusted; Series ID: LNU04000000
Duration – Average Weeks Unemployed, Number of weeks, U.S. civilian population 16 years and over; not seasonally adjusted; Series ID: LNU03008275

Predicting Days On Market: The Influence Of Environmental And Home Attributes

Robert P. Culp*

ABSTRACT

This paper estimates the difference in the number of days a home will remain on the market based upon its environmental attributes. Using on-site inspections of 3088 home sites, the results, using two-stage least squares, show that time on market is reduced and price increased by a variety of green features such as trees, landscaping, open spaces and parks, while time on market is increased and/or price decreased by man-made obstructions such as power lines, roads near the home, train tracks, and apartments. This research finds home orientation to and not just the distance from roads has a significant impact on home price and time on market regardless of traffic volume. Apartments in view are found to significantly reduce home prices and increase time on market while cathedral ceilings increased home price. Homes in subdivisions were found to sell for higher prices and sell more quickly while the price of homes was not influenced by a hill obstructing the rear even though time on market was significantly increased.

INTRODUCTION

While much analysis has been done on how environmental and various other attributes influence the selling price of a home, less work has been done examining the factors influencing time on market. Time on market, the time from when a home is listed until there is an agreement for sale, can be very important to homeowners and to real estate agents. For the homeowner there are real costs. The homeowner may have to maintain two residences with two mortgage payments. It might also be necessary to maintain a show appearance for the home and make time available for visits by potential buyers. The homeowner may also have to maintain the yard and garden until the home sells. Additionally, some homeowners may not be able to purchase their desired new residences until their current home has sold. Besides the real costs, additional time on market has emotional costs. Homeowners unable to sell their homes in a timely fashion may experience emotional distress from financial concerns, being unable to schedule movers or make various other moving preparations, and from not knowing if they will be able to meet various important deadlines such as school or job start dates. For real estate agents, homes that stay on the market longer mean that the real estate agent must devote more time and resources for each sale and may cause the loss of potential future clients who may question the agent's effectiveness.

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Time on market is also critical for builders and developers. Extra time on market means extra interest costs. Additionally, builders who build on speculation, particularly small builders who have borrowing constraints, may not be able to obtain funds to construct a new home until their inventory of existing homes has sold. These factors reduce profitability. This paper examines how various environmental attributes whether man-made or green features influence time on market and market price. Time on market is examined in a form that allows for easy interpretation of not only whether a feature will increase or reduce time on market but also estimates the expected additional time on market for each feature.

PREVIOUS RESEARCH

While a significant amount of work has been done to examine the impact of environmental attributes on home price, few of these papers involve actual physical inspection of the area surrounding each home, and fewer still have examined how environmental attributes influence time on market. Instead, most papers examining environmental attributes perform simple hedonic valuation using geographic information systems (GIS) data to determine the proximity of each home to various structures such as roads, schools, shopping, and parks so the value of these attributes can be obtained.

The advantage of a GIS approach is that data collection is easy and these studies can obtain large samples. However, physical inspections of each home can provide more detailed information about tree cover, views, home orientation, and obstructions that are not available in GIS reports. The amount of recent research done using physical inspections is very limited. While MLS data include physical inspections of some basic home features, these inspections do not typically or consistently include information regarding trees and landscaping, the home's proximity to parks, roads, or man-made structures. Much of the previous research has examined the role of environmental attributes in home prices, but has not examined time on market. For example, Des Rosiers et al. (2002) examine how home prices are influenced by landscaping and tree cover. Later, Des Rosiers (2002) examines how power lines influence home prices while Bourassa, Hoesli, and Sun (2005) estimate the value of water views, the value of neighborhood improvements, and the value of landscaping in the neighborhood by hedonic valuation.

While recent research using physical inspections has been limited, research into how environmental attributes influence time on market has been done by only a handful of researchers. Haurin (1988) examined how time on market was influenced by the uniqueness of a home's attributes. He developed an atypical index to describe the relative uniqueness of homes and found that homes with atypical features had increased time on market. Haurin only examined time on market in relation to his index. He did not examine each attribute individually and only examined the environmental impact of roads and views. He did not consider other environmental attributes or home orientation to those roads. Jud and Frew (1990) use Haurin's atypical index to estimate apartment vacancies and find results similar to Haurin's work on homes. Glower, Haurin, and Hendershott (1998) examine how seller motivation influences time on market using Haurin's index. Anglin, Rutherford and Springer (2003) found in their empirical study that higher listing prices increase time on market. More recently, Allen, Faircloth and Rutherford (2005) found that setting a range of prices rather than one listing price did not reduce time on market. However, none of these papers closely examined environmental attributes. An exception is Ong and Koh (2000) who examine time on market for high-rise flats. Although they find that flat owners with the best views keep their homes on the market longer to obtain a higher price, they do not examine any other environmental attribute.

Other papers examining time on market have approached the topic from a theoretical perspective, such as Miceli (1989) and Geltner, Kluger, and Miller (1991) who examine optimal contact theory, or Taylor (1999) who examines theoretically how setting a listing price can be a signal to buyers of quality, or Genesove and Mayer (2001) who find sellers expecting to sell at a loss in nominal terms will set their list price at a higher value and will tend to obtain a higher price than those not expecting to sell at a loss.

DATA AND MODEL

While time to sale data is usually analyzed using hazard or survival models, these models provide results in probability terms and do not estimate time to sale. For example, a hazard model can indicate a home with a particular attribute will be 10 percent more likely to sell before a home without that attribute but is not able to estimate how much more quickly the home will sell. A common misinterpretation of hazard model results is to conclude that if a home is 10 percent more likely to sell before another home, that it will therefore sell 10 percent more quickly. This is not the case. The average difference in time on market could be virtually identical or could be significantly shorter. For example, suppose two sprinters are compared and one is 10 percent more likely to win than the other. This does not mean that the first sprinter is 10 percent faster on average, only that he is more likely to finish first by some unknown amount.

For people involved in real estate, it is not enough to know that a home with a certain attribute will take longer to sell; they need to know how much longer it will take to sell. So while hazard models can be very useful, applying them to the real estate market does not provide very useful information.

Accordingly, rather than using a hazard or survival model, this paper will use standard regression procedures to estimate time on the market. While hazard models are more efficient, linear models are appropriate and have frequently been used to model time on market. Additionally, recent research by McElroy et al. (2005) comparing hazard model estimates to linear measures shows that linear measures are robust for estimating survival time. While a simple ordinary least square model could be used to estimate time on market, this approach ignores the interdependence between how long a home stays on the market and its selling price and between selling price and how long the owner decides to keeps the home on the market. Therefore, given the interaction between these two variables, this paper will use a two equation system estimating time on market and selling price simultaneously.

Using this approach will allow for estimates of each home's predicted time on market depending upon the individual characteristics of the home while taking into account each home's selling price.

The home price equation (1) can be written as:

$$\ln(SP_i) = \alpha + \beta X_{Pi} + \theta \ln(DOM_i) + \psi(LP) + \varepsilon_i \qquad (1)$$

where SP_i represents the selling price of the ith property, X_{Pi} represents a vector of each home's physical, environmental, and time variables, ln(DOM) represents the natural logarithm of the number of days the property was on the market, and LP is the list price to account for home over pricing. The days on market equation (2) is written as:

$$\ln(DOM_i) = \gamma + \pi \ln(SP_i) + \eta X_{Di} + \varphi (LP) + v_i, \qquad (2)$$

Where X_{Di} represents a vector of the property attributes and time variables to control for the quarter in which the home was sold. LP is the list price of the home to account for the extra time on market for higher priced homes.

The selling price is the price at which the transaction occurred without regard to the actual amount the home homeowner nets after paying commission and fees. The coefficients of these equations are estimated using two-stage least squares (2SLS), following the method applied by Munneke and Yavas (2001) with location and time data (the quarter in which the home sold) being used as instrument variables for the 2SLS.

The data consist of 3088 home sales occurring in the Parkland School District in Lehigh County, Pennsylvania between the summer of 1999 and the summer of 2005. Lehigh County is located close to New Jersey in eastern Pennsylvania; 88 miles from New York City. The area has seen an increase in population from residents relocating from New Jersey to take advantage of the area's relatively low cost of living. While the school district's average income in 2006 of $59,419 (VISC, 2008) is higher than in the surrounding rural areas, it is very comparable to other suburban districts in the region and slightly below the New Jersey median household income of $65,370 (U.S. Census) The 1999-2005 time period saw home prices in the Lehigh Valley rise and does not include the decline in home prices that occurred by 2007. The sales data and various home attributes were obtained from the local multi-list service, Lehigh Valley Association of Realtors. The environmental data were obtained by this researcher examining the exterior of 3122 homes from Fall 2005 to Spring 2006 to determine the various environmental attributes possessed by each home. One limitation of the method of data collection is that these homes were observed in winter of 2005-2006 and not at the time of sale. Some fast-changing attributes such as landscaping may have changed in some cases. Other factors such as new roads, apartments, and parks are known not to have significantly changed over the period covered by this study, however, traffic patterns and volume of traffic changes could have changed during the examined period. Therefore, some caution should be used when evaluating these outcomes.

After removing home observations which had missing information, 3088 observations remained. A description of each variable considered is shown in Appendix 1 and the final model results are shown in Table 1. Variables were eliminated using the backward elimination procedure in the regression software. This procedure removed variables not satisfying the incremental F test at a 5 percent level of significance. Therefore, the results in Table 1 show only variables explaining a significant amount of the variation in time on market or market price with the exception of attributes that described the magnitude of an attribute, such as the number of tree lines or the frequency of car traffic. These variables were kept in the model for comparison purposes.

ANALYSIS OF RESULTS

The results of the simultaneous system of equations are shown in Table 1. Since the time on market equation is in natural logarithmic form, interpreting each attribute's impact on time on market varies depending upon the magnitude of the other coefficients. The coefficients of Table 1 provide an estimate of the percentage change in price and time on market for a change in each attribute.

While the R square for the time on market (TOM) equation is low, this result is not unexpected given the underlying variation of the data and is consistent the R squares obtained from prior research, and as the F statistic shows, the model is significant. ANOVA results are presented in Table 2. The coefficients from the regression results are of the expected sign for the statistically significant environmental attributes with views and parks, trees and landscaping, and roads and man-made structures all having a significant impact on home price and time on market. The one exception is that mid volume roads in front of the home were found to increase home price. One would have expected that a more frequently traveled road would create noise or privacy issues and reduce home price. Perhaps homes on these more frequently traveled routes gain more exposure to potential home buyers and thus sell for higher prices or maybe these homes are situated closer to shopping features that home buyers enjoy.

Trees and Landscaping

Of the tree features, tree lines on three sides had the largest impact on time on market but little impact on price. Time on market for these homes is reduced by more than 50 percent compared to a home without a tree line on three sides. Homes with tree lines on fewer than three sides had no statistically

Table 1: Regression Results

	Dependent Variable:		t stat and Sig. for Price		t stat and Sig. for T.O.M	
Attributes[1]	**LNTOM**	**LNPrice**	**t**	**Sig.**	**t**	**Sig.**
Trees and Landscaping						
Tree Line: One Side	-.070	.009	.988	.323	-1.321	.187
Two Sides	.064	.022	1.446	.148	.699	.484
Three Sides	-.517*	.017	.442	.659	-2.651	.008
Trees Overhang: One	-.073	-.037*	-2.454	.014	-.817	.414
Two Sides	-.280	.004	.147	.883	-1.905	.057
Three Sides	.018	.006	.165	.869	.088	.930
Four Sides	-.035	-.049	-1.263	.207	-.150	.881
Tall Mature Trees	-.073	.031*	3.414	.001	-1.399	.162
Large Trees Back	-.120*	.003	.310	.756	-2.247	.025
Mat. Landscaping	-.210*	.025*	2.248	.025	-4.160	.000
Views, Parks, Orientation, and Neighborhood						
Park Near	-.370*	.044*	2.629	.009	-6.330	.000
Green space	-.037	.022	1.927	.054	-.547	.584
Partial View	-.046	.047*	4.762	.000	-.786	.432
View	.054	.048*	4.236	.000	.800	.424
Impressive View	-.146	.040*	2.873	.004	-1.888	.059
In subdivision	-.328*	.041*	2.272	.023	-4.006	.000
Cul-de-sac	.094	-.004	-.233	.815	.990	.322
Corner	.079	.013	1.179	.238	1.255	.210
Hill Obstructs Rear	.266*	.001	.088	.930	4.027	.000
Roads and Man-Made Structures						
Road Front: High	.144	.002	.115	.909	1.177	.239
Mid	-.005	.041*	2.335	.020	-.045	.964
Low	.046	-.016	-1.003	.316	.503	.615
Road Back: High	.427*	-.049	-1.834	.067	3.292	.001
Mid	.501*	-.050	-1.565	.118	3.210	.001
Low	.224	-.033	-1.264	.206	1.500	.134
Power Back Major	.342	-.042	-1.207	.228	1.774	.076
Power Front Major	.502	-.086	-1.038	.299	1.046	.296
Highway View	-.025	-.004	-.297	.767	-.319	.750
Train Tracks	.729*	-.031	-.579	.562	2.649	.008
Apartments in View	.388*	-.090*	-4.065	.000	3.790	.000
Home's Physical Characteristics						
Central AC	-.027	.080*	6.543	.000	-.369	.712
Cathedral Ceilings	-.097	.033*	3.221	.001	-1.714	.087
Number of Cars	.012	.041*	9.666	.000	.497	.619
Fireplace Number	.102*	.037*	4.777	.000	2.518	.012
Years Old	-.001	-.002*	-10.190	.000	-.952	.341
Sq. Footage (1000s)	.007	.021	1.905	.057	1.026	.305
Stories	.065	-.002	-.269	.788	1.793	.073
Number Bathrooms	.185*	-.004	-.490	.624	7.828	.000
Heat Pump	-.002	-.033*	-3.930	.000	-.040	.968
LnPrice (1000s)	.003*				9.121	.000
LnTOM		.035	.960	.337		
Listing Price (1000s)	.003*				25.495	.000
Adjusted R Square	.227	.833				

[1] Quarter and Location Variables Omitted for Brevity
* Significant at the 5 percent level

Table 2:

ANOVA

Dependent Variable: LNTOM

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1300.498	65	20.008	14.943	.000
Residual	4046.197	3022	1.339		
Total	5346.694	3087			

ANOVA

Dependent Variable: LNPrice

	Sum of Squares	df	Mean Square	F	Sig.
Regression	582.007	66	8.818	234.456	.000
Residual	113.625	3021	.038		
Total	695.632	3087			

significant impact on price or time on market, i.e. we cannot conclude they sold faster or at a higher price. The enhanced value of the tree line on three sides may result from the extra privacy a tree line on three sides provides.

The largest estimated impact on price from trees and landscaping is trees overhanging on one side. This feature reduced home price by an estimated 3.7 percent while mature trees on the property added an estimated 3.1 percent to home price. Even though trees overhanging a home have been shown to reduce air-conditioning costs, the limited aesthetic value of non-landscaping trees and the potential for debris from these trees may explain their negative impact on price. Previous research by Des Rosiers et al. (2002) showed that as tree coverage increased value increased until the coverage became excessive then value declined. The explanation for this outcome is that trees provide much needed shade and privacy but too many trees block out too much of the sun, potentially creating a dark and gloomy environment. The results in this paper are consistent with Des Rosiers' work. The analysis found that homes with trees overhanging on four sides lost 4.9 percent of their value.

Large trees in the rear of the home reduced time on market but had no significant impact on price perhaps because large trees may also increase the home owner's potential maintenance and liability costs or simply because nearly 42 percent of homes in the Parkland school district have large trees in the rear and therefore these are not a selling feature of the home. Finally, landscaping reduces estimated time on market by 21 percent and increased home selling price by 2.5 percent. Similar results were found for mature trees which reduced time on market by 7.3 percent and increased home price by 3.1 percent. While this result is slightly lower than results reported in the American Nursery & Landscape Association (ANLA) fact sheet of a 7 percent increase in home price for landscaping of "excellent" quality, the difference may result from the fact that the data used for this paper did not attempt to quantify whether landscaping quality was "excellent".

Views, Parks, Orientation, and Neighborhood

According to the regression results, as one might expect, views from the home had a significant impact on home price. In fact, homes rated as having an impressive view, meaning one can see an estimated three miles from the home, increased home price by an estimated 4 percent with lesser views also increasing home price. Only homes with impressive views were found to have a significant reduction in time on market—reducing time on market by an estimated 14.6 percent.

While being located near a park added an estimated 4.4 percent to the home's value and reduced time on market by 37 percent, a park located behind the home was statistically insignificant and was dropped from the model. Perhaps homes located next to a park lose privacy and suffer from the noise that a park generates while homes located near the park get the benefits of the park without the negative consequences. This speculation is consistent with the positive value associated with green space. While green spaces afford the owner some of the benefits of a park, they do not create the extra foot traffic that a park generates and as such the model estimated they reduced time on market by 3.7 percent.

Subdivisions were found to increase home value by 4.1 percent and reduce time on market by 32.8 percent. This finding could be the result of homeowners, particularly those with young children, wanting to locate near other families, or perhaps homes in subdivisions benefit from having more traffic from potential buyers. Location on a cul-de-sac or corner did not have a significant impact on time on market. While a corner lot may not be desirable from a privacy standpoint, homes on corners tend to have larger lots which may explain the positive, but not statistically significant, impact on price. Hills which block use of the back yard did not significantly reduce price, but time on market was increased by 26.6 percent. This result is consistent with Haurin's finding that the owners of atypical homes will keep their homes on the market longer to find someone who values, or in this case does not mind, the addition of the attribute.

Roads and Man-Made Structures

As expected, roads generally reduced selling price and increased time on market with busier roads reducing price more than less traveled routes. Unlike previous research, this study examined whether roads located in the front or the rear of the home had differential impacts. One would expect that homeowners would prefer a road to be located in front of their home rather than behind because backyards are typically a place for activities where privacy is particularly important. The regression results confirm this suspicion and show that roads behind the home have a larger impact. For example, a high volume road in the front of the home increases time on market by 14.4 percent but the same volume road located in the rear of the home increases time on market by 42.7 percent. Even low volume roads located in the rear of the home have a large impact on estimated time on market. Low volume roads in front increase time on market by only 4.6 percent but a low volume road in the back increases estimated time on market by 22.4 percent. Homes not located next to a major road but with a highway in view were not found to suffer a statistically significant reduction in home price.

As one would expect train tracks increased time on market by 72.9 percent but did not have a statistically significant impact on price. This outcome may be the result of an increasing home price market where owners of these homes benefited from a rising home market obscuring the impact on price of this feature. Major power lines behind the home had much less impact on home selling price than power lines in front, reducing price by only 4.2 percent compared to 8.6 percent. However, this result could occur because major power lines in the rear of the home generally have green space around them maintained by the power company providing additional space and privacy to the homeowner.

This research also found a significant impact of apartments in view of a home. The results indicate home prices are reduced by 9 percent if an apartment is in view and time on market increased by a staggering 38.8 percent —an amount only exceeded by train tracks, major power lines or high volume road in back of the home.

Home’s Physical Characteristics

Physical attributes, while not the focus of this study, also play an important role in home selling price. Cathedral ceilings increased home price by 3.3 percent and reduced time on market by 9.7 percent. While this may suggest these ceilings are highly valued, it may also be highly correlated with one story homes which are more expensive to build and may be more likely to use cathedral ceilings, or in the case of two story homes; cathedral ceilings eliminate the use of the space above the first floor reducing the cost advantages of two story homes.

Finally, central air-conditioning had a large impact on selling price, increasing home price by 8 percent.. Home age was also found to be a significant factor reducing home price but having no impact on time on market. While the impact on home price for two story homes compared to one story homes was statistically insignificant, time on market for two story homes was found to be significantly longer than for one story homes, increasing time on market by 6.5 percent. The negative coefficient on price for the number of bathrooms might seem surprising at first since more bathrooms should be preferable to fewer bathrooms, but the regression analysis holds everything else constant so a home with the same square footage as another home but with one more bathroom will have less living space available in other rooms. What this indicates is that people prefer, on the margin, more space devoted to other rooms than to the addition of a bathroom.

CONCLUSIONS

The results in this paper provide estimates of how time on market is influenced by a variety of environmental attributes in a form which is easy to interpret. Given that the population of the Lehigh Valley is not atypical from other suburban communities, many of the results found in this paper should be applicable to other parts of the country, however, given the relatively high supply of certain environmental attributes such as homes with views, trees, and the availability of land for new homes, the value of these environmental attributes may be underestimated compared to communities with a paucity of these resources where buyers may vigorously compete for these scarce attributes

The results in this paper are useful not only to real estate agents trying to provide their clients with reasonable predictions for how long it will take to sell their homes, but also to a variety of other professions involved in real estate. Landscapers will find the reduced time on market provided by landscaping as an additional selling point to their product because not only can landscaping increase home price, it also reduces a home’s time on market. Additionally, homeowners and real estate agents will find it useful to have estimates on how various attributes can reduce a home’s time on market and increase selling price. Finally, builders deciding on which properties to build could use the information presented in this paper to make a more informed decision about potential sites not only in terms of home selling price but also how quickly the lots will likely sell.

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Appendix 1: Description of Variables

Variable	Description	Source of Data
Location and Time Variables:		
Allentown	Home is located in Allentown portion of Parkland School District	MLS data
Coplay	Home is located in Coplay township	MLS data
Corner	Homes is located at intersection of two roads	Inspection
Cul-de-sac	Home was located in the circular part of a Cul-de-sac	Inspection
In Subdivision	Home located within a subdivision	Inspection
Mid Vol. Month	Home sold during months of Jan, Feb, or Aug-Oct	MLS Data
Nbhood. on Slope	Neighborhood is located on slight hill	Inspection
North Whitehall	Home is located in North Whitehall township	MLS Data
Q2-Q26	Quarter in which home was sold	MLS Data
South Whitehall	Home is located in South Whitehall Township	MLS Data
Years Old	Age of home at time of sale	
Physical Characteristics:		
Aluminum	Home has aluminum siding only	MLS Data
Aluminum Brick/Stone	Home has brick or stone and aluminum siding	MLS Data
Asbestos	Home contains asbestos	MLS Data
Brick/Stone Stucco	Home has brick or stone and stucco siding	MLS Data
Brick/St.and other	Home has brick or stone and vinyl, aluminum, or wood siding	MLS Data
Brick/Stone Only	Home has brick and stone only	MLS Data
Central AC	Home has central air conditioning	MLS Data
Completely Finished	Entire basement area is finished	MLS Data
Daylight	Daylight basement.	MLS Data
Detached Garage	Home has detached garage	MLS Data
Fireplace Number	Number of fireplaces in home	MLS Data
Heat Pump	Home uses heat pump	MLS Data
Lot Size – Sq Ft	Size in square feet on lot	MLS Data
N. of Bathrooms	Number of bathrooms in home	MLS Data
Number of Cars	Number of cars that can be parked in garage	MLS Data
Partially Finished	Basement is partially finished	MLS Data
Radiator	Home uses radiator heat	MLS Data
Square Footage	Square footage of heated home not located in basement	MLS Data
Stories	Number of stories home possesses	MLS Data
Stucco and Vinyl	Home has stucco and vinyl siding	MLS Data
Stucco Only	Home has stucco siding	MLS Data
Trees		
Large Trees Back	Trees taller than 35 feet in rear of home	Inspection
Matr. Landscaping	Landscaping equivalent to estimated five years worth of growth.	Inspection
Tall Mature Trees	Trees over 15 feet tall but not more than 35 feet tall.	Inspection
Tree Line 1	Wall of trees located on the home’s property line	Inspection
Tree Line 2	Tree line located on home’s property line on two sides	Inspection
Tree Line 3	Trees line the property line on three sides	Inspection
Tree Lined Street	Street has shade trees on both sides	Inspection

Variable	Description	Source of Data
Trees Overhang 1	Trees overhang home on one side	Inspection
Trees Overhang 2	Trees overhang home on two sides	Inspection
Trees Overhang 3	Tall trees overhang the home on three sides	Inspection
Trees Overhang 4	Trees overhang home on all four sides	Inspection
Wood 1	Woods are on one side of the property	Inspection
Wood 2	Woods are one two sides of the property	Inspection
Wood 3	Woods are located on 3 sides of the property	Inspection
Green Space		
Backs up to Field	Home has a field located in backyard	Inspection
Backs up to Home	Another home located within an estimated 100 feet of rear	Inspection
Detention Pond	Home backs up to pond designed to temporarily hold rain water	Inspection
Green Space	Mowed grass area located next to home	Inspection
Hill Obstructs Rear	Less than 15 feet of flat space in rear from downward sloping hill	Inspection
Park in Back	Rear of home backs up to park	Inspection
Park Near	Park located in two block walking distance w/o crossing busy road.	Inspection
Partial View	Views not visible from home's property but from neighborhood	Inspection
Private Home	Indicates home located out of view of any road	Inspection
Private Nghborhd.	Neighborhood with private drive and homes not visible from roads	Inspection
Protective Hill	Upward sloping hill located after at least 50 feet of flat lot	Inspection
Regular Pond	A natural pond is on property	Inspection
Secluded	Home is not near other homes or well-traveled areas	Inspection
Stream	Home has stream located on its property or line	Inspection
Man-Made Structures		
Business Buildings	Business buildings are in view	Inspection
Cell /Water Tower	Home has cell or water tower in view	Inspection
Industrial Area	Home is located within 1 block of light industrial area	Inspection
Maj. Power Back	Major transmission lines at home's rear	Inspection
Maj. Power Front	Major transmission line located on property front	Inspection
Min. Power Front	Home power transmission lines are not buried and located on front	Inspection
Min. Power Rear	Power lines to home above ground and visible in backyard of home	Inspection
Road Back High	Traffic on road behind home exceeds estimated 10 cars per minute	Inspection
Road Back Low	Traffic on road behind home is less than 2 cars per minute	Inspection
Road Back Mid	Traffic on road behind home is between 3 cars to 9 cars per minute	Inspection
Road Front High	Traffic on road in front of home exceeds 10 cars per minute	Inspection
Road Front Low	Traffic on road in front of home is less than 2 cars per minute	Inspection
Road Front Mid	Traffic on road in front of home is between 3 cars to 9 cars per minute	Inspection
Road Not Close	Road that is more than 100 feet from rear of home	Inspection
Shopping Center	Shopping center is visible from property	Inspection
Train Tracks	Home has train tracks within view	Inspection
Views:		
Apts. in View	Apartments can be seen from home's property	Inspection
Highway View	Home is within estimated 500 feet of highway	Inspection
Impressive View	Home has a greater than an estimated 3 mile view.	Inspection
Power Line View	Power lines are within 1000 feet of home but not on property	Inspection

Variable	Description	Source of Data
View	Home had a view estimated to be 2-3 miles	Inspection

Appendix 2: Descriptive Statistics

Attributes*	Proportion of Homes with Characteristic	Std. Deviation
Trees and Landscaping		
Tree Line: One Side	0.28	0.451
Two Sides	0.08	0.264
Three Sides	0.01	0.104
Trees Overhang: One	0.07	0.253
Two Sides	0.02	0.152
Three Sides	0.01	0.104
Four Sides	0.01	0.098
Tall Mature Trees	0.36	0.483
Large Trees Back	0.42	0.494
Mat. Landscaping	0.31	0.462
Views, Parks, Orientation, and Neighborhood		
Park Near	0.18	0.386
Green space	0.12	0.328
Partial View	0.35	0.478
View	0.23	0.418
Impressive View	0.16	0.368
In subdivision	0.85	0.361
Cul-de-sac	0.06	0.231
Corner	0.14	0.347
Hill Obstructs Rear	0.13	0.338
Roads and Man-Made Structures		
Road Front: High	0.05	0.210
Mid	0.05	0.227
Low	0.07	0.248
Road Back: High	0.03	0.168
Mid	0.02	0.137
Low	0.02	0.142
Power Back Major	0.01	0.112
Power Front Major	0.00	0.044
Highway View	0.09	0.280
Train Tracks	0.01	0.078
Apartments in View	0.05	0.218
Home's Physical Characteristics		
Central AC	0.81	0.391
Cathedral Ceilings	0.19	0.396
	Quantitative Attributes (Average)	
Number of Cars	1.75	0.985
Fireplace Number	0.70	0.616
Year Built	1978.64	28.294
Square Footage	2182.31	1237.27
Stories	1.77	0.616
Number Bathrooms	2.72	0.887
Heat Pump	0.32	0.465
Price	$222,685	$107,759
TOM	53.07	66.12

The Effect of Capital Ratios on Credit Union Rates Nationwide

Robert J. Tokle* and Joanne G. Tokle**

INTRODUCTION

The average net worth ratio of credit unions has increased substantially over the past twenty years. The net worth ratio is defined as capital minus anticipated charge-offs divided by total assets. During this time period, there has been a little pressure by the National Credit Union Administration (NCUA)[1] to increase this ratio. Before the 1990's, a federal credit union had to have a capital-to-asset ratio[2] of at least 4 percent and have acceptable credit union examinations to meet requirements for capital. By the late 1990's, NCUA deemed a "well-capitalized" credit union to have a net worth ratio of 7 percent.

However, Table 1shows that the average net worth ratio of credit unions has increased significantly since 1985 to well beyond the well-capitalized ratio of 7 percent. The large increases came between 1985 and 1997, with the average net worth increasing from around 6.5 percent to just over 11 percent, and stabilizing since then. Much of this increase came in the early 1990's, when falling interest rates, due to an easy monetary policy, helped increase net income for depository institutions. This is because loans (their major asset) have longer maturities and hence re-price at a slower rate than do deposits (their major liability).

Table 1

Year	Credit Union Average Net Worth
December 2006	11.40 %
December 2003	10.68 %
December 2000	11.36 %
December 1997	11.01 %
December 1994	9.61 %
December 1991	7.66 %
December 1988	6.85 %
December 1985	6.49 %

Source: CUNA *Credit Union Report*, 2006.

Some in the credit union industry feel that the current average net worth ratio is too high. For example, Bill Hampel, an economist for the Credit Union National Association (CUNA), wrote, "it wasn't all that long ago that retaining earnings for the purpose of building capital wasn't considered the credit union thing to do. The prevailing wisdom held that credit unions, as cooperatives, were obliged to return much of net income to members as soon as it was earned. Bonus dividends were much more common than they were today" (Hampel, 1995).

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With the average net worth ratio at around 11.4 percent in 2007, how high this ratio should be has continued to be an issue. This topic was addressed in a number of articles in credit union publications during 2007. For example, Cooke (2007) wrote that "too high a level of net worth means credit unions are not serving their members to their full potential, CUNA Chief Economist Hampel inferred recently." In addition, Molvig (2007) wrote in *Credit Union Magazine* that "Credit unions' compulsion to be overcapitalized is another growth deterrent, Hampel argues. Rather than building capital, he would like to see credit unions focus on giving back to members - or attracting new members – through raising rates on savings, lowering loan rates, charging fewer fees, or improving convenience." Also, Dawson (2007) stated that he feels that current credit union net worth ratios are too high. He wrote in an opinion published in the *Credit Union Times*: "The principles of a financial cooperative mandate that after the required reserves are set aside to meet state and federal regulatory requirements and other safety and soundness requirements, all income should go to members."

Gentile (2007) also wrote that while the current high levels of net worth highlights the soundness of the credit union industry, it also "calls into question whether there are CUs carrying too much capital." Barlett (2007) noted in the *Credit Union Journal* that CUNA economist Mike Schenk also has argued that credit union capital may be too high.

Schenk stated that credit unions “have the flexibility to bring capital and net worth down a bit and use it to build more branches, offer better rates, invest in technology, a myriad of things to attract people.” And, Rubenstein (2007) wrote in the *Credit Union Times* that Bob Hoel of the Filene Institute said that “perhaps credit unions should be much more open to enhancing member benefits though returning some capital to members or at least by refraining from building capital ratios too high.”

There are two basic arguments that credit unions should maintain a lower net worth. First, since credit unions are cooperatives, any retained earnings greater than what is needed, given their risks, should go back to the credit union members. Second, credit unions may have to restrict growth if they try to maintain a higher net worth ratio than what is needed. This can come at a cost of not serving new members who could benefit from credit union membership. The following equation illustrates this point. The required return on assets (ROA) is equal to (the growth rate) times (net worth). So, if a credit union is growing at 10 percent with a net worth goal of 12 percent, it will need a ROA = 10(.12) or 1.2. However, if the net worth goal is 8 percent, it will need a ROA = 10(.08) or 0.8. Since the average ROA for credit unions for year-end 2006 was 0.83 (CUNA *U.S. Credit Union Profile,* 2006), the average credit union could grow by at most 6.9 percent and still maintain a 12 percent net worth ratio.

However, adequate net worth is needed to maintain credit union soundness and to protect against interest rate risk and credit risk. To guard against the risks of a typical credit union, NCUA, as mentioned above, deems a 'well-capitalized" credit union to have a net worth of 7 percent. So, are there any arguments in favor of having net worth ratios averaging over 11 percent? One would be that with such a strong net worth ratio, a credit union would be able to withstand better any unforeseen large risks that may occur, including interest-rate and credit risks.

A second possibility would be if credit unions with higher net worth ratios actually do give some of it back in the form of more favorable interest rates on deposits or loans. In a sense, the credit unions have existing net worth (capital) to use at a zero cost. Hence, "institutions with higher capital ratios tend to have a more stable and lower source of funds from which loans and investments can be financed" (CUNA Chief Financial Officer Council, 1996, page 39). Jeff Rush, CEO of Firestone Federal Credit Union, wrote an opinion published in the *Credit Union Times* in 2007 supporting this view point on the benefits of obtaining a higher net worth ratio. He wrote (page 17) that “if the earnings on capital are being used to bolster dividends on share accounts or maintain lower rates on loans, what is the problem?” He goes on to provide examples of how higher capital benefits their members.

We found only one paper that examined how credit unions with higher net worth ratios may use it. Tokle and Tokle (2004) added the net worth ratio as an independent variable to a structure-performance model that they had used before, to examine if credit unions with a higher net worth might pass on any reduced cost-of-funds in the form of lower interest rates on used-vehicle loans. Since the net worth ratio variable was insignificant in their model, they found no evidence that credit unions with a higher net worth ratio return some of it back to their members via lower interest rates on used-vehicle loans. Their sample included all credit unions in Idaho and Montana, using 1997 data. This study uses a variation of that model, but adds to their previous study by updating to 2004 data and using a nationwide sample. The next section of this paper briefly discusses the sample. This is followed by a presentation of the model. Then, the results and implications of the regression model are discussed, followed by a conclusion.

SAMPLE

The sample consists of all the credit unions (298) in 25 mid-sized cities across the U.S. These cities were selected to be in rural areas and not part of a larger urban area in order for the cities to represent distinct local markets. Hence the local market is taken to be the cities and not the counties. See the Appendix for a table of these 25 cities.

THE MODEL AND DATA

The interest rate on used-vehicle loans is the dependent variable used in an OLS regression model and is used in natural log form. Feinberg (2001) used as a dependent variable in a regression model new-vehicle bank loan rates because they “seemed mostly likely to be provided in a local market.” Since a somewhat larger percentage of used-vehicle than new vehicle loans tend to be made by local lending institutions, the used-vehicle lending markets should be even more local in nature. The data for used vehicle interest rates and for all of the independent variables come from the NCUA web site, taken from individual credit union call reports for June 2004. All of the following independent variables are tested with one-tailed tests unless otherwise indicated.

1. Credit Union Growth (Growth).

Credit union growth is a proxy measure for stronger demand. We expect a positive sign because higher growth may lead to higher interest rates (Tokle and Tokle, 2002). Growth is measured by the percentage change in total credit union assets, taken from June 2003 to June 2004.

2. Credit Union Size (Size).

Credit union size, measured by total credit union assets, is a proxy variable for economies-of-scale. In previous studies, depository institution size has often been used to try to capture economies-of-scale (for example, see Hannan and Liang, 1995). Because a larger size should mean lower average cost via economies-of-scale, we expect a negative sign (Tokle and Tokle, 2002). Size is used in natural log form.

3. Average Deposits/Member (Average Deposit).

A higher average deposit/member will allow a credit union to have, ceteris paribus, a more efficient operation. Because total deposits drive the credit union asset size, a higher deposit balance per member will allow the credit union to be larger with the same number of employees and hence be more efficient. Because increased efficiency may help to decrease loan rates, we expect a negative sign. In the regression analysis, the average deposit is in units of $1,000s to keep its coefficient from being too small.

4. Average Salary and Benefits (in thousands of dollars)/Employee (Salary).

Following Calem and Carlino (1991), higher wages may reflect higher costs, but higher wages may also reflect higher worker productivity. Hence, higher wages may lead to either lower or higher loan rates, and thus Salary is a two-tailed test (Tokle and Tokle, 2002).

5. Net Charge-offs/Average Loans (Charge-offs/Loans).

Charge-offs are measured as the total loans charged-off during the previous 12 months divided by total loans. We expect a positive sign because the higher costs associated with higher charge-offs could lead to higher loan rates (Tokle and Tokle, 2004).

6. Net Worth/ Total Assets (Net Worth/Assets).

Following Tokle and Tokle (2004), we expect a negative sign because a higher net worth/assets might lead to lower interest rates on used vehicle loans. This is because a credit union can use its net worth (which can also be referred to as capital or retained earnings) at a zero percent cost, while it pays a positive interest rate plus has transaction costs to maintain deposits. For example, suppose that there are two credit unions with $100 million in asset size (a typical size for a credit union in 2008). Assume that credit union A has an 11 percent net worth ratio, while credit union B has a 7 percent ratio and that the interest rate needed to attract new CD deposits in the local market requires a 5 percent interest rate. Then, credit union A has a cost advantage over credit union B in the uses of funds of $4 million times 5 percent, which equals $200,000. Some of this cost advantage could be used to fund loans at lower interest rates. Hence, it is hypothesized that a credit union with a higher net worth may pass on some of its lower overall cost of funds in the form of lower loan interest rates.

7. Fee Revenue/Total Assets (Fee/Assets).

Fee revenue has increasingly become a more important source of revenue to depository institutions, including credit unions, over the past five to ten years. On one hand, a credit union with a larger fee revenue source may in turn charge lower interest rates on loans. On the other hand, if a credit union is under pressure to increase its revenues, it may charge both higher fees and loan rates. Hence, Fee/Assets is a two-tailed test.

8. Credit Union Membership Statewide/ State Population (Members/Pop).

In a regression model that also had loan interest rates as the dependent variable, Feinberg (2001) used credit union membership as a percentage of the state population as an independent variable, "to proxy the supply elasticity (essentially the ease of expansion)" (page 561). In addition, surveys of consumer interest rates have repeatedly demonstrated that credit unions overall charge lower rates on loans than do banks. Also, Tokle and Tokle (2000) and Feinberg, (2001) found that a larger credit union presence also leads to better rates for bank customers. Thus, more credit union competition may also lead to lower loan rates at credit unions. We expect a negative sign for the coefficient of Members/Pop.

RESULTS

The descriptive statistics for all the variables are shown in Table 2. All the variables show reasonable means and ranges for the sample of credit unions taken from June 2004. For example, the used-vehicle loan rates have a mean of 6.47 percent, with a range of 3.64 to 15.00 percent. The independent variable of the most interest in this study, Net Worth/Assets, has a mean of 12.91 percent. This is just slightly over the average net worth for all credit unions nation wide for 2004 (see Table 1). And, the net worth range is quite large, with a minimum net worth ratio of 1.33 percent (which signals that a credit union is nearly insolvent), while the maximum net worth ratio is nearly 40 percent. The minimum charge-offs with a negative number reflects that some credit union had more in recoveries from previous bad loans than were already charged-off during the time period. And, the minimum salary of $ 4,800 probably comes from a very small credit union in the sample that employs only one or two part-time workers.

Table 2. Descriptive statistics of the variables.

Variable	Mean	Minimum	Maximum
Interest Rate	6.47 %	3.64 %	15.00 %
Growth	3.87 %	- 21.22 %	71.56 %
Size (millions)	$ 64.26	$ 0.24	$ 2,691.86
Average Deposit	$ 4,924	$ 594	$ 19,690
Salary	$ 38,440	$ 4,800	$ 77,985
Charge-offs/Loans	0.61 %	-3.81 %	10.37 %
Net Worth/Assets	12.91 %	1.33 %	39.09 %
Fee/Assets	0.45	0.00	5.09
Members/Pop	27.02 %	17.30 %	43.60 %

The ordinary least squares regression results are reported in Table 3. Of the 298 credit unions in the sample, 6 were dropped due to missing data. The model explains 24 percent of the variation of used-vehicle interest rates. Four of the eight independent variables, Growth, Average Deposit, Salary and Net Worth/Assets were not significant.

The coefficient for Size was negative as expected and significant at the 1 percent level. Currently, economies-of-scale seems to be an extremely important factor in many aspects of credit union behavior and structure. For example, Wilcox (2005) wrote that "larger credit unions, on average, have decidedly lower costs and higher net incomes, as we might expect in the presence of important economies of scale." As expected, credit unions with higher Charge-offs/Loans had, with significance at the one percent level, charged higher interest rates for used vehicle loans. The coefficient for Fee/Assets was positive and also significant at the one percent level. Fee/Assets is a two-tailed test. Hence, it appears that credit unions in this sample seek to increase revenues by charging both higher fees and higher loan rates. And, the coefficient for Members/Pop was negative as expected and significant at the 10 percent level.

The independent variable of the most interest in this study, Net Worth/Assets, was insignificant, as it also was in the 2004 Tokle and Tokle paper. Thus we cannot find any evidence that credit unions with a higher net worth ratio return some of it back to their members in the form of lower interest rates on used-vehicle loans. It is possible that credit unions with a higher net worth ratio benefit credit union members in other areas. We did try to model Net Worth/Assets as an independent variable for three other interest-rate variables (new vehicle loans, certificates of deposits and money market) as well as for fee revenue/assets. We were unable to find net worth as a contributing factor for any of these dependent variables.

Table 3. Dependent Variable: Used-vehicle loan rate (Natural log).

Variable	Coefficient	t-value	P-value
Constant	2.9248		
Growth	0.0011	0.68	0.25
LnSize	- 0.0645	- 4.98	0.00
Average Deposit	- 0.0051	- 0.72	0.24
Salary	- 0.0007	- 0.47	0.64
Charge-offs/Loans	0.0463	3.47	0.00
Net Worth/Assets	0.0026	0.76	0.23
Fee/Assets	0.0856	2.66	0.01
Members/Pop	-0.0027	-1.34	0.09

292 cases used; 6 contained missing values. Adjusted R-Squared = 24.0 %.

CONCLUSION

Credit unions with a higher net worth ratio may be using it to benefit its members in ways other than charging lower interest rates on used-vehicle loans. For example, some credit unions may be offering more services and/or maintaining more branches. Alternatively, a higher net worth may also allow some credit unions to operate less efficiently. If the latter is the actual reason, then CUNA economist Bill Hampel may be right: "Rather than building more capital, he would like to see credit unions focus more on giving back to members" (Molvig, 2007). Further research may shed more light on how credit union capital is used.

END NOTES

1. The NCUA charters and examines all federal credit unions, but also provides deposit insurance for most state chartered credit unions. In 2006, there were 8,853 credit unions, with 5,306 having a federal charter (CUNA: *Credit Union Report*, 2006 Mid-Year).
2. In that late 1990's, NCUA also started to use net worth ratios rather than capital ratios in their capital requirements.

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APPENDIX

List of cities in Sample

1. Pocatello, ID
2. Billings, MT
3. Redding, CA
4. Eau Claire, WI
5. Spokane, WA
6. Jackson, MS
7. Peoria, IL
8. Cedar Rapids, IA
9. Flagstaff, AZ
10. Lubbock, TX
11. Asheville, NC
12. Knoxville, TN
13. Pueblo, CO
14. Sioux Falls, SD
15. Topeka, KS
16. Pine Bluff, AR
17. Saginaw, MI
18. Dayton, OH
19. Tallahassee, FL
20. Macon, GA
21. Manchester, NH
22. Charleston, WV
23. Rochester, NY
24. Erie, PA
25. Waterbury, CT

Fall 2008

REFEREES

1. Darius Conger
2. Lester Hadsell
3. Elia Kacapyr (2)
4. Kent Klitgaard
5. Thomas Kopp
6. Patrick Meister
7. Frank Musgrave
8. Ted Schmidt
9. Dona Siregar
10. Don Trippeer
11. David Yerger

The New York State Economics Association (NYSEA)
60th Annual Conference
2007

SIENA*college*

Friday and Saturday, October 5 & 6, 2007

Friday, October 5th
5:15 pm - 6:45 pm – Friday Reception, Siena Hall, Main Foyer
7:00 pm - 7:45 pm – Federal Reserve Governor Kevin M. Warsh, Key Auditorium
7:45 pm – Dinner (Boland Room, Alumni House)

Saturday, October 6th
8:00 am - **5:00 pm** – Conference and Business meeting: Siena College, Sarazen Student Union (SSU)
8:00 am - 8:45 am – Registration/Continental Breakfast
8:45 am - 9:00 am – Welcome
9:00 am - 10:15 am – Technical Session I
10:15 am - 10:45 am – Coffee Break
10:45 am - 12:00 pm – Technical Session II
12:00 pm - 1:30 pm – Luncheon
1:30 pm - 2:45 pm – Technical Session III
2:45 pm - 3:00 pm – Coffee Break
3:00 pm - 3:45 pm – Technical Session IV
4:00 pm - 5:00 pm – Business Meeting (All are Welcome)

Conference Sessions

Friday, October 5, 2007
5:15 pm - 6:45 pm – Reception/ Tour of Hickey Financial Technology Center **Siena Hall, Foyer**

7:00 pm - 7:45 pm – Lecture **Roger Bacon Hall, Key Auditorium**

Kevin M. Warsh
Board of Governors of the Federal Reserve System

Mr. Warsh began his term on the Board of Governors in 2006. Prior to his appointment, Mr. Warsh served as Special Assistant to the President for Economic Policy and as Executive Secretary of the National Economic Council from 2002 until February 2006. From 1995 to 2002, he was a member of the Mergers & Acquisitions Department of Morgan Stanley & Co., in New York, ultimately serving as Vice President and Executive Director. He served as financial adviser to numerous companies, helping structure capital markets transactions and facilitate fixed income and equity financings.

Kevin Warsh was born on April 13, 1970, in Albany, New York. He received an A.B. in Public Policy (Honors) from Stanford University in 1992 with significant course work in Economics and Statistics. Mr. Warsh went on to study Law, Economics, and Regulatory Policy at Harvard Law School and received a J.D. (Cum Laude) in 1995.

8:00 pm – Dinner **Alumni House, Boland Room**

Saturday, October 6, 2007
8:00 am - 8:45 am – Registration/Continental Breakfast Maloney Great Room

8:45 am - 9:00 am – Welcome SSU, Room 243

9:00 am - 10:15 am – Technical Session I

Session 1A: Understanding Well-Being SSU, Molinari Room
Session Chair: Darius Conger (Ithaca College)

Tavis Barr (Long Island University) — Evaluation of Subjective Job Satisfaction Measures
Discussant: Darius Conger (Ithaca College)

Elia Kacapyr (Ithaca College) — What Can We Learn from Cross-Country Comparisons of Happiness?
Discussant: Mary Ellen Mallia (Siena College)

Mark Gius (Quinnipiac University) — The Effect of Government Health Care Expenditures on Life Expectancies and Infant Mortality Rates

Session 1B: Econometric Estimates and Forecasts SSU, Room 241
Session Chair: Scott Trees (Siena College)

Lester Hadsell (SUNY Oneonta) — Efficiency in Deregulated Electricity Markets: The Evidence So Far
Discussant: William Kolberg (Ithaca College)

Jeffrey Wagner (Rochester Institute of Technology) — Evaluating Panels of Fixed-Event Forecasts: A Microeconomic Application
Discussant: William O'Dea (SUNY Oneonta)

John Heim (Rensselaer Polytechnic Institute) — Was Keynes Right? Comparing Keynesian and Friedman/Modigliani Consumption Functions
Discussant: Scott Trees (Siena College)

Session 1C: Student Papers SSU, Room 235
Session Chair: Maryann J.F. DiLiberto (Bloomfield College)

Nancy Weils (Siena College) — What Determines a College Student's GPA and his/her Interest in Attending Non-Traditional Classes
(Manimoy Paul-Faculty Advisor)
Discussant: Raymond MacDermott (Virginia Military Institute)

Arthur Johnston (Rochester Institute of Technology) — A Path Dependent Model of Course Selection
(Jeffrey Wagner, Faculty Advisor)
Discussant: Robert Jones (Skidmore College)

Alexander Hansen (Marist College) — How Do Government Institutions Affect Economic Growth? A Multi-Variable Study of Nineteen Nations, Both Developed and Developing
(Della Sue, Faculty Advisors)
Discussant: Maryann J.F. DiLiberto (Bloomfield College)

Dan Pontillo (Rochester Institute of Technology) — Tax Abatements and RIT College Town
(Jeannette Mitchell, Faculty Advisor)

Discussant: David Trzaskos (Siena College)

Session 1D: Student Papers **SSU, Room 315**

Session Chair: Richard Dietz (Federal Reserve Bank of New York)

Angele Veleke (Rochester Institute of Technology) — International Trade and the Distribution of Income in the United States (Jeannette Mitchell, Faculty Advisor)
Discussant: Richard Shirey (Siena College)

Daniel Whalen and David Israelow (Ithaca College) — The Ithaca College Paper Trader (Abraham Mulugetta, Faculty Advisor)
Discussant: John Piccione (JWP Consulting)

Bryon McKim (Siena College) — Compact Fluorescent Light Bulb Changes in Residence Halls (James Booker, Faculty Advisor)
Discussant: Richard Dietz (Federal Reserve Bank of New York)

Christine Longo (Rochester Institute of Technology) — A Marketable Permit Approach to Interstate Municipal Solid Waste Disposal (Jeffrey Wagner, Faculty Advisor)
Discussant: Florence Shu (SUNY Potsdam)

10:15 am - 10:45 am – Coffee Break **Maloney Great Room**

10:45 am - 12:00 pm – Technical Session II

Session 2A: Investment and Investments **SSU, Molinari Room**

Session Chair: John Piccione (JWP Consulting)

Dr. K.V.S.S. Narayana Rao (National Institute of Industrial Engineering, Mumbai, India) — Portfolio Analysis: Application and Evaluation in Indian Stock Market
Discussant: John Piccione (JWP Consulting)

Bala Veeramacheneni and Richard Vogel* (SUNY Farmingdale) and E.M. Ekamayake (Bethune Cookman College) — Public and Private Schools in Rural India
Discussant: Stephen Younger (Ithaca College)

John Heim (Rensselaer Polytechnic Institute) — How Much Does the Prime Rate Affect U.S. Investment?
Discussant: Tom Kopp (Siena College)

Session 2B: Economics, Teaching and Learning I **SSU, Room 241**

Session Chair: Della Lee Sue (Marist College)

Robert Culp (Penn State Lehigh Valley) — IS/LM Analysis in Principles Classes: Is the Difficulty of the Materials the Reason for its Declining Use?
Discussant: Florence Shu (SUNY Potsdam)

Della Lee Sue (Marist College) — Gender Differences in Test Performance in Economics Courses
Discussant: Edwin J. Portugal (SUNY Potsdam)

Florence Shu, Edwin J. Portugal, Henry Sieg, and Mark Burns (SUNY Potsdam) — The Creation of Interactive and Participatory Learning
Discussant: Robert Culp (Penn State Lehigh Valley)

Session 2C: Student Papers **SSU, Room 235**

Session Chair: William Kolberg (Ithaca College)

Jonathan Thomas (Rochester Institute of Technology) — Getting the Carbon Tax Right: Issues in Carbon Tax Design Policy (Jeffrey Wagner, Faculty Advisor)
Discussant: W. Scott Trees (Siena College)

Chris Panton and Ned Marzigliano (Siena College) — Variables in Day to Day College Lifestyle Influencing GPA (Manimoy Paul, Faculty Advisor)
Discussant: William Kolberg (Ithaca College)

12:00 pm - 1:30 pm – Luncheon **SSU, Room 243**

Luncheon Speaker: James R. Follain, Ph.D.
Visiting Professor of Economics, Siena College

"The Evolving and Unwinding Story of Subprime Market Lending"

Dr. Follain is a financial economist with extensive experience relating to the measurement and management of the risk associated with lending and investing in the mortgage and housing markets. The author of over one hundred publications, he was a Consultant and Senior Economist at the Federal Reserve Board before joining the faculty of Siena College in 2007. Earlier in his career, he was a tenured faculty member at the University of Illinois and Syracuse University's Maxwell School, and held positions with Freddie Mac and Fidelity National Information Services.

*** = Presenter**

1:30 pm - 2:45 pm – Technical Session III

Session 3A: Regional Development in New York State **SSU, Room 241**

Session Chair: Jeffrey Wagner (Rochester Institute of Technology)

Robert Jones (Skidmore College) — The Geographic Distribution of Unemployment
Discussant: David Trzaskos (Siena College)

Craig D. Rogers (Canisius College) — Spatial Concentration and Spatial Isolation of Poverty: An Examination of the Spatial Distribution of Poverty in the Buffalo-Niagara Falls, New York Metropolitan Statistical Area (MSA): 1970 to 2000.
Discussant: Jeffrey Wagner (Rochester Institute of Technology)

Richard Vogel (SUNY Farmingdale) — Impact of State National Guard and Military Reserve Activations on Gross State Product: 1977 to 2005
Discussant: Richard Dietz (Federal Reserve Bank of New York)

Session 3B: Economics, Teaching and Learning II **SSU, Molinari Room**

Session Chair: Lester Hadsell (SUNY Oneonta)

Maryann J.F. DiLiberto (Bloomfield College) — Prior Operational Knowledge of Mathematics and the Acquisition of Written Economic Information
Discussant: Raluca Polimeni (Siena College)

Raymond MacDermott (Virginia Military Institute) — The Effects of Dropping a Grade in Intermediate Macroeconomics
Discussant: Lester Hadsell (SUNY Oneonta)

Mary Ellen Mallia — Use of Clickers in Economics: A Literature Review
(Siena College)
Discussant: Bríd Gleeson Hanna (Rochester Institute of Technology)

Session 3C: Labor and Education **SSU, Room 235**
Session Chair: Tavis Barr (Long Island University)

Jonathan Schwabish, Molly Dahl, Thomas DeLeire**, And Jonathan A. Schwabish* (Congressional Budget Office) — Variability in Workers' Earnings: The Frequency of, Trends in, and Causes of Large Changes in Earnings
Discussant: David Ring (SUNY Oneonta)

Matthew Wiswall (New York University) — Volunteering for Merit Pay?: Evidence from Minnesota's Q Comp Teacher Program
Discussant: Tavis Barr (Long Island University)

Donald Vitaliano (Rensselaer Polytechnic Institute) — Corporate Social Responsibility and Labor Turnover
Discussant: Richard Shirey (Siena College)

2:45 pm - 3:00 pm – Coffee Break **Maloney Great Room**

*** = Presenter** **** = Also with Michigan State University**

3:00 pm - 3:45 pm – Technical Session IV

Session 4A: Market Behavior **SSU, Room 241**
Session Chair: Patrick Meister (Ithaca College)

William Kolberg (Ithaca College) — Converting Firm-Level Demand with Price Competition into Firm-Level Demand with Quantity Competition in Oligopoly Models with Cobb-Douglas Demand
Discussant: William O'Dea (SUNY Oneonta)

Robert Culp (Penn State Lehigh Valley) — When Low Ball Bidding is an Optimal Strategy: Evidence from the Housing Market
Discussant: Patrick Meister (Ithaca College)

Session 4B: Economics, Teaching and Learning III **SSU, Molinari Room**
Session Chair: Matthew Wiswall (New York University)

Lester Hadsell (SUNY Oneonta) — Promoting a Learning-Orientation in Students by De-Emphasizing Grades
Discussant: Dr. Mojtaba Seyedian (SUNY Fredonia)

Manimoy Paul (Siena College) — Effect of Healthy Students' Habits on their Academic Performance
Discussant: Matthew Wiswall (New York University)

Session 4C: Regional Development in New England **SSU, Room 235**
Session Chair: Richard Vogel (SUNY Farmingdale)

Chris Fedoryshyn (American University) — Cultural and Recreational Centers: How They Influence Where You Build Your House
Discussant: Elia Kacapyr (Ithaca College)

Bríd Gleeson Hanna (Rochester Institute of Technology) — An Empirical Study of Income Growth and Manufacturing Industry Pollution in New England, 1980-1990

Discussant: Richard Vogel (SUNY Farmingdale)

4:00 pm - 5:00 pm – Business Meeting (All are Welcome) **SSU, Room 235**

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NYSEA

61ST ANNUAL CONFERENCE

FRIDAY AND SATURDAY

OCTOBER 10-11, 2008

@

ITHACA COLLEGE, ITHACA, NY