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Occupational Structure and Growing Wage Inequality in the U.S., 1983 - 2002

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Occupational Structure and Growing Wage Inequality in the U.S., 1983 - 2002

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to my ailing father

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Occupational Structure and Growing Wage Inequality in the U.S., 1983 - 2002

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Since the 1980's, wage inequality in the U.S. has been dramatically increasing. I investigate the impact of occupational structure, measured at the three-digit level, on this trend of growing wage inequality. The investigation is conducted in terms of three major research tasks.

First, I test the validity of the 'disaggregate structuration' view in relation to growing wage inequality. The 'disaggregate structuration' view is suggested as an alternative to big class theories. Theorists of the 'disaggregate structuration' view assert that an occupation is a gemeinschaftlich community characterized by internal homogeneity. Thus, this view implies that most of

the rise in inequality occurs between occupations and that within-occupational inequality is actually decreasing, due to the progress of 'occupationalization.'

My analyses, however, find that the majority of the growth in inequality has occurred within occupations. Secondly, I thus seek a more delineated explanation for the causes of rising within-occupational inequality. I investigate whether previously proposed hypotheses can account for this phenomenon. Hypotheses that I test include demographic change, deindustrialization, unions, insecure employment relations, increases in the return to skill, and changes of firm organizations.

Although smaller than within-occupational inequality, between-occupational inequality has also been growing during this period. Thirdly, I therefore investigate the changes of between-occupational inequality. Since between-occupational inequality is a weighted sum of occupational mean wages, I examine whether the same hypotheses tested for within-occupational inequality can explain the changes in occupational mean wages over time.

Using the Current Population Survey (CPS) from 1983 to 2002, I find that as within-occupational inequality has grown faster than between-occupational inequality, the direct association between occupational structure and wage inequality has declined over this period. While the importance of general skills (i.e., education) in determining workers' wages is growing, the importance of occupation-specific skills is declining. For regression models of hourly wages, the amount of R-squared increase by adding three-digit occupational codes (331 occupational dummies) in addition to general skills (5 dummies of education) has decreased for this period. Therefore, the strong version of 'aggregate structuration' and 'occupationalization' is not supported. I would like to note, however, that the R-squared of hourly wage increases jumped significantly when we use three-digit occupational codes instead of one-digit occupational codes even after adjusting for the degrees of freedom. Thus, the weak version of structuration is not rejected.

For multivariate tests, inequality indexes and other variables by detailed occupation are extracted from each year's CPS and merged into one panel data file with occupation as a unit of analysis. Multi-level growth models are then estimated using detailed occupational categories as the unit of analysis in order to assess how the structural characteristics of occupations affect changes in mean wages and wage inequality over this time period.

Contrary to the expectations of the skill-biased technological change hypothesis, changes in the distribution of education do not affect the growth of wage inequality within occupations. In contrast to the traditional view of unions as promoting wage equality, within-occupational inequality is increased by unionization. The increase of female labor market participation seems to pull down inequality in an occupation. Deindustrialization does not account for the rise of intra-occupational inequality, while insecure employment relations do. As expected by the organizational change view, inequality grows faster in high skill jobs and service jobs.

Regarding between-occupational inequality, traditional explanations do better jobs in accounting for its change than for within-occupational inequality. Skill biased technological changes and unions have positive effects on occupational mean wages. Deindustrialization has a negative effect on occupational mean wages.

Multi-level growth models provide additional evidence against disaggregate structuration. The disaggregate structuration view assumes that occupational common interests will be achieved as accomplishment of active occupational associations. Thus, the changes of occupational mean wage, which is a clearly common interest of members in an occupation, should be explained by occupation itself, not by other demographic and institutional variables. Contrary to this expectation, most of the within-occupational variation are not explained well by other demographic and institutional variables, including race, gender, and unions.

In conclusion, although sociologists often view occupation as the backbone of the stratification system, the rise in within-occupational inequality suggests that broader, more complex approaches may be needed in order to better explain the increasing disparity in wages. I suggest that more attention should be given to firm level studies in which changes inside and between firms are investigated.

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Chapter 1

INTRODUCTION

The reduced economic mobility and the declining real value of workers' wages at the lower end of the distribution (Gottschalk 1997; Farley 1996; Morris and Western 1999; Levy 1998; Bernhardt et al. 2001) imply that, for the first time in recent American socioeconomic history, the succeeding generation of the non-college population can now reasonably expect its standard of living to remain stagnant or to actually decline. It is also well known that, for the upper quintiles, incomes have concurrently been increasing, so that inequality in the overall distribution has grown substantially during the past several decades (Karoly 1993; Levy 1987; Morris and Western 1999; Piketty and Saez 2003). The combined effects of these two trends actually lend some credence to the old adage that "the poor get poorer and the rich get richer."

Given the dramatic nature and significance of this substantial increase in economic inequality, it is surprising that this phenomenon has been largely ignored by sociologists, for whom inequality has traditionally been a topic of keen concern. They seem to have unfortunately taken all too seriously Grusky's (2001:21) remark that "most sociologists seem content with a disciplinary division of labor that leaves matters of income to economists." Whatever the reasons for the neglect, the sociological sources of this important increase in income inequality are rarely studied and thus poorly understood. In my view, this lacuna represents a major shortcoming of contemporary research in the sociology of stratification and inequality.

This neglect stems in part from the sort of topics that have been emphasized in sociological research on stratification and inequality. The first is the study of occupations. They are often believed to be the "backbone of the reward structure" (Parkin 1971:18). For this reason, many sociologists have focused on occupational attainment as the primary outcome of interest (e.g., Blau and Duncan 1967; Featherman and Hauser 1978; Goldthorpe 1987; Grusky 2005; Grusky and Sørensen 1998; Kelley and Evans 1993; Weeden and Grusky 2005; Wong 2002). Even in neo-Marxist studies that seek to develop their own distinctive approach to studying inequality, occupational variables nonetheless continue to play an important role in their depiction of the class structure, albeit in terms of a more refined nomenclature (Wright 1984, 1997).

Another common concern in stratification research has been individual differences in income attainment (e.g., Eliason 1995; Hollister 2004; Kalleberg, Wallace, and Althauser 1981; Morgan and Morgan 1998; Weeden 2002). In this regard, a major interest in recent years has been differentials by race/ethnicity and gender (e.g., Grodsky and Pager 2001; McCall 2000, 2001; Peterson and Morgan 1995; Reskin and Bielby 2005; Western 2002). Although certainly important, this research does not seek to ascertain the sources of increased dispersion in the overall distribution of income.

Sociological studies of aggregate inequality do exist, but they are older and use cross-sectional data that largely predate the recent rise in the dispersion of inequality (Bloomquist and Summers 1982; Jacobs 1985; Nelson and Lorence 1988; Sakamoto 1988). A few more recent studies of household income inequality have appeared, but their focus is on global inequalities (Alderson and Nielsen 2002; Firebaugh and Goesling 2004; Nielsen and Alderson 1995). One sociological study of household income inequality across U.S. counties investigates the effects of "farm/non-farm sector dualism" (Nielsen and Alderson 1997:21) and other factors. None of these studies directly consider, however, the sources of the trend towards dramatically increased wage inequality in the U.S. labor force in recent decades.

A few studies (Grodsky and Pager 2001; McCall 2001; Peterson and Morgan 1995; Kilbourne, England, and Farkas 1994) have recently adopted occupational approaches in studying income or wage inequality. But their interests are mostly about gender or racial wage gaps rather than about the growing wage inequality itself. They have focused on how occupations work in maintaining gender and/or race inequalities. I admit that studies of inequalities between demographic groups, including racial, ethnic, and gender groups, are important. However, focusing only on these between group inequalities limits the sociological contribution to understanding the recent unexpected and problematic for most sociologists, growth of inequality, especially inequalities within demographic groups, which accounts for most inequality.

In studies of inequality between demographic groups, sociologists have mostly tested the effect of the compositional changes of occupations and/or the effect of between-occupational differences. This approach assumes homogeneity of an occupation, which has long been supported in the study of stratification. The beginning of this approach goes back to the founding fathers of sociology, including Durkheim. Using this assumption, sociologists have established many fruitful theories and have tested them empirically. Status attainment theorists, who have studied stratified positions by detailed occupations, as well as class theorists, who have preferred to use reclassified groups rather than occupation itself in their studies, have constructed and tested their hypotheses under this assumption. Emphasis on occupation has even intensified in recent years, as epitomized by the theory of "disaggregate structuration" (Grusky and Sørensen 1998; Weeden 2002; Grusky and Sørensen 2001; Grusky 2005). According to this view, detailed occupational categories are the critical and most fundamental components of social stratification and inequality.

The notion of occupational homogeneity is not limited to sociologists. Ordinary people around the world have also perceived occupations as distinct homogeneous groups and a legitimate basis for differential income (Treiman 1976; Hout and DiPrete 2006). Individuals across countries widely agree on which occupations should be paid more; however, individuals have different opinions on adequate remuneration for such high-paying occupations (Kelley and Evans 1993).

This assumption may also be implicitly shared by economists. In the study of wages, economists have included occupation as a proxy variable representing skill differences among workers (Juhn, Murphy, and Pierce 1993; Levy and Murnane 1992). Economists have paid relatively more attention to the growing wage inequality itself than sociologists have, but they have not tested the legitimacy of occupational homogeneity nor studied within-occupational variation. In many economics studies, occupations are used as control variables rather than as the main subject of interest (Nickell and Layard 1999).

Recent studies show that inequalities within gender, race, educational level, and industrial sectors have grown for the last quarter century and that they have outgrown between-group inequalities (Morris and Western 1999; Gottschalk 1997; Karoly 1993; Juhn et al. 1993; Gustafsson and Johansson 1999; Juhn 1999; Levy and Murnane 1992). There is no reason to limit sociological interest to between-occupational variations when within-group inequalities are growing faster. And it is necessary to scrutinize the legitimacy of the assumption of occupational homogeneity as well as its limitations. By doing so, we can enrich sociological understanding of the relation between occupation and the recent growth of inequality.

As a start, we need to have a basic understanding of occupational wage inequality. At a given point in time, do all occupations show similar levels of wage heterogeneity/homogeneity? If some occupations have higher levels of inequality than others, what are the sources of this variability? Next, we need to understand the trends of between- and within-occupational inequality over time. Do the changes of between- and within-occupational inequalities show similar patterns over time? Are the amounts of change of within-occupational-inequalities similar across occupations? Or do occupations show variant amounts of increasing or decreasing within-group inequalities? By answering these questions, we can test the legitimacy of the disaggregate structuration theories.

If the direction and amount of change of within-occupation inequality differ significantly across occupations, the sources causing these differences should be investigated thoroughly. Several explanations of the growing inequality have been proposed so far, including demographic change deindustrialization, skill biased technological change (SBTC), institutional change, and organizational culture change. One of the reasons why there are so many possible explanations, of which no one is sufficient, is that, among others, growing inequality can not be differentiated by group characteristics. All ages, cohorts, genders, and even industrial sectors show similar patterns of growing inequality.[1] Even among union members, within group inequality is growing. If there are significant variations in patterns of changing inequality across occupations in contrast to other variables, different characteristics by occupations could be a promising source in finding the causes of growing wage inequality. This does not necessarily mean that existing explanations are wrong. Rather, testing these possible causes in the context of occupational structure can help to clarify which theory is more plausible. I will investigate the effects of the suggested factors in occupational context. This study would provide a better understanding of the mechanisms involved. These multivariate analysis can also provide indirect evidence for the hypotheses of disaggregate structuration. Thus, in this research, I am following the sociological tradition, which assumes that occupations are a fundamental context for the generation of inequality.

The rest of the dissertation will be organized into six chapters. Chapter 2 will review the theory of "disaggregate structuration" and previously proposed explanations for growing inequality and will result in several related hypotheses. Chapter 3 will describe the procedure used to construct the data and the statistical methods used to empirically test the suggested hypotheses. Chapter 4 will present the results regarding "disaggregate structuration." Chapter 5 will show the multivariate test results investigating the causes of within-occupational inequality. Chapter 6 will discuss between-occupational inequality. And finally, Chapter 7 will summarize and discuss the implications of the findings.

[1]These phenomenon are also observed in almost all developed countries.

Chapter 2

THEORETICAL BACKGROUND

2.1 Disaggregate structuration

In traditional sociological research on socioeconomic inequality, occupation has often been seen as the backbone of the stratification system, or at least as the primary dependent variable of interest (e.g., Blau and Duncan 1967; Featherman and Hauser 1978; Hall 1969; Sorokin 1959; Kelley and Evans 1993; Treiman 1976). One of the core themes in the classic debate of stratification between Davis and Moore (1984) and Tumin (1953) was how to interpret the roles of certain occupations in a society. Almost all studies on social mobility between generations are based on the occupational mobility between father and son (Lipset et al. 1959; Featherman, Jones, and Hauser 1978; Grusky and Hauser 1984). Status attainment theorists have explicitly used occupation as a basic unit of stratification (Blau and Duncan 1967; Sewell et al. 1969;

Hodge 1981; Treiman 1976). Neo-Weberian class theorists like Goldthorpe (1987) and Erikson and Goldthorpe (1992) have classified distinctive classes based on occupation. Even neo-Marxists like Wright (1984) have also sorted out their classes using occupation. Gradational models of stratification have chosen disaggregated occupations as a fundamental analytic unit, and categorical models of class have had occupations grouped in various ways (Grusky and Sørensen 1998). Thus, the sociological study of inequality could not be performed without occupation.

This general tradition has enjoyed a renewed impetus and extension in recent years in terms of a theory of "disaggregate structuration." This approach "rests on the realist claim that occupations are often *gemeinschaftlich* communities as well as positional sources of exploitation and inequality" (Grusky and Sørensen 1998:1191). That is, at the level of detailed categories, occupations are assumed to be relatively homogeneous groups of workers who share similar socioeconomic rewards and interests, processes of market and social closure, political awareness, propensities for collective action, "lifestyles and dispositions," as well as personal identity (Grusky and Sørensen 1998). Grusky (2005) defines occupations as local organizations that "act collectively on behalf of their members, extract rent and exploit nonmembers, and shape life chances and lifestyles" (67). "Disaggregate structuration" has been proposed as a "realist" model of class structure that is said to represent the solution to an "ongoing retreat from class analysis," which reflects an increasing dissatisfaction with the analytical and explanatory power of "big social classes" (Grusky and Sørensen 2001; Grusky 2005).

As noted by Sørensen (2000:1526), conceptualizations of class structure typically involve some description of differences in "life chances." In other words, the components of a class scheme are usually proposed to be, at least to some extent, correlated with variations in socioeconomic rewards such as prestige, work conditions, income, or protection from exploitation. In the case of "disaggregate structuration," the correlation between socioeconomic inequalities and detailed occupational categories is implicitly presumed to be quite high. As a general mapping of the "site of production," detailed occupational categories are said to represent the most fundamental unit at which the nexus of social closure, training opportunities, wages and income, prestige, exploitation, and the extraction of rents all purportedly converge in the generation of positional inequality (Grusky and Sørensen 1998; Weeden 2002; Grusky 2005). That is, according to Grusky et al., detailed (or 3-digit) occupations are real classes.

2.1.1 Occupation-Specific Skill and Wage Inequality

Based on the Durkheimian tradition of class analysis, theorists of the disaggregate structuration view assert that unit occupations are social barriers constructed through closure generating devices of various kinds (Grusky 2005). Through diverse procedures such as social closure against members of different occupations, collective action, and identification in everyday interactions, occupations become communities. Grusky (2005) calls this procedure "occupationalization." These occupational communities may act as classes, as traditional class theorists have expected. That is, disaggregate structuration of occupations is a class system of a society, and occupationalization is a process of class formation.

Although what makes occupations 'occupationalized' occupations (e.g., occupations as classes) is not simply occupation-specific skills, the most basic material foundation that defines an occupation as a distinguishable unit must be shared functions, principal duties and tasks, and similar technical skills by workers. Otherwise, the reasons for an occupation to form as an independent group beyond the sites of production (firms or establishments) and the final products/services that workers produce (industry) can not be accounted for. The concept of occupation as shared occupation-specific skills therefore seems to be similar to the Marxist concept of class-in-itself , while an occupationalized occupation is to the concept of class-for-itself. For Marxist theorists, class-in-itself refers to a class defined objectively by its socio-economic conditions, and class-for-itself denotes a class with a self-consciousness and a unifying ideology (Thompson 1966).

Davis and Moore's (1945) classic argument of occupational importance starts from the fact that skills of some occupations are hard to be obtained and therefore require the investment of individuals' time, including mental and physical efforts as well as financial assets. Hauser and Warren (1997) define an occupation as an abstract category used to group and classify similar jobs. The similarity of jobs is determined by the similarity in typical activities, the form of job tenure, the product or service that results from the job, and the skill requirements of the job (Hauser and Warren 1997:180). Put simply, the technical division of labor is fundamental to occupational classification. Without occupational skill barriers, it would be much easier for workers to switch from one occupation to another, creating a situation in which the occupation a worker has at a given time is less deterministic of his/her life chances. Given these traits of occupations, if the importance of occupation-specific skills in deciding workers' life chances has dwindled, it is harder for an occupation to be a distinct class via "occupationalization."

Indeed, Grusky (2005) himself asserts that what makes 'functionally similar jobs' relatively homogenous categories is 'social clothing.' What he emphasizes in this assertion is 'social clothing,' but his starting point is nonetheless functional similarity.[1] The fundamentality of occupation-specific skill in disaggregate structuration is reconfirmed in Grusky's own discussion of incomplete occupationalization in the lower manual sector. He says that "occupationalization has not yet taken hold in the lower manual sector, presumably due to low skill levels, limited investments in training, and relatively rapid changes in manufacturing process" (63).

As discussed above, "disaggregate structuration" presumes that the correlation between socioeconomic inequalities and detailed occupational categories is high. Further embedded in this view is the implication that these detailed occupational categories are relatively homogeneous.[2] Given the assumption that detailed occupations represent gemeinschaftlich communities as well as "realist" structures of exploitation and inequality, the theory proposed by Grusky and Sørensen (1998) indirectly underscores the significance of between-occupational inequality. That is, socioeconomic inequality is viewed as deriving primarily from mean differences between detailed occupational categories, not from inequalities (i.e., dispersion in socioeconomic rewards) within these categories. Indeed, Grusky (2005) argued that disaggregate structuration can capture much of the important variability in life chances and other outcomes of interest. He asserts, "We have thus defined unit occupations in

[1] In this sense, the Durkheimian version of 'social clothing' seems to differ from the social constructionism of post-modernism, which denies objective (or fundamental) criteria for defining a variety of social classifications. Grusky starts from functional similarity, which is surely an objective criteria.

[2] This assumption seems entirely compatible with the status attainment tradition.

terms of the social boundaries that are constructed through closure-generating devices of various kinds" (Grusky 2005:66). This implies that a substantially large amount of inequality should be derived from between occupational differences. Thus, changes in the aggregate level of inequality should derive primarily from changes in the occupational structure.

The 'disaggregate structuration' view implies that the recent rise of wage inequality is a result of reinforced determinant forces of occupation-specific skills. In other words, this view implies that the between-occupational inequality, which is mainly grounded in different occupation-specific skills, may be prevalent in this period of growing inequality. It also implies that the amount of changes of within-occupational inequality may be negligent. If these assumptions were not true, the growing wage inequality will be irrelevant (or at best marginally relevant) phenomenon with disaggregate structuration, and making a focus on disaggregate structuration will be much less beneficial in studies of social inequality and stratification.

2.1.2 "Occupationalization" and Wage Inequality

Although fundamental, occupation-specific skills are not all that occupations represent . Theorists of the 'disaggregate structuration' view insist that members of an occupation use a 'language of occupation' and interact with each other on a daily basis; such actions effectively create a *gemeinschaftlich* occupational community. Thus, an occupation provides a 'master identity' for its members and becomes a unit of collective action for the common interests of its members (Grusky 2005:67-72). Collective action by members of an occupation does not necessarily include all of the occupation's members. Sometimes collective action is carried out by a majority of the occupation's members and other times by a small portion of the members. This variation depends on the degree of occupationalization (Weeden 2002), as the actions of aggregate classes depend on the degree of class formation (Thompson 1966).

Theorists of the disaggregate structuration view also assert that Weber's closure theory can be reinvented through occupations. The 'real' working institutions of closure are largely local associations, and the underlying mechanisms of closure occur at the more detailed occupational level (Grusky 2005:67-72). Social closure occurs "wherever the competition for a livelihood creates groups interested in reducing that competition" (Weeden 2002:58). And "occupational closure is a specific instance of social closure" (59). Therefore, occupationalization through social closure may reduce competition within the occupation. Given such discussions from theorists of disaggregate structuration, we can infer that occupationalization will reduce within-occupational inequality.

Occupational closure, however, does not necessarily mean that every member of an occupation will earn the same wage. The level of benefits enjoyed by members in an occupation, thanks to closure, can be heterogeneous among members, due to other social factors. The distribution of rewards, mainly measured by wages, inside an occupation will be determined by other market and social forces. Within-occupational inequality would presumably reflect the influence of factors such as gender, race/ethnicity, education, industries, firms, and other sociological variables.

To the extent that socioeconomic inequalities within occupations are large, then the assumption that the latter determine or at least structure those inequalities seems less substantively obvious and requires further theoretical clarification. While "disaggregate structuration" does not explicitly deny the relevance of these latter variables (e.g., race and gender), neither does it systematically incorporate them. In order for occupations to somehow remain the fundamental components of the class structure, as envisioned by 'disaggregate structuration,' however, these other variables should presumably be considered as influencing socioeconomic inequalities within occupational categories, as the relevant contextual unit (e.g., Grodsky and Pager 2001).

For example, race or gender may affect the amount of benefits that each individual member in an occupation received from closure (Weeden 2002:59). This argument implies that other market and social components will explain within-occupational inequality. That is, the amount of variation explained by these variables (i.e., R-squared for models of the changes of within-occupational inequalities) should be relatively large within an occupation. When the effects of social factors other than occupation, such as gender, race, union, or industries, is diminishing, the distribution of rewards within an occupation should be narrowed. With deeper occupationalization, within-occupational inequality should recede although the degree of such recession could vary.

Despite the possibility of within-occupational variation, the variation in an occupation should be as small so as not to harm the pursuit of the common interest of that occupation. Weeden (2002) states that "the social conditions that characterize an occupation will benefit (or harm) all its members, albeit to different degrees" (59). The pursuit of common interests through occupationalization connotes that the gains or losses of common merits of an occupation will be achieved actively by diverse kinds of occupation-specific actions, rather than they will be enforced passively by the results of changes of other social and economic elements. That is, when occupationalization is mature, occupational collective action or occupational closure will bring about common benefits for its members. In addition, the effects of other elements, including race, gender, or industrial composition, which create within-occupational heterogeneity will be minimal.

Regarding wage, this expectation entails that the changes of occupational mean wages over time, which is clearly a common interest of members within an occupation, will be explained by characteristics of the occupation itself, rather than by other variables. In terms of statistical models, this implies that the total variation in the changes of occupational mean wage over time explained by other variables (i.e., R-squared for models of the changes of occupational mean wages) will be small.

All the traits of occupation discussed above are something class theorists, including Marxists, have tried to find in aggregate classes. Occupations as classes connotes that occupation plays a pivotal role in social conflicts over the distribution of economic, political, and social goods. Thus, social and economic institutions deeply embedded in social conflicts should work through occupational structure. For example, unions, which directly affect the wages of their members by collective negotiation and indirectly affect the wages of non-members by wage spillover effects or by union closure effects, should have the greatest effects within occupations. Although the complexity of contemporary union organization can make these expected effects of occupation unionizing unrealistic (Weeden 2002:64), the extension of union memberships within an occupation should work to, at least marginally, reduce within-occupational inequality.

How unions and occupations are related, however, is not discussed intensively among disaggregate structuration theorists, indicating that a consensus has not been reached among them. Weeden (2002) expects that unions will work through occupations. Since unions work successfully only through industries, she cautions that the observed effects of unionization on an occupation's rewards should be carefully interpreted. However, Grusky (2005) sees unions as organizations competing against occupations, implying that unions can disturb the formation of an occupation as a class. For Grusky, this is one of the reasons why blue collar, manual occupations, where unionization is relatively high, show low occupationalization. If we accept Weeden's assumption, we can expect that the reduction of unionization rates increase within-occupational inequality by small amounts or not at all. However, if we accept Grusky's assumption, we will expect that the reduction of unionization rates will decrease within-occupational inequality, because the reduction of unionization will remove heterogeneity among workers in the same occupation, thus it will facilitate the progress of occupationalization.

The foregoing views motivate the general objective of this research, which is to investigate the role of occupational structure in the trend in aggregate wage inequality. I use three-digit occupational categories, which are the most detailed in my data, to investigate this relationship. This increases the number of occupations in the analysis and thus increases the possible explanatory power of occupational structure (at least in a statistical sense). The use of three-digit occupational categories is more consistent with the "disaggregate structuration" approach of Grusky et al. My findings are thus directly relevant to the empirical testing of this theory.

2.1.3 Previous Empirical Researches

Despite sociologists' traditional enthusiasm for occupation, the above assumptions are huge and cannot be accepted without careful empirical scrutiny. For example, how occupational structure relates to aggregate income inequality remains largely unknown. To the extent that sociologists have investigated aggregate income inequalities (i.e., Morris and Western 1999; Bernhardt et al. 2001), occupation is notably absent. Although Weeden (2002) includes the characteristics of detailed occupational categories as contextual effects on workers' earnings in a hierarchical model using cross-sectional data, aggregate inequality in wages is considered only as an afterthought that arises when the variance of the error terms are reported. Sociologists have not analyzed how occupational structure systematically relates to the increasing level of aggregate wage inequality that has been occurring over time as a critically important trend in its own right.

The one exception is Raffalovich (1993). He investigates earnings inequality from 1968 to 1982. His results indicate that the increase in inequality in the last few years of his data was not significantly related to employment changes in occupations, as indicated by a categorization consisting of 10 groups. According to his decomposition, the increase in earnings inequality occurred within occupations and did not derive from a between-occupational component that would reflect changes in the employment of workers across occupational categories.

Generally speaking, economists have paid more attention to increasing wage inequality (Autor and Katz 1999; Bound and Johnson 1992; Card and DiNardo 2002; Gottschalk 1997; Juhn, Murphy and Pierce 1993; Levy

1998; Levy and Murname 1992). Their results confirm that, by any measure of inequality, the dispersion in wages and earnings has certainly been increasing since 1980. This economics literature has not, however, sufficiently considered occupation because it does not play any significant conceptual role in microeconomic theory. One study (i.e., Juhn, Murphy and Pierce 1993) does include one-digit occupational groups as miscellaneous control variables in their regression analysis, but the assumption seems to be that occupation simply indicates human capital that is not indicated by schooling (rather than representing a structural position in the labor force). In any event, Juhn, Murphy and Pierce (1993) find that the increases in wage inequality among men from 1963 to 1989 occurred within these occupational categories; changes in employment across one-digit occupational groups were mostly unrelated to increases in wage inequality.

2.1.4 Analytical Strategies

In assessing the role of occupational structure in affecting wage inequality, I investigate two sorts of empirical relationships. First, I analyze bivariate descriptive statistics that refer to the extent to which wage inequality is between occupations (i.e., derives from differences in mean wages across occupations) rather than within them (i.e., reflects wage inequalities within occupations). I consider this descriptive approach to represent the most direct test of 'disaggregate structuration' theory in its strongest form. That is, if detailed occupational categories are indeed the most fundamental class structure that generates socioeconomic inequalities in advanced capitalist societies, then detailed occupational categories should be directly and highly correlated with wage inequality and its growth in recent years. In other words, most wage inequality (and most of the growth in wage inequality) should be between occupations.

The second empirical relationship that I investigate involves the multivariate analysis of the mean wage and of wage inequality within occupations. This part of my research attempts to explain temporal changes in the mean and the dispersion of wages in terms of other sociological variables, while using occupation as the unit of analysis. Given the importance of improving the sociological understanding of the growth in wage inequality, I believe that this part of my investigation is substantively significant in its own right. In addition, however, this part of the analysis may be viewed as constituting an indirect test of Grusky et al.'s 'disaggregate structuration' theory in a weaker form. That is, even if most wage inequality (and its growth) is not primarily between detailed occupational categories, these detailed occupational categories may nonetheless be considered a "fundamental" class structure in some sense. This may be the case if occupational categories are an appropriate and useful unit of analysis in explaining wage inequality and its growth. In the next section, I will review the suggested sociological variables that could account for temporal change in the mean and the dispersion of wages.

2.2 Linking Occupational Structure with Growing Wage Inequality

2.2.1 Demographic Change: Increase of Female Workers

The simple economic logic that the increase of labor supply puts downward pressure on wages leads us to consider demographic change as a primary cause of inequality growth. All supply side explanations follow the same logic.

An influx of baby boomers into the labor market is expected; thus it is not surprising that a supply side argument was once popular. However, the effect of the baby boomers on the labor market is known to be small, and there is a time mismatch between the peak entry years of the baby boomers and the historical trends of wage inequality (Dooley and Gottschalk 1982; Morris and Western 1999). And even though it is true that the entry of baby boomers may have lowered the wages of unskilled workers, this does not provide an explanation for why the wages of skilled workers are rising. As is well known, the disproportionate increase in the upper tail of the wage distribution has played a big role in the recent growth in inequality. According to Dooley and Gottschalk (1985), even the decline of wages of low skilled workers can not be fully accounted for by the influx of baby boomers. After controlling for cohort size as well as levels of education and experience, they found that the proportion of men with low earnings still showed an upward trend from 1967 to 1978.

Moreover, the inequality within cohorts is bigger than the inequality between cohorts. Juhn, Murphy, and Pierce (1993) analyzed the changes in inequality by cohort between 1963 and 1989, finding that changes of within-group inequality for all age cohorts show basically the same pattern. There is little difference between the newly entered baby boomers and old workers. Juhn et al.'s (1993) result shows "an accelerating increase in inequality with time that cannot be explained by any combinations of cohort and age effects."

Unlike the cohort effect of baby boomers, which was early on eliminated from the possible list of causes of increasing wage inequality, the female effect, which has been intensively discussed, has not yet been eliminated due to a lack of universal agreement. The relationship between occupation and the gender wage gap has been the subject of prior research. For example, Peterson and Morgan (1995) investigate the sources of the wage gap between men and women using establishment-level data. They find that, within establishments, the largest component of the gender wage gap derives from the allocation of men and women into different job categories, while gender differences in wages within job categories are relatively small. They argue that "occupational segregation accounts for about 40 percent of the wage gap, while human capital and other variables account for about 40 percent" (Peterson and Morgan 1995:361). In addition, jobs that have a larger proportion of female workers tend to have lower wages. This latter pattern has been further studied in the comparative worth literature (England 1992; Kilbourne et al. 1994). Also, the fact that female workers are likely to have less experience than male workers, net of age (Smith and Ward 1989), could be a source of a gender wage gap within the same occupation. Cultural feminists explain these phenomena as a result of valuative discrimination, and neoclassical theorists attribute these phenomena to the result of compensating differentials (Kilbourne et al. 1994). Whatever the logic, both theories predict a net negative effect of a higher proportion of female workers on the average wage in an occupation.

Although informative, this literature has not sufficiently investigated the role of increasing numbers of female workers on the trend in wage inequality. The issue is briefly raised by Morris and Western (1999), but they do not investigate it using multivariate analysis. Dooley and Gottschalk (1985) suggest that the increasing labor supply of women could increase the proportion of male workers with low earnings, but their study does not find strong evidence to support this hypothesis. As Dooley and Gottschalk (1985) noted, the general labor supply theory may predict that an increase in the proportion of female workers would bring an increase in inequality. The logic is that women's wages are, on average, substantially lower than men's wages, and therefore. as more female workers enter into the low end labor market, the unskilled labor market becomes more competitive. This, in turn, puts downward pressure on male workers' wages at the lower tail. That is, the increase of women's labor market participation would increase inequality by further lowering unskilled male workers' wages.

But this argument is not supported by empirical evidences (Morris and Western 1999). In this regard, it should be noted that occupational segregation between men and women is substantial (Weeden 1998; Peterson and Morgan 1995), so female workers are not perfect substitutes for male workers. Furthermore, the increasing labor supply of women during the past few decades seems an unlikely significant factor in the increase in inequality at the upper end of the distribution of wages.

On the contrary, empirical studies have found that the increase in the number of female workers did not affect male workers' wage distribution or even negatively affect inequality by reducing male workers' wages at the upper end of the distribution (Juhn and Kim 1999; Hyslop 2001). Juhn and Kim (1999) attributes this to the heightened competition at the upper end. They found that since the 1980s, well-educated women with upper-middle class family backgrounds have mostly contributed to the growth of female participation (Juhn and Murphy 1997; Juhn and Kim 1999; Maxwell 1990). That is, increased female labor market participation since the 1980s is mostly due to the influx of highly educated female workers. College educated women substitute for college educated men, not less educated, unskilled male workers. This finding seems to suggest that the increase in female labor participation suppressed, if not lowered, the further increase in inequality. The effect of female labor force participation on inequality, however, looks to differ by the unit of analysis. Hyslop (2001) shows that the female labor supply accounts for over 20 percent of the increase in family inequality and 50 percent of the increase in female inequality. Maxwell (1990) also reported that the increase of female workers did not change the distribution of income of male-headed families and female-headed families but it did widen the dispersion of dual-income families.[3] This positive effect of female labor force participation on family inequality was an unobserved phenomenon before the 1970s, in which female labor participation was relatively higher among poor families.

Nonetheless, given that female workers tend to have lower wages than male workers, whether due to comparative worth considerations or other reasons, I predict that increases in the proportion of female workers within an occupational category will increase the category's aggregate wage inequality, ceteris paribus. From the perspective of microeconomic theory as well, the

[3] Unlike other studies, Nielsen and Alderson (1997) and Cancian and Reed (1999) reported that increased female participation decreased family income inequality.

increase in labor supply (deriving from the increased labor force participation rates of women) is likely to drive down wages for some occupations, due to the resulting increased competitiveness. Because women tend to have lower wages than men, occupations in which the proportion of female workers increases over time will likely have below average wages. Increases in the proportion of female workers in an occupation will further lower the average wage in that occupation, which will thus result in increased between-occupational inequality, unless the increase of female participation is mostly observed among skilled occupations. We therefore arrive at the following two hypotheses.

Hypothesis 1-A: Increases in the proportion of female workers within an occupation will, ceteris paribus, increase growth in wage inequality in that occupation.

Hypothesis 1-B: Increases in the proportion of female workers within an occupation will reduce the occupation's growth in mean wage and will therefore tend to increase between-occupational wage inequality, ceteris paribus (since occupations with increasing proportions of female workers will tend to have mean wages that are below the overall average).

2.2.2 Deindustrialization

Industrial change—in terms of changes in the proportions of the labor force—that is employed in various industrial categories is another source of increasing wage inequality. As is well known, industries have substantial net effects on wages even after controlling for the human capital and occupational characteristics of workers (Krueger and Summers 1988). Net of these variables, the industrial composition of the labor force therefore affects inequality in the distribution of wages (Sakamoto 1988). The most influential theory of the relationship between industrial composition and income inequality was proposed by Kuznets (1955) which was recently revisited by Nielsen and Alderson (1995, 1997) and Alderson and Nielsen (2002).

Kuznets (1955) explained the rising inequality in terms of the change of industrial composition. He argued that at the early stage of industrialization, inequality would grow due to the income gap between agricultural sector and industrial sectors, but inequality would decrease as the proportion of agriculture diminishes and the proportion industrial sector grows. Thus at the later stage of industrialization, most workers engage in industrial sector so that wage gap between agricultural and industrial sectors does influence little on the distribution of wage of a society. Indeed, until the early 1970s, historical trends of inequality of the United States and other European countries shows the inverted-U pattern.[4] Sometimes Kuznets thesis is said to be that economic development is curvilinearly related with inequality. This curvilinear relation is still widely tested through international comparison or in intranational spatial labor market settings (e.g., Nielsen and Alderson 1997; Milanovic 1994). Put summarily, Kuznets' thesis suggests that the change of wage inequality depends on the economic development and accompanying change of industrial composition.

Recent debates of deindustrialization focus particularly on the effect of decreased manufacturing sector. As reviewed by Sakamoto (1988) and Alderson and Nielsen (2002), previous studies based on cross-sectional data

[4] Piketty and Saez (2003), however, argues that the inverted-U pattern observed in America from the early 20th century to the 1970s is not the result of the changes of industrial composition of Kuznets thesis, but the outcome of progressive taxation and other haphazard factors. Piketty (2003, 2005) shows that the same pattern of inequality change as observed in America is also found in other advanced capitalists countries such as France and Britain.

typically find that increases in employment in the manufacturing sector decreases income inequality. Many of "good jobs" especially for high school educated workers were traditionally concentrated in manufacturing sectors. Those manufacturing jobs used to be well paid and provide chances for upward promotion within internal labor markets. The decrease of manufacturing sector, deindustrialization, caused by globalization and/or outsourcing could reduce the supply of these good jobs. And newly created jobs in service industries are mostly low paying and low skilled jobs (Bluestone and Harrison 1988; Lorence and Nelson 1993). Thus, deindustrialization increases inequality mainly by substituting good jobs of manufacturing sectors with bad jobs of service sectors.

With the panel analysis of 1970 and 1980 U.S. Census data from the largest 124 Metropolitan Statistical Areas, Lorence and Nelson (1993) concludes that "Service Sector growth generates more bifurcated occupational structures with greater percentages of high-paying managerial and low-paying service positions" (172). Bloomquist and Summers (1982) also contend, by doing cross-sectional comparison between non-metropolitan areas, that compositional changes of industry cause the change of occupational mix and it, in turn, induces the increase of workers with low earning and therefore higher levels of inequality. And an international comparative study of Gustafsson and Johansson (1999) finds that deindustrialization brings about the increase of inequality.

But other scholars did not find strong correlations between deindustrialization and growing inequality. Murphy and Welch (1993) showed that most of inequality changes come from within industrial sectors and the amount of change due to shifting compositional mix is small. Juhn, Murphy, and Pierce

(1993) analyzed the change of inequality of male workers, reaching the same conclusion that compositional change accounts for less than 15 percent of total inequality change. They have studied the role of occupation in the context of industry. In their analysis, however, occupation was just a proxy variable representing skill differences. They insisted that increased inequality cannot be explained by the characteristics of industry, because most industries have experienced the same direction of change and within industrial change is far more important. Although they do not deny that deindustrialization did play some role in increasing inequality but they argue that the amount of its effect is tiny.

Some researchers insists that even substantial correlation between deindustrialization and inequality could not tell the whole story of inequality growth. Regional concentration of manufacturing sectors and their declines has been said to be reasons of limitation of deindustrialization hypothesis. Morris and Western (1999) say that although the decline of manufacturing can explain the increase of inequality in traditional manufacturing cities in the northern states, it cannot explain the increase of inequality in other states where manufacturing sectors never occupy a significant portion of labor forces. They also argue that the deindustrialization hypothesis is supported at the state level, but it is not consistently supported at the national level.[5]

In addition to industrial compositional change, the widening mean wage gaps between industries can also cause the increased inequality. Some industries respond well to the change of outside environments while others do not.

[5]Some argued that the effects of deindustrialization vary by demographic groups. Lorence and Nelson (1993) said that the increase of the service sector employment has less of an effect on female earnings distribution than on male earnings distribution. And Wilson (1996) pays attention to racial variation of the effects of deindustrialization. He attributes the decline of wages of urban African-Americans to deindustrialization.

When high wage industries respond better to the changes than low wage industries, this could result in increased differences of productivity and increased wage gaps. Raffalovich (1993) argued that "change in ... between-industry earnings differentials has contributed substantially to total inequality change" (130), while industrial restructuring has done little with the growth of inequality as discussed in the previous chapter. That is, without compositional changes of industries, decrease of average wages of manufacturing sectors—either because of the reduction of average wage at all levels of manufacturing workers or because of the decline of opportunity of upward mobility of internal labor markets without reduction of wages of entry level manufacturing workers—could bring about the increase of total inequality. We therefore investigate the following two hypotheses.

Hypothesis 2-A: Reductions in the proportion of workers that are employed in the manufacturing sector will increase growth in within-occupational wage inequality, ceteris paribus.

Hypothesis 2-B: Because the manufacturing sector has traditionally supported the wages of semi-skilled and low-skilled workers (who otherwise would earn below-average wages), decreases in employment in the manufacturing sector will, ceteris paribus, increase growth in between-occupational inequality.

2.2.3 Unions

During the 1970's and 1980's, the proportion of the U.S. labor force that was unionized declined by about one-half percentage point per year. This decline in the proportion unionized has probably been an institutional factor that has contributed to increasing inequality.[6] Freeman (1993) estimates that a 10 percent decline in the proportion unionized explains about half of the observed growth in the variance in earnings among blue-collar workers from 1978 to 1988. Freeman (1993) also argues that the proportion unionized reduces within-group inequality because the distribution of wages is more equal within the union sector than within the non-union sector (see also Freeman and Medoff 1984; Nickell and Layard 1999; Hedström and Swedberg 1985). Freeman (1993) estimates that about 20 percent of the increase in within-group earnings inequality can be attributed to the decline of the proportion unionized. Similar conclusions are discussed by Card and DiNardo (2002).

Additional evidence of a union effect is provided by studies involving international comparisons (Dinardo and Lemieux 1997; Alderson and Nielsen 2002; Atkinson 1999; Gottschalk and Smeeding 1997; Gustafsson and Johansson 1999).[7] Countries with higher proportions of their labor force unionized tend to have lower levels of wage inequality. In the international context, an

[6] In addition to unions, the level of the minimum wage could be another institutional factor. The relative level of the minimum wage compared to the mean wage has dropped from 50 percent to 20 percent during the last two decades. Western (1995) asserts that 17 percent of the growth in the gap between college and high school graduates is driven by the stagnant minimum wage (Morris and Western 1999). Dinardo and Lemieux (1997) contend that the change in union density and the change in the minimum wage accounted for a third of the difference in inequality between Canada and the United States. Some economists argue that the increase in the minimum wage will bring about the growth in the unemployment of unskilled workers. And, in turn, the increased unemployment accelerates competition among unskilled workers and lowers their wages. But evidence supporting this argument is scarce (Nickell and Layard 1999).

[7] DiPrete and McManus (1996) argue that we cannot adequately observe the effects of institutional factors by comparing the effects over time in one nation. They assert that institutional factors include general culture and whole institutions that can only be investigated by comparing different nations. This logic attributes all national differences that are not explained by other factors to institutional factors. In their model, all residuals are considered to be a result of institutional differences. This assumption could be too broad to be tested as a scientific hypothesis.

additional factor is the institutional setting of the wage-bargaining process. European nations with centralized wage-bargaining systems (e.g., Sweden or Germany) tend to have less inequality than nations with less centralized bargaining systems such as the U.S. or Canada (e.g., Western 1995).

Although cross-sectional comparisons exhibit a substantially negative relationship between the proportion unionized and inequality (see e.g., Freeman 1980), a high proportion unionized does not, by itself, guarantee decreasing wage inequality over time. Even countries with the highest proportions unionized (e.g., Sweden and Norway) have experienced increases of inequality in recent years. Thus, in regard to the temporal growth in wage inequality, the initial level of the proportion unionized may be less significant than changes in the proportion unionized.

An additional effect of unions is the spillover effect, which refers to the upward pull of the unionized sector on the average wage of non-union members (Freeman and Medoff 1984; Leicht 1989). This pressure occurs as non-union firms try to prevent the unionization of their workers. To keep so-called "healthy labor relations," firms provide wages equivalent to those provided by union firms. In other cases, unionized firms offer the same wages to non-union members and union members to preclude further unionization. The spillover effect often reduces inequality, as it raises the wages of workers who would otherwise have below average wages (Freeman and Medoff 1984). Unions seek to reduce wage inequality within firms because union decisions are based on a political process in which the majority rules, and the majority of workers is likely to have below average earnings. Also, union members are likely to favor a less-dispersed distribution of earnings because of ideological reasons and organizational solidarity (Freeman and Medoff 1984:16-17). The spillover effect may be especially equalizing when the proportion unionized is quite high and unions have significant power over broad segments of the labor force, or society more broadly.

The equalizing force of the spillover effect is not, however, inevitable, as it is only an empirical tendency rather than a theoretically logical consequence. That is, if the spillover effect is small or negligible, then the monopoly effect of unions may dominate (Freeman and Medoff 1984). In this case, unions increase inequality because the average wages of union workers increase while the wages of other non-union lesser-skilled workers do not. Indeed, the average wages in the non-union sector may even decline due to the excess labor supply that is generated by the high wages of union workers (Pindyck and Rubinfeld 2001). This latter scenario portrays unions as primarily a monopolistic institution that increases inequality between union workers and non-union workers (e.g., Weeden 2002). Freeman and Medoff (1984) found that unions have a substantial monopoly wage impact; thus, unionized workers earn more than non-unionized workers of equal skill.

In spite of these monopoly effects, unions can promote wage equalization by increasing the wages of blue-collar workers relative to the wages of white-collar workers. Freeman and Medoff (1984) argue that the inequality-reducing effects of unionism outweigh the inequality-increasing effects, despite the monopoly effects of unionism. Indeed, inequality between white-collar workers and blue-collar workers inside the unionized sector has traditionally been low. However, this within-group equalizing force seems to be changing. Whereas in previous decades the wage setting policies of unions specified a single wage for a broad array of union members, in recent years unions have lost their negotiation power as universal wage setters (Western 1995), and unions are more likely to accept differentiated wages for their members according to individual workers' productivities.

It does not seem likely that this trend of diminishing power of unions will be reversed in the future (Hirsch and Schumacher 2001), given that most of the decline in union membership is due to differential employment growth rates across industries. Such differential growth rates are, again, due largely to broader market and regulatory forces rather than changes in union organizing activity (Farber and Western 2001). In addition to this, the change in wage determination norms among union members may be further weakening the inequality-reducing function of unionism. Unions have recently been more likely to withdraw the policy of a universal wage for their members and to accept differentiated wage settings by the skill levels of their members (Mitchell 1985). This trend might increase inequality within firms and therefore within occupations. Unions may thus be becoming less successful at establishing similar wages across a large number of unionized workers. Given these facts, the level of inequality among union workers may be rising to the level among non-union workers.

In sum, unions traditionally have promoted equality by reducing within-sector inequality and by raising the average wages of non-union workers (via the spillover effect). However, both of these processes may be declining, as unions lose their bargaining power in the context of reduced union membership and political power in the U.S. labor force. Therefore, the net effects of unions on wage inequality needs to be further investigated empirically. I propose the following hypotheses.

Hypothesis 3-A: Reductions in the proportion of unionized workers in an occupation will increase both within-occupational and between-occupational *wage inequality, ceteris paribus.*

Hypothesis 3-B: Since unions have protected the wages of semi-skilled and low-skilled workers, a decline of the proportion of unionized workers will increase between-occupational wage inequality, ceteris paribus.

2.2.4 Insecure Employment Relations

Since the 1970's, cost reduction has become a critically important basis of competition. This tendency may be exacerbated by the "shareholder revolution," which encourages companies to be more interested in short term gains rather than in long term development. Both of these considerations may lead to increases in the employment of contingent workers. These workers may help firms reduce their short-term labor costs by hiring the cheapest possible workers for a particular set of jobs. However, this "casualization" in the labor market may increase wage inequality. This may occur both as because contingent workers tend to have lower wages and because firms are usually uninterested in promoting or training such workers for higher skilled and better paying positions, which are often, to some extent, eliminated by the increased employment of contingent workers.

During the 1980s, the number of contingent workers increased significantly. Belous (1989) reports that while the total labor force grew by 14 percent during this period, part-time employment grew by 21 percent. In 1989, the proportion of part-time workers among the total labor force was 18 percent. Since the late 1950s, the fraction of part-time workers has grown gradually, rising from 12.1 percent in 1957 to 18 percent in 1989 (Tilly 1991). Part of the reason for this growth is due to the relatively rapid growth of the industries that use the most part-timers. But the demand of part-time workers by employers of other industries has also grown (Hipple and Stewart 1996). Companies have shifted to part-time employment because as a way to cut labor costs. The wage gap between full-time and part-time workers has widened (Tilly 1991). This trend of growing contingent workers seems to hold in the 1990s, despite the strong labor market (Hipple 2001). This trend, if continued, is very likely to increase wage inequality.

Some empirical evidence regarding these processes is provided by McCall (2000), who analyzes inequality in many local areas in the U.S. Her results indicate higher levels of inequality in places with higher rates of flexible and insecure employment patterns. To measure the latter, she uses the unemployment rate, the proportion of part-time workers, and the proportion of immigrant workers. She argues that in explaining within-group inequality, insecure employment conditions are more important than technological change or industry.

Between-occupational inequality is most likely increased by the expansion of part-time workers, who tend to have lower wages and are often concentrated in "bad secondary jobs" (e.g., Tilly 1991). To be sure, contingent workers are not limited to low income jobs. High-skilled or high-educated independent contractors may actually earn more than their counterparts in traditionally secure employment relations (Hipple and Stewart 1996; Polivka 1996). These sorts of workers are, however, only a tiny proportion of those who are employed on a part-time basis, in terms of hours worked per week (and the latter measure is the indicator that is available to us in the data that we use). I therefore propose the following hypotheses that may be empirically investigated using my data.

Hypothesis 4-A: Growth in wage inequality will be greater in occupations that are experiencing an increase in the proportion of part-time workers, ceteris paribus.

Hypothesis 4-B Between-occupational inequality will be increased to the extent that the proportion of part-time employment in an occupation increases, ceteris paribus.

2.2.5 Increases in the Return to Skill

Recent technological developments may have increased the demand for high skilled workers but may have decreased the demand for low skilled workers. This explanation is known as the skill-biased technological change (SBTC) hypothesis and has been popular in economics (Atkinson 1999; Murphy and Welch 1997). According to this view, increased demand for (and hence returns to) skilled labor is the primary cause of the increases in wage inequality in recent years. While high skilled workers are now earning more than before, the wages of low skilled workers are not increasing and may even be declining. Underlying the increased demand for skilled labor is technological change, which is becoming increasingly complex and hence requires the sophisticated work skills of more highly educated workers.

The SBTC hypothesis is popular among economists because it is inherently compatible with their view of the labor market as highly competitive and relatively efficient. Unlike institutional perspectives, which emphasize forces that are largely outside of market processes, the SBTC view explains increasing inequality in terms of the traditional economic framework of supply and demand. Within this framework, sociological or special theoretical innovation is not required, implicitly confirming the explanatory power of conventional economics.

The 1970's is known as a period of declining inequality in educational gaps (e.g., Featherman and Hauser 1978; Farley 1996). The increased supply of highly educated labor was further exacerbated by the entry of the baby-boom cohort into the labor force as they became of working age. Consequently, the wage differential between high school graduates and college graduates narrowed throughout the 1970's. In keeping with the basic economic principles of supply and demand, the decline in the college premium is usually explained by the increased supply of educated labor during the 1970's (Levy and Murnane 1992; Karoly 1993; Murphy and Welch 1993; Morris and Western 1999).

The narrowing wage differential was, however, reversed in the 1980's. During this decade as well as in the 1990's, the college premium rose, despite the increased number of workers with a college degree. At first glance, this result seems inconsistent with the basic operation of supply and demand, since the increased supply should drive down the college premium, similar to what occurred during the 1970's (Thurow 1975). However, in spite of an increased supply of college graduates, the labor return to college education has risen since the 1980s. This seemingly contradictory result is easily explained by the SBTC view, however, as an upward shift in the demand function for highly educated labor has outweighed the increased supply (Juhn et al. 1993). In the 1980s, the demand for college graduates has increased more due to global competition and key technological change. Thus, the relative supply of college graduates has declined compared to the relative supply of college graduates in the 1970s.

While the deindustrialization hypothesis focuses on global competition, which reduces the needs of manufacturing sectors, the SBTC hypothesis does not explain why the need for college graduates has increased in manufacturing sectors as well as in other sectors. The educational composition within manufacturing sectors, which used to be disproportionately comprised of high school graduates, has shifted towards a higher proportion of college graduates. Employment has shifted toward industries and occupations that demand more skilled workers, even in the face of rising skill premiums (Juhn et al. 1993).

Occupations are often used as an indicator of different skill levels. Indeed, the Dictionary of Occupational Titles Index classifies occupations by various skill criteria. Thus, the rise in the demand for skilled workers implies that the increase in the demand for skilled occupations and the faster growth of income within these occupations will result in a widening wage gap between highly skilled and unskilled occupations. Therefore, the SBTC hypothesis may envisage the growth of between-occupational inequality.

The skill premium is not limited to having a college degree. Technological change may have increased the demand for other types or indicators of various work skills, broadly construed. These other types of skills (e.g., perseverance, reliability, creativity) are, however, typically difficult to measure directly. The focus on educational attainment is to some extent due to the availability of data on this skill indicator. For example, Autor, Katz, and Krueger (1998) tried to find the answer on why skill demand rises in the computer revolution. They ran regression analyses with skill demands and computer usage rates as independent variables, reporting that industry skill upgrading is more intensive in computer-intensive sectors. They insist that the computer revolution caused the widening productivity gap and thus resulted in growing inequality. For this reason, my hypotheses are also stated in terms of educational attainment.

Hypothesis 5-A: Ceteris paribus, wage inequality will increase in occupations that experience increases in the variability of educational attainment.

Hypothesis 5-B: Ceteris paribus, increases in the proportion of college educated workers in an occupation will increase between-occupational inequality.

2.2.6 Changes of Firm Organizational Culture

Lindbeck and Snower (1996) propose a new approach, the change of organizational cultures. They insist that the mechanism determining workers' wage levels in organizations has been altered fundamentally. They call this organizational change the organizational revolution, which refers to a shift from Tayloristic organizations to holistic organizations. Holistic organizations, they argue, are characterized by a flatter structure, greater production flexibility, more individual treatment of employees, and multi-tasking over occupational or divisional boundaries. In Tayloristic organizations, what determines workers' wages is not actually how much productivity workers exert, but what kind of task workers perform and/or to which departments in the division of labor workers belong. This kind of wage determination system is well described by a sociological view that attributes marginal productivity to jobs rather than to individuals (Thurow 1975; Granovetter 1981). That is, productivity belongs to the tasks workers perform, not to workers themselves.

The organizational revolution does not simply increase the need for skilled workers; it also redefines what the required skills are (Snower 1998). Contrary to Tayloristic organizations, holistic organizations do not limit individual workers' tasks to one division in an organization. Workers are more likely to perform tasks across divisions. As information technology develops, more and more data is accumulated at the site of production. In addition to this cross-divisional multi-tasking, analyzing, interpreting, and making decisions regarding this accumulated data becomes more important than ever before. Newly required skills include versatility across tasks, the ability to learn new tasks, the aptitude to take advantage of complementarities between different tasks, and the ability to communicate. Divisional boundaries that distinguish production from the customer service become obscure. All divisions share the same goal, customer satisfaction. Communicative skills are necessary for all workers. That is, general skills are required more than task-specific skills.

In addition to this, the development of information technology allows employers to better gauge individual workers' productivity. Because employers can provide the 'objective' (numerical) data on individual workers' productivity, employees are also more likely to accept employers' judgements of their productivity. Thus, in holistic organizations, workers' wages are more likely to be determined by individual workers' own productivity, rather than by tasks workers perform. In this regard, the wage deterministic system of holistic organizations would seem to be more consistent with neoclassical human capital theory which attributes productivity primarily to something belonging to individual workers.

Unlike traditional human capital theory, theorists of the organizational change view argue that the college premium arises not because college graduates learn new skills in college but because college graduates are more likely to be versatile and to learn new and adequate skills quickly. Within-educational group inequalities are rising because workers with equal educational levels have different abilities for multiple tasks.

Some scholars of this view assert that (skill-biased) technologies and organizational changes are complementary to each other. Caroli and Reenen (2001) call the organizational changes "skill-biased organizational change." Using firm-level data, Bresnahan, Brynjolfsson, and Hitt (2002) shows that introducing information technologies (e.g., more usage of personal computers) in a firm does not guarantee the improvement of productivity. Rather, without accompanying occupational changes, a simple increase of information technologies usage drops productivity. Caroli and Reenen (2001) also find a similar result with British and French establishment-level data.

The organizational change view seems to provide an answer to the productivity paradox of information technology (Brynjolfsson, Hitt, and Yang 2002; Bresnahan et al. 2002). A paradox arose as, in spite of increased investment in information technology in the 1980s, productivity did not increase at the same pace. However, as organizational adjustments spread in the 1990s, productivity increased, perhaps retroactively. This view implies that the increase in inequality may happen across firms, which are the principal bodies required to implement organizational changes. While some firms succeed both in the investment in new information technologies and in the process of organizational redesign, other firms fail at both or one or the other of these productivity increasing activities, and thus, in terms of productivity, get left behind. As productivity gaps across firms widen, so does inequality across firms. Indeed, using manufacturing sector data from 1975 to 1992, Dunne et al. (2004) finds that virtually the entire increase in overall dispersion in hourly wage is accounted for by the between-plant components.

For scholars of this view, the decline of centralized bargaining is seen as a reflection of these changes in organizations. Where workers' wages are determined by individual workers' own productivity, materialistic bases for equal pay for equal work are eroding. Especially since equal work is usually judged by the definition of tasks, the increased requirement of versatile ability across tasks seems to be an obvious factor in the corrosion of material bases for equal pay for equal work. In addition to this, Snower (1998) asserts that the reason why the gender gap is narrowing is that women are more likely than men to have temporal flexibility, interpersonal skills, and the ability to multi-task; thus, employers have begun to prefer women over men.

It might be difficult, however, to test their argument directly because data limitations. For this reason, I will test this hypothesis indirectly. From the argument that occupational barriers become obscure and workers' versatile ability becomes more important, we can expect the following;

Hypothesis 6-A: Within-occupational inequality will grow faster in high skill jobs, which have a higher proportion of college graduates and in service jobs, which require more communicative skills.

Hypothesis 6-B: Among highly educated workers, between-occupational inequality will decrease faster because occupational barriers are less determinative.

Chapter 3

DATA AND METHODS

Given my research agenda, I utilize the Current Population Survey Merged Outgoing Rotation (CPS-MORG) 1982-2002 files. First, I test bivariate relationships between occupation and growing wage inequality using the CPS-MORG. Then, I construct longitudinal datasets using CPS-MORG to test the hypotheses of Chapter 2. The identifying unit of these newly constructed longitudinal data is the three-digit occupational code.

3.1 Methodological Issues

The causes of inequality can be studied best with longitudinal data, but it is difficult to find a dataset that has a big enough sample size and a long enough time period. Most big datasets are cross-sectional, and panel data usually have small samples and may only cover specific cohorts.

Because of these limitations, scholars apply two alternative strategies. One is to use cross-sectional data at two or more different time points and compare the results (Borjas et al. 1996; Cancian and Reed 1999; Levy and

Murnane 1992; Murphy and Welch 1993; Weeden 1998). To do this, first they run the wage regression model for each different group. Using a regression decomposition method, the amount of total change is decomposed into rate change and compositional change. This is a good way to find the effect of growing between-group differences by comparing the change of parameter estimates across groups. With this method, however, we can only infer the causes of growing within group inequality indirectly. Growing within group inequality is explained indirectly with the residual variance.

The other strategy is to compare different geographic regions that show different amounts of inequality (McCall 2000; Grodsky and Pager 2001). Most international comparison studies (Atkinson 1999; Dinardo and Lemieux 1997; DiPrete and McManus 1996; Gottschalk and Smeeding 1997) use this strategy. Comparing states across the U.S. is methodologically similar. This method can tell us the sources of inequality; however, such sources are not necessarily the causes of growing inequality. The study of the effect of unions is a good example. In nations where union density is high, wage inequality tends to be lower in a given year. However, such nations have experienced the same amount of inequality growth over time as other nations. Some scholars use multi-level models with individual data, setting individual characteristics as level one (i.e., micro level) and regional characteristics as level two (i.e., macro level). This appears to be a better way to identify the sources of inequality over comparing the coefficients of different regions. However, we are interested in the growth of inequality over time, not regional differences.

To overcome these weaknesses and to study the causes of growing inequality, we need to construct longitudinal data. Unfortunately, there is no feasible individual level longitudinal data. One alternative is to construct a group level data set that has summary descriptive statistics by group. Using group level data in the study of inequality is not rare. For instance, Gustafsson and Johansson (1999), Autor et al. (1998), and Lee (2004, 2005) use group level inequality data across regions. For group level longitudinal data, group identity should stay unchanged over the time period so as to be comparable over time. A group category satisfying this condition could be occupation. By using this kind of data, we can test the causes of growing inequality directly.

3.2 Data

For this research, the Current Population Survey, which is a fairly large data set collected annually, is utilized. I use the data files for the Merged Outgoing Rotation Groups of the Current Population Survey (CPS-MORG) from 1983 to 2002. These data have been used in previous research by economists (e.g., Juhn et al. 1993), as the CPS-MORG provides reliable information on hourly wages. Furthermore, during this time period, the CPS-MORG uses a consistent occupational classification, which is critical for my study, given the important role of occupation in the hypotheses that I wish to investigate.[1]

My target population for the analysis includes the non-institutionalized, non-military population aged 18 to 65 who were employed in the labor force at some time during the survey year. Self-employed persons were deleted from my sample, however, because their income data are subject to greater measurement errors (Lillard et al. 1986) and because the self-employed tend

[1]Prior to 1983, the CPS-MORG used the 1970 U.S. Census occupational classification, which is difficult to compare at the three-digit level with the 1980 U.S. Census occupational classification that has been used since 1983 for the CPS. Although additional changes to this occupational classification were made in 1998, they are relatively minor.

to represent a separate labor market sector that is not critical to my research hypotheses. Hourly wages are adjusted for inflation during this time period using the Consumer Price Index (i.e., CPI-X) to convert all wages to 2002 constant dollars. For salaried workers, I compute the hourly wage based on weekly earnings and hours worked during the week. I impute hourly wages for persons with top-coded values on wages or earnings based on the assumption of a log-normal distribution.[2]

In order to ensure sufficiently reliable estimates of occupational characteristics, I limit the analysis to those three-digit occupational codes for which a sample size of at least 100 is available in each year from 1983 to 2002. Occupational categories that had sample sizes of less than 100 were collapsed together (often with the corresponding "other" or "miscellaneous" category) until a sufficient sample size was obtained. This process yielded a total of 331 occupations consisting of either separate three-digit codes or slightly grouped categories of three-digit codes.[3]

For each of these occupations in each year, I compute indices of wage inequality as well as a variety of other variables, which are used to construct a new dataset. In order to further reduce the influence of random sampling variability, all of the occupation-specific statistics were computed using three-year moving averages. In sum, using the occupational category as the unit of analysis, the total sample size is 5,958, which encompasses 331 three-digit occupational categories observed over 18 years. This newly constructed longitudinal data set is used for my multivariate analysis.

[2]I used a log-normal distribution instead of the more popular Pareto distribution to avoid arbitrary cutting points of the Pareto distribution. Similar results were obtained using the Pareto distribution with various cutting points.

[3]For example, "miscellaneous precision workers n.e.c." were combined with other specific sorts of precision workers. See Appendix A for the complete list of 331 occupations.

3.3 Measures of Wage Inequality

The Gini index is perhaps the most popular measure of inequality and is written as:

$$Gini = \frac{\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}|y_i - y_j|}{2\bar{y}} \tag{3.1}$$

where N refers to the total number of persons, y_i refers to the wage of the individual i, and $\bar{y}$ refers to the grand mean. The Gini index is thus equal to the average absolute difference between all pairs of wages divided by twice of the mean. I use the Gini index in my descriptive statistics to measure the growth of wage inequality. As is well known, the Gini index ranges from 0 to 1, where higher values indicate greater inequality. Unlike other measures of inequality, however, the shortcoming of the Gini index is that it cannot be uniquely decomposed into between-group and within-group components (Allison 1978).

Because different measures of inequality have different degrees of sensitivity to transfers at different parts of the wage distribution (e.g., the Gini index is usually most sensitive to transfers in the middle of the distribution), I also compute other indices of inequality for my descriptive statistics, including the Theil index, the Mean Logarithmic Deviation (MLD), and Half the Square of the Coefficient of Variation (HSCV), which have minimum values of zero (for perfect equality) and unbounded upper values (Allison 1978). The Theil index, the MLD, and HSCV are based on entrophy theory. Among them, the

MLD is more sensitive to transfers at the lower end of the distribution, while the HSCV is more sensitive to the upper end of the distribution. The Theil index is equally sensitive to transfers throughout the distribution.

$$MLD = \sum_{i=1}^{N} \frac{1}{N} \ln \frac{\bar{y}}{y_i} \tag{3.2}$$

$$Theil = \frac{1}{N} \sum_{i=1}^{N} \frac{y_i}{\bar{y}} \ln \frac{y_i}{\bar{y}} \tag{3.3}$$

$$HSCV = \frac{1}{\bar{y}} \left[\frac{1}{N} \sum_{i=1} N(y_i - \bar{y})^2 \right]^{1/2} \tag{3.4}$$

The MLD, the HSCV, and the Theil index may each be additively decomposed into between-group versus within-group components. For example, in the case of the Theil index can be decomposed as:

$$Theil = \sum_{k} \frac{y_k}{\bar{y}} T_k + \sum_{k} \frac{y_k}{\bar{y}} \ln \frac{y_k/\bar{y}}{n/N} \tag{3.5}$$

where y_k refers to the mean wage of the kth subgroup and T_k refers to the Theil index for the kth subgroup. The first component on the right-hand side of the equation 3.5 is thus the within-group inequality, and the second component is the between-group inequality. As shown in Equation 3.5, within-group inequality is a weighted average of inequality in each subgroup, where weight is $y_k/\bar{y}$. The sum of the weight will sum to one for the Theil index but will not sum to one for the MLD or the HSCV (Cowell 1995).

The final measure of inequality that I calculate is the Atkinson index, which is based on a social welfare approach. Like the Gini index, the Atkinson index of inequality ranges from 0 to 1, with a larger value indicating a more unequal wage distribution.

$$A_\varepsilon = 1 - \left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\bar{y}}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{3.6}$$

Equation 3.6 shows the formula for the Atkinson index. Atkinson indexes are constructed to measure inequality based on the social welfare function. The Atkinson index can be interpreted as the percent of transferred income required to maximize the social welfare. The inequality aversion parameter, ε, is a special feature of the Atkinson index and indicates the degree of sensitivity towards inequality that a researcher wishes to assume. A larger, more positive aversion parameter implies greater sensitivity to transfers at the lower end of the wage distribution and less sensitivity to transfers among top income recipients (Jenkins 1999; Coulter 1989). For inequality aversion parameters, I used 0.5, 1, and 2.

$$A_{w(\varepsilon)} = 1 - \sum_j \left[\frac{y_j}{\bar{y}^2}\frac{n}{N}\left(\sum_{i=1}^{n}\frac{1}{n}y_i^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}\right] \tag{3.7}$$

$$A_{b(\varepsilon)} = 1 - \frac{\left(\sum_{i}^{N}\frac{1}{N}y_i^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}}{\sum_k\left[\frac{y_k}{\bar{y}^2}\frac{n}{N}\left(\sum_{i=1}^{n}\frac{1}{n}y_i^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}\right]} \tag{3.8}$$

The Atkinson index can be decomposed, albeit not additively. The within-group Atkinson inequality index can be written as equation 3.7 and between-group Atkinson inequality can be formulated as equation 3.8. Unlike the generalized entropy measures, the sum of the between-group and within-group components of the Atkinson inequality index is not the total inequality of Equation 3.6.

3.4 Statistical Models

I estimate multi-level growth models to test hypotheses described in Chapter 2. First, I investigate models to study within-occupational inequality. In this part of the analysis, the dependent variable is the level of wage inequality in each occupation, while the independent variables are relevant descriptive statistics for each occupation in each year. The model of within-occupational inequality also tests the homogeneity of an occupation after controlling for variables other than occupation itself. If an occupation is a homogeneous group and its heterogeneity is caused by intervention of other social and demographic factors as the disaggregate structuration theorists insist, the majority of within-occupational inequality should be explained by other social and demographic variables such as race, gender, and industry. That is, the variation explained by these independent variables should be large.

In the subsequent part of the analysis, the concern is with understanding the sources of between-occupational inequality. For these multi-level growth models, the dependent variable is the occupation-specific mean wage. Although I do not directly compute between-occupational inequality with these models that use mean wage as the dependent variable, between-occupational inequality may be assumed to be increasing to the extent that the mean wage is reduced in low-wage occupations or that it is increased in high-wage occupations.

The model of occupational mean wage is testing whether an occupational common interest, which is mean wage in my model, is driven by occupational associations themselves. The disaggregate structuration theorists assert that through occupationalization, occupations become classes and occupational associations pursue their common interests. Thus, changes of the occupational mean wage, which is clearly a common interest of an occupation, should be driven by occupations themselves, not by 'other variables.' Therefore, the amount of R-squared explained (=Proportionate Reduction in Error) by 'other variables' in the model of occupational mean wage should be small.

3.4.1 Within-Occupational Inequality

The Baseline Model is the unconditional growth model that contains no substantive predictors. As is shown in equation 3.9, this model includes the year as the only independent variable. In particular, the first line of equation 3.9 shows the level 1 model in which $INEQ_{jt}$ refers to the Gini index of wage inequality in occupation j at time t. Thus, this model investigates within-occupational inequality, which is specified to be a function of the initial level of wage inequality (α_j) and its yearly change (β_j). The initial level of inequality and the yearly change in inequality are specified as random variables that vary across occupations. Time, T is centered to the initial year, 1983-85, thus it is ranged from 0 to 17.

$$
\begin{aligned}
INEQ_{jt} &= \alpha_j + \beta_j T_t + \varepsilon_{jt} \\
\alpha_j &= \alpha + u_{1j} \\
\beta_j &= \beta + u_{2j}
\end{aligned}
\tag{3.9}
$$

The second and third lines of equation 3.9 define the level 2 portion of the growth model. Both the initial levels of inequality and their yearly change vary across occupations. The initial level of inequality consists of the grand mean for inequality across all occupations, α, and the deviation of occupation j from the grand mean, u_{1j}. Similarly, the yearly change consists of the grand mean of yearly change for all occupations, β, and the deviation of occupation j from the grand mean, u_{2j}.

$$
INEQ_{jt} = \alpha_j + \beta_j T_t + \boldsymbol{\gamma} X_{jt} + \boldsymbol{\delta}(T_t \times \bar{X}_{j.}) + \boldsymbol{\zeta} \bar{X}_{j.} + \varepsilon_{jt} \tag{3.10}
$$

To extend the Baseline Model, three sets of predictors are added to obtain Model 1, which is shown by equation 3.10. The first of predictors includes the explanatory variables, X_{jt}, which refer to the occupation-specific proportions for each of the following characteristics: female, African American, Hispanic, other race,; Southern residence, college graduate, the educational diversity index, public sector employment; unionized; and manufacturing sector employment. X_{jt} is a $JT \times K$ matrix with k explanatory variables, which are measured 18 times ($t = 0, \ldots, 17$) for j occupations. The parameter estimates for the net effects of these variables (i.e., γ) indicate the extent to which the growth of wage inequality within an occupation is affected by each explanatory variable.

The second set of predictors consists of interaction terms between the occupation-specific means of the explanatory variables and time (i.e., $T_t \times \bar{X}_j$). These occupation-specific means are by definition constant across all years. The coefficients for these interaction terms (i.e., δ) refer to the changes in the net effects of the explanatory variables without compositional change. The last set of variables in equation 3.10 includes the unchanging occupational characteristics themselves, which are simply the occupation-specific means (i.e., $\bar{X}_j$) that are associated with the coefficients referred to as ζ. The coefficients in the vector refer to the net effects of changes in the independent variables on changes (i.e., *growth*) in wage inequality over this time period. The effects of the occupation-specific means (i.e., ζ) predict variation in wage inequality across occupations in any cross-sectional year, while the δ coefficients for the interaction terms between year and the independent variables may be interpreted as the increase in wage inequality within a given independent variable over this time period.

A common issue in panel models with random effects is that the random effects may be correlated with one or more of the explanatory variables (which are also occupation-specific), thus causing estimation bias. For this reason, Halaby (2004) and Wooldridge (2004) suggest a fixed-effects specification. In my particular application, equation 3.10 includes the group means of the explanatory variables (i.e., $\bar{X}_j$), which, as in the fixed-effects model, eliminates the problem of correlation between the random effects and the explanatory variables (Kittel and Winner 2005). Hausman test statistics for my results clearly indicate that I can fail to reject the null hypothesis that the random effects are uncorrelated with the explanatory variables.

$$\begin{aligned} &INEQ_{jt} = [\alpha + \beta T_t + \boldsymbol{\gamma} X_{jt} + \boldsymbol{\delta}(T_t \times \bar{X}_{j.}) + \boldsymbol{\zeta}\bar{X}_{j.}] + [u_{1j} + u_{2j}T_t + \varepsilon_{jt}] \\ &\qquad \text{where,} \\ &\varepsilon_{jt} \sim N(0, \Sigma) \quad \text{and} \quad \begin{bmatrix} u_{1j} \\ u_{2j} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix} \right) \end{aligned} \tag{3.11}$$

Equation 3.11 shows the composite model where $[\alpha+\beta T_t+\boldsymbol{\gamma} X_{jt}+\boldsymbol{\delta}(T_t\times \bar{X}_{j.})+\boldsymbol{\zeta}\bar{X}_{j.}]$ refers to its structural components and $[u_{1j}+u_{2j}T_t+\varepsilon_{jt}]$ refers to its stochastic elements. For the purpose of estimating this model, I assume that the growth of wage inequality over time is normally distributed, conditional on the sample data for the explanatory variables. The stochastic element for the intercept,(i.e., u_{1j}) and the stochastic element for the growth rate, (i.e., u_{2j}), are assumed to be jointly normally distributed with zero means and a given variance-covariance matrix. In particular, σ_1^2 represents the amount of variability in the intercepts across occupations, and σ_2^2 refers to the amount of variability in the slopes over time. The reductions in and relative to the Baseline Model given by equation 3.11 indicate the variation that is explained by the explanatory variables.

The level 1 error component, ε_{jt}, has a mean of zero and a variance of Σ. The Baltagi-Li test for first-order serial correlation for the random effects model is statistically significant. In order to control for this serial correlation at level 1, a covariance-structure known as "Toeplitz with two Bands" is assumed. According to this assumption, the (i,j) element of Σ when $i \neq j$ is equal to $\sigma_{|i-j|+1}1(|i-j| < 2)$, where $1(|i-j| < 2)$ equals 1 if $|i-j| < 2$, and 0 otherwise. Thus, the diagonal matrix Σ (a $T \times T$ matrix) is σ_{ε}^{2}s, while one column or row off the diagonal component is $\sigma_{toep(2)}$.[4] When $i = j$, Σ is 1.

A zero correlation between occupations is assumed, given that the values on the occupation-specific explanatory variables are based on individuals in each occupation who were randomly sampled by the survey. This assumption may further be justified on the grounds that the 331 occupations are randomly sampled from a larger population of occupations. To empirically consider the hypothesis of a cross-occupational correlation, however, I also estimated the panel-corrected standard-error model (Beck 2001), using the same data and variables. The results were substantively very similar to those discussed in following chapters.

3.4.2 Between-Occupational Inequality

Equation 3.12 is essentially the same as equation 3.11 except that the former uses a different dependent variable, namely, the mean wage in the jth

[4] Although the assumption of $AR(1)$ autocorrelation is popular, it did not work well in the estimation of my model.

occupation. As expressed in equation 3.5, between-occupational inequality is a weighted sum of occupational mean wages. The parameter estimates of equation 3.12 refer to the net effects of the explanatory variables on the occupation-specific mean wage and thus indirectly indicate the sources of between-occupational inequality.

$$\begin{aligned} MEANWAGE_{jt} = & [\alpha + \beta T_t + \boldsymbol{\gamma} X_{jt} + \boldsymbol{\delta}(T_t \times \bar{X}_{j.}) + \boldsymbol{\zeta} \bar{X}_{j.} + \boldsymbol{\theta}(X_{jt} \times D_{j.})] \\ & + [u_{1j} + u_{2j} T_t + \varepsilon_{jt}] \end{aligned} \tag{3.12}$$

In order to facilitate the latter interpretation more clearly, equation 3.12 includes interaction terms between the time-variant explanatory variables and two dichotomous variables, which indicate high-income occupations and low-income occupations, respectively (i.e., $X_{jt} \times D_{j.}$). High-income occupations are defined as those where the mean wage is greater than \$21.20 per hour, which is more than one standard deviation above the grand mean (i.e., \$15.5 per hour). Low-income occupations are defined as those where the mean wage is less than \$9.82 per hour, which is one standard deviation less than the grand mean.[5] For example, if the coefficient for the interaction between female and high-income occupations is highly negative while the coefficient between female and low-income occupations is highly positive, then female employment can be

[5] Wages are in 2002 constant dollars throughout the analysis.

interpreted as reducing between-occupational inequality. This is because the combination of these highly negative and highly positive coefficients indicates a reduction in the mean wage of high-income occupations but an increase in the mean wage of low-income occupations.

3.4.3 Dependent and Independent Variables

Table 3.1 shows the list of dependent and independent variables applied in these analyses.

Dependent Variables

For the models of within-occupation inequality discussed above, the Gini inequality index is used as a dependent variable because of its popularity. The use of alternative inequality indexes do not change the substantial findings reported in the following chapters. Gini inequality indexes used in actual estimations are multiplied by 100, making the range of within-occupational inequality, $INEQ_{jt}$, 0 to 100.

The yearly mean wage by occupation is used as a dependent variable for the estimation of between-occupational inequality. Thus, estimated coefficients of models of between-occupational inequality capture the net dollar change of the mean wage of an occupation by the unit change of the independent variables.

Independent Variable

Table 3.1: List of Dependent and Independent Variables

Variables	Notation	Remarks
Dependent Variables		
Within-Occupational Inequality	$INEQ_{jt}$	Gini inequality index of Occupation j at time t. Multiplied by 100.
Mean Wage	$MEANWAGE_{jt}$	Mean Wage of Occupation j at time t
Independent Variables		
Time		
Year	$\mathtt{T}_{t}$	Year point change. Centered to the initial value, thus year 1983-85 set to 0.
Slope Change by the Change of Proportion		
%Δ Female	$\mathtt{Female}_{jt}$	Percent point change of female of occupation j at time t from time 0
%Δ Black	$\mathtt{Black}_{jt}$	Percent point change of blacks of occupation j at time t from time 0
%Δ Hispanics	$\mathtt{Hisp}_{jt}$	Percent point change of Hispanics of occupation j at time t from time 0
%Δ Other Races	$\mathtt{Others}_{jt}$	Percent point change of other races of occupation j at time t from time 0
%Δ Southern State Residents	$\mathtt{South}_{jt}$	Percent point change of Southern state residents of occupation j at time t from time 0
%Δ Bachelor or more	$\mathtt{BA+}_{jt}$	Percent point change of the bachelor degree or more of occupation j at time t from time 0
%Δ Educational Diversity	$\mathtt{Edu.Div}_{jt}$	Point change of educational diversity index of occupation j at time t from time 0.
%Δ Public Sector	$\mathtt{Public}_{jt}$	Percent point change of public sector of occupation j at time t from time 0
%Δ Part Time Workers	$\mathtt{PartTime}_{jt}$	Percent point change of part time workers of occupation j at time t from time 0

Continued on next page

Table 3.1, cont.

Variables	Notation	Remarks
Continued from previous page		
%Δ Union Membership	$\texttt{Union}_{jt}$	Percent point change of union members of occupation j at time t from time 0
%Δ Manufacturing Sector	$\texttt{Manuf}_{jt}$	Percent point change of manufacturing sectors of occupation j at time t from time 0
Interaction Effects		
Interaction between part-time and sales occupations	$\texttt{PartTime}_{jt} \times \texttt{Sales}_j$	Percent of part time of occupation j at time t times dummy variable of sales occupation (1 for sales occupation, 0 for the others)
Interaction between part-time and service occupations	$\texttt{PartTime}_{jt} \times \texttt{Service}_j$	Percent of part time of occupation j at time t times dummy variable of service occupation (1 for service occupation, 0 for the others)
Interaction between female and sales high-wage occupations	$\texttt{Female}_{jt} \times \texttt{HighWage}_j$	Percent of female of occupation j at time t times dummy variable of high-wage occupation (1 for high-wage occupation, 0 for the others)
Interaction between part-time and sales high-wage occupations	$\texttt{PartTime}_{jt} \times \texttt{HighWage}_j$	Percent of part-time of occupation j at time t times dummy variable of high-wage occupation (1 for high-wage occupation, 0 for the others)
Interaction between public sector and sales low-wage occupations	$\texttt{Public}_{jt} \times \texttt{LowWage}_j$	Percent of public sector of occupation j at time t times dummy variable of low-wage occupation (1 for low-wage occupation, 0 for the others)
Interaction between union members and sales low-wage occupations	$\texttt{Union}_{jt} \times \texttt{LowWage}_j$	Percent of union members of occupation j at time t times dummy variable of low-wage occupation (1 for low-wage occupation, 0 for the others)
Yearly Slope Change of Group Mean		
Year times Mean of % Bachelor or more	$\texttt{YEAR}_t \times \overline{\texttt{BA+}}_{j.}$	Year t times Group mean of percent of the bachelor degree or more of occupation j over the given time period

Continued on next page

Table 3.1, cont.

Variables	Notation	Remarks
	Continued from previous page	
Year times Mean of Educational Diversity	$\mathtt{YEAR}_t \times \overline{\mathtt{Edu.Div}}_{j.}$	Year t times Group mean of educational diversity index of occupation j over the given time period
Year times Mean of % Public Sector	$\mathtt{YEAR}_t \times \overline{\mathtt{Public}}_{j.}$	Year t times Group mean of percent of public sector of occupation j over the given time period
Year times Mean of % Part Time	$\mathtt{YEAR}_t \times \overline{\mathtt{PartTime}}_{j.}$	Year t times Group mean of percent of part time workers of occupation j over the given time period
Year times Mean of % Union Member	$\mathtt{YEAR}_t \times \overline{\mathtt{Union}}_{j.}$	Year t times Group mean of percent of union members of occupation j over the given time period
Year times Mean of % Manufacturing Sector	$\mathtt{YEAR}_t \times \overline{\mathtt{Manuf}}_{j.}$	Year t times Group mean of percent of manufacturing sectors of occupation j over the given time period
Effect of Group Mean		
Mean of % Female	$\overline{\mathtt{Female}}_{j.}$	Group mean of percent of female of occupation j over the given time period
Mean of % Black	$\overline{\mathtt{Black}}_{j.}$	Group mean of percent of blacks of occupation j over the given time period
Mean of % Hispanic	$\overline{\mathtt{Hispanic}}_{j.}$	Group mean of percent of Hispanics of occupation j over the given time period
Mean of % Other Races	$\overline{\mathtt{Others}}_{j.}$	Group mean of percent of other races of occupation j over the given time period
Mean of % Southern State Residents	$\overline{\mathtt{South}}_{j.}$	Group mean of percent of southern state residents of occupation j over the given time period
Mean of % Bachelor or more	$\overline{\mathtt{BA+}}_{j.}$	Group mean of percent of the bachelor degree or more of occupation j over the given time period
Mean of Educational Diversity Index	$\overline{\mathtt{Edu.Div}}_{j.}$	Group mean of educational diversity index of occupation j over the given time period
	Continued on next page	

Table 3.1, cont.

Variables	Notation	Remarks
	Continued from previous page	
Mean of % Public Sector %	$\overline{\texttt{Public}}_{j.}$	Group mean of percent of public sector of occupation j over the given time period
Mean of % Part Time	$\overline{\texttt{PartTime}}_{j.}$	Group mean of percent of part time workers of occupation j over the given time period
Mean of % Union	$\overline{\texttt{Union}}_{j.}$	Group mean of percent of union members of occupation j over the given time period
Mean of % Manufacturing Sector	$\overline{\texttt{Manuf}}_{j.}$	Group mean of percent of manufacturing sectors of occupation j over the given time period

The independent variables consist of five parts: (1) time, (2) slope change by the change of proportion, (3) yearly slope change of group mean, (4) effect of group mean, and (5) interaction effects. Except for the 'time' variable, each part consists of the combination of eleven variables, which are classified into four groups.

These are (1) demographic variables, including percent female (`Female`), percent black (`Black`), percent Hispanic (`Hisp`), and percent living in southern states (`South`); (2) education variables, including percent college graduate or advanced degree holders (`BA+`) and the educational diversity index (`Edu.Div`); (3) industrial change variables, including percent public sector (`Public`) and percent manufacturing sector (`Manuf`); (4) institutional variables, including percent part time workers (`PartTime`) and percent unionized or union covered workers (`Union`).

Except for `Edu.Div`, all variables indicate the percent share in an occupation j at time t and range from 0 to 1. For the convenience of interpretation, I multiply all variables by 100. Thus, the parameter coefficients refer to the point change of the inequality index for a 1 percent point increase in the independent variable.

The educational diversity index indicates the educational diversity within an occupation j and ranges from 0 to 1. Simpson's Diversity Index is applied to estimate the educational diversity. Simpson's Diversity Index can be written as $1 - \sum(n_k/N)^2$, where n_k refers to the number of workers at education level k and N refers to the total number of workers at occupation j. The higher the index, the greater the variability of educational attainment in the particular occupation. In this data there are five levels of educational attainment, and the the maximum number of `EduDiv` is .8, when all educational categories are evenly found in an occupation. I also multiply this index by 100.

Among the interaction terms, `Sales` and `Service` refer to the sales industrial sector and service industrial sector dummy variables, respectively. `LowWage` and `HighWage` refer to the high-wage occupation and low-wage occupation dummy variables. Thus, interaction effects estimate the additional effect of each independent variable. For instance, the coefficient of `Public`×`LowWage` indicates the expected Gini inequality change by one percent point change in percent public sector among low-wage occupations. I also tested the models including other interaction effects (e.g., such as `Manufacturing`×`LowWage`), but the interactions were not statistically significant; thus, in order to maintain parsimony, I do not include them in my models.

As shown in Table 3.1, only six variables are used for the group of 'yearly slope change of group mean' to obtain parsimonious results. I also estimated a model using all eleven variables in 'yearly slope change of group mean,' finding substantially equal results, as reported in the following chapters.

Chapter 4

THE DECLINING SIGNIFICANCE OF OCCUPATION

Figure 4.1 shows the trend in the Gini index from 1983 to 2002. As is evident in Figure 4.1, wage inequality increased sharply during the early 1980's and then tapered off during the late 1980's and early 1990's. Since that time, wage inequality has again continued to increase.[1] The Gini was .313 in 1983-1985

[1]Similar results for the 1980's and 1990's are provided by Bernstein and Mishel (1997). Card and DiNardo (2002) insists that inequality growth has leveled off in the 1990s. They assert that most of the rise of inequality happened in the early 1980s and that after that no significant increase of inequality is observed. In their analysis, they restricted their sample to full-time-full-year workers, ignoring all part-time and part-year workers. They did not treat top-coding appropriately. They adjusted top-coding by multiplying all top-coding by 1.4, regardless of the diversity of top-coding across the year. Inconsistent with Card and DiNardo's argument, Mishel et al. (1999) found that hourly wage inequality (Gini inequality index) after various top-code adjustments has continued to grow in the 1990s, although at a slower rate than the 1980s. Mishel et al. (1999) obtained the same results using both the March CPS and CPS-MORG data.

and .337 in 2000-2002. The first question is what amount of this increase can be accounted for by occupation.

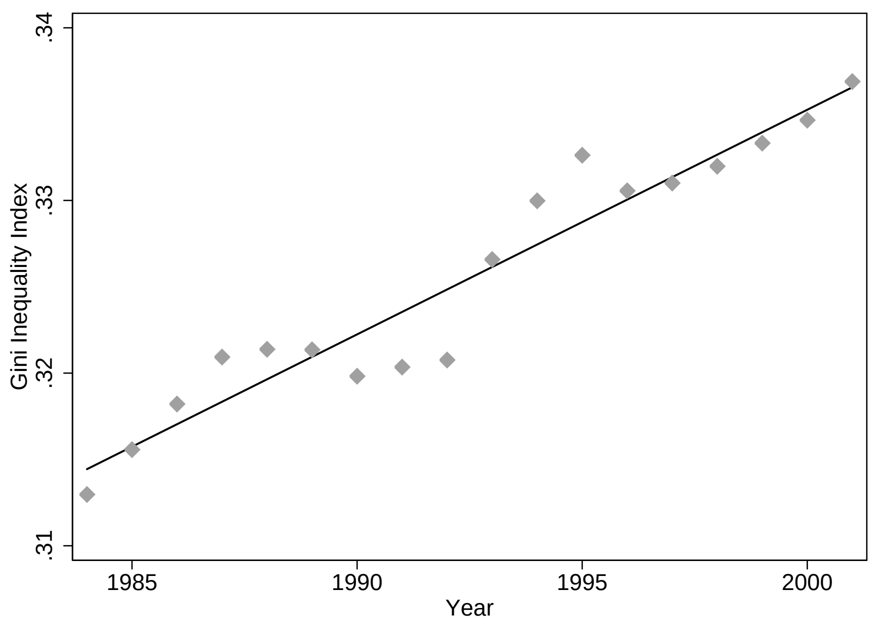

Figure 4.1: Gini Index of Wage Inequality from 1983-1985 to 2000-2002

4.1 Declining Explanatory Power of Occupation

Table 4.1 shows the R-squareds (or coefficients of determination) for regression models of wage inequality in which dummy variables are used as independent variables to indicate occupations, industries, and educational categories. As shown in Table 4.1 for 1983 to 1985, using 330 dummy variables to indicate 331

Table 4.1: Explanatory Power of Occupation, Industry, and Education on Hourly Wage

	Occupation[a]				Industry		Education[g]
	Total	BA+[b]	≤HSG[c]	1 digit[d]	3 digit[e]	1 digit[f]	
1983-85	.2856	.2019	.2555	.1559	.1585	.0545	.1230
1990-92	.2751	.1689	.2301	.1552	.1468	.0550	.1632
2000-02	.2454	.1396	.1885	.1546	.1088	.0253	.1807
%△ btw 83-85 and 00-02	−.141	−.309	−.263	−.008	−.314	−.546	+.469

Notes: Numbers in the table are R^2s of regression analysis of each explanatory variable on hourly wage. Source: Author's own calculation using the same data as Table 4.3.
(a) Three digit occupation code.
(b) Among college-graduate or more.
(c) Among high-school-graduate or less.
(d) Technician, Service, Precision Workers, and Laborers. Reference group is Manager/Professional.
(e) Three digit industry code.
(f) Manufacturing, Transportation, Sales, and Services. Reference group is Agri/Mining/Construction.
(g) High-school-graduate, some-college, BA, and graduate-degree. Reference group is less-than-high-school.

three-digit occupations yields an R-squared of .2856, while for 1990 to 1992 the corresponding R-squared for this model is .2751, and for 2000 to 2002, it is .2454. The R-squared of this model is down by 14.1 percent from 1983-1985 to 2000-2002. That is, the amount of between-occupational variance in wages declined over this period from .2856 to .2454, which implies that the amount of within-occupational wage variance (i.e., the additive reciprocal) increased from .7144 (in 1983 to 1985) to .7546 (in 2000 to 2002). In sum, Table 4.1 shows that three-digit occupations are becoming less predictive of wages and that about three-quarters of all of the variance in wages is currently within three-digit occupational categories.

When levels of employees' general skill, which is usually estimated by levels of Education, are controlled for, the decline of the explanatory power of occupation seems to be even more obvious. Among workers with at least a college degree, the amount of explained variance by occupation is .2019 in 1983-1985. This explanatory power is reduced to .1689 in 1990-1992 and further down to .1396 in 2000-2002. This decline represents a 30.9 percent decrease over this period. The similar amount of decreased explanatory power of occupation is observed among workers with a high school degree or less. The same model, which yields an R-squared of .2555 for 1983-1985, renders only an R-squared of .1885 for 2000-2002. That is, coefficients of determination for occupation on wages diminished by 26.3 percent for the given period.

Table 4.1 does show, however, that occupations do better than industries in explaining the variance in wages. The R-squareds for the model that uses dummy variables to indicate three-digit industries are substantially smaller than the R-squareds for the model that uses three-digit occupations. In making this comparison, however, it should be noted that the number of dummy variables used to indicate three-digit industries is about 235 (it varies slightly by year), which is significantly fewer than the 330 used to measure three-digit occupations. The regression model using more than 200 dummy variables to indicate detailed industries yields an R-squared of .1585 for 1983-1985. The R-squared is reduced to .1468 for 1990-1992 and reduced further to .1088 for 2000-2002. Only slightly more than 10 percent of the wage variation can be explained by industry type. Furthermore, the percentage decline in the

R-squared for the three-digit industry model is much greater than the decline in the R-squared for the three-digit occupation model, over this time period. Between 1983-1985 and 2000- 2002, the R-squared accounted for by detailed industries is down by more than 30 percent.

To compare the association between occupation and wage inequality with the association between education and wage inequality, I estimate a model of wages, which includes four dummy variables for occupation (listed in the column labeled "1-digit" in Table 4.1), and another model, which includes four dummy variables for the highest level of education completed (listed in the last column of Table 4.1). As shown in Table 4.1 for the 1983 to 1985 period, the R-squared for this one-digit occupation model is .1559, while the R-squared for the education model is .1230 for the same time period. For the 2000-2002 period, the R-squared for the occupation model is .1546, indicating little change from the earlier period. However, the R-squared for the education model for the 2000-2002 period increases to .1807. That is, when measured using the same number of dichotomous variables, the explanatory power of education is greater than occupation, at least in terms of predicting wages. There is now more variance in wages between broad educational categories than between broad occupational categories.

Sociologists have concentrated on occupational and industrial differences of wages in an effort to illustrate the organizational bases of stratification (e.g., Thurow 1975; Kalleberg et al. 1981; Jacobs 1985). According to this tradition, in addition to the individual sources of inequality caused by different levels of marginal productivity, organizational characteristics are predicted to create the other sources of wage inequality. And organizational sources of inequality cannot be reduced to individual sources. The findings of Table 4.1 suggest that the importance of occupation and industry as organizational sources of inequality has diminished in recent years.

Both occupation and education represent workers' skill levels. Thus, both wage differences by occupation and by education represent differentiated returns according to workers' skill levels. But the implications of these two wage gaps are different. The wage gap by education indicates individual differences, which become an individual source of inequality, while the wage gap by occupation signals positional differences beyond gaps due to individual difference of ability. Such a gap by occupation is acknowledged as a structural source of inequality. Especially when occupational wage differentials persist after controlling for education, a structural source of inequality is evident. The findings of Table 4.1 show that, in determining wages, the importance of structural position decreases, while the importance of individual difference becomes more powerful.

These findings, coupled with Hollister's (2004) finding that shows that the amount of variation explained by firm size is also down for the last two decades, implies that the rise of wage inequality parallels the decline of traditional structural sources of inequality. The decline of structural sources of inequality, however, does not indicate that a structural explanation is wrong. Instead, it suggests that rather than occupation or industry, which have traditionally been given attention, other structural sources might be becoming more important as structural determinants of wages.[2]

Regarding skills, education indicates workers' general skills and occupation signals workers' occupation-specific skills. Thus, the wage gap across education can be attributed to the differentiated return to general skills, which are mostly obtained in school, while the wage gap across occupations after controlling for education can be ascribed to the differentiated return to occupation-specific skills, which are mostly learned on the job. Therefore, the declining explanatory power of occupations coupled with the growing explanatory power of education on wages connotes that the effects of general skills have caught up with or overtaken the effects of occupation-specific skills .

Table 4.1 gives us additional understanding regarding the occupational bases of stratification. Grusky and Sørensen (1998) ask, "Does disaggregation greatly increase the explanatory power of class models?" (1222). Table 4.1 shows that 3-digit occupational categories explain wage inequality significantly better than one-digit occupational categories.[3] F-test statistic of the difference in explanatory power between a regression model with 1-digit occupation dummy variables a regression model with 3-digit occupation dummy variables is statistically significant at any conventional level. That is, at least in terms

[2] It is important to investigate the systematic study of this correlation between growing inequality and diminishing institutional effects on wages, but this topic is beyond the scope of my dissertation. Thus, I will limit my discussion to the relation between occupation and inequality.

[3] In other results, however, there is only modest improvement in the explanatory power of three-digit occupations relative to two-digit occupations (which are represented by only 44 occupational categories rather than the 331 occupational categories for the three-digit codes).

of wages, disaggregate structuration seems to improve the explanatory power of class models substantially.

Table 4.1 focuses on the contrast between 1983-1985, 1990-1992, and 2000-2002. In order to provide more information about the entire period, Figure 4.3 shows the R-squareds for each year in regression models of individual wages. The graph for all workers (as shown in the graph on the left side of Figure 4.3) again illustrates the basic pattern of a trend towards declining R-squareds across this time period, depicting regression models using 330 dummy variables to indicate occupation. This same basic downward trend is also evident among workers when they are broken down (in the same graph) by high-skilled (i.e., workers with a college degree or more) or by low-skilled (i.e., no more than a high school degree).

When broken down by gender, however, slight variations on this overall pattern are evident. For men, as shown in the graph in the middle of Figure 4.3, the R-squareds actually increase until the early 1990's and then begin declining after that. For both low skilled workers and high skilled workers, a similar trend is evident in Figure 4.3. The R-squareds for high-skilled male workers grew in the 1980s and it decreased in the 1990s. For low skilled workers, the R-squareds remained stable until the early 1990s and then started to go down after that. The R-squared for male workers is down for this period, when broken down by skill levels. For women, as shown in the graph on the right side of Figure 4.3, the general trend is downward, but the annual fluctuations are much larger during the 1990's (especially for low-skilled female workers).

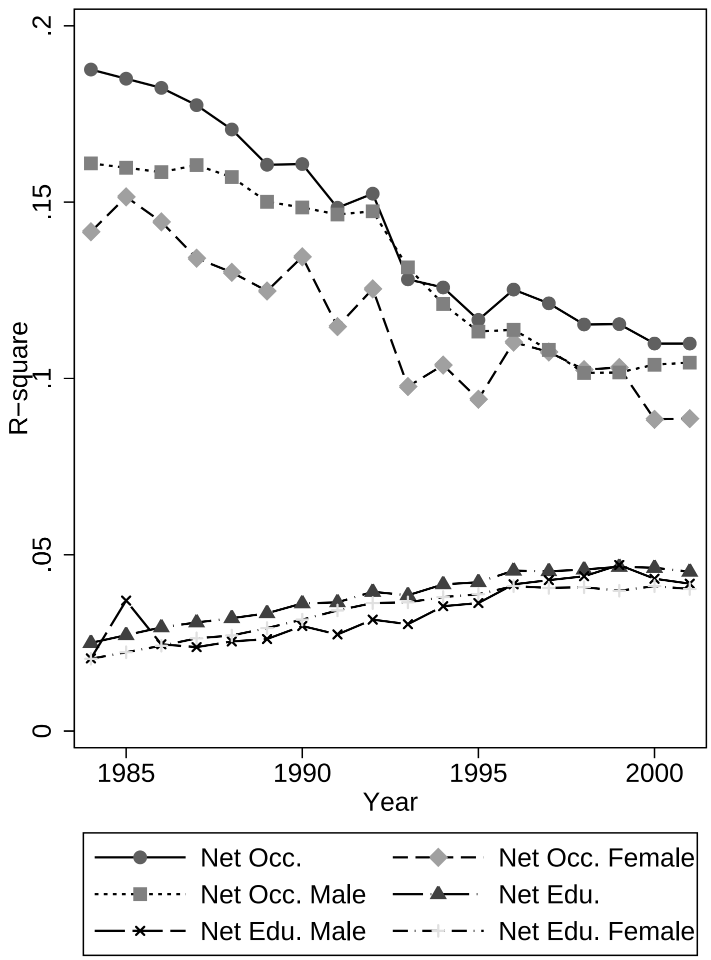

Figure 4.2: Incremental R-squared for Occupation and Education in Regression Models of Individual Wage

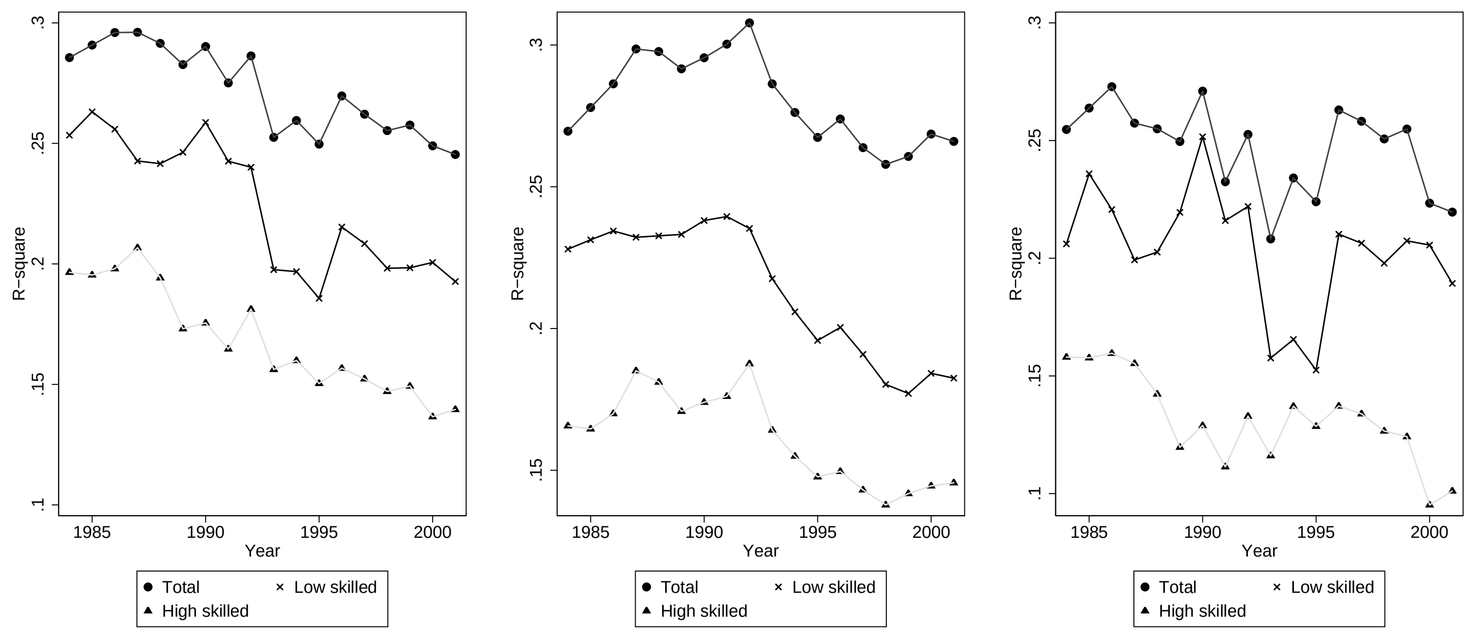

Figure 4.3: R-squared for Regressions of Individual Wage for Total Workers, Male Workers, and Female Workers

These fluctuations observed in Figure 4.3, however, disappear when we control for the effect of education. Figure 4.2 shows the incremental R-squareds of occupation and education in regression models of individual wages across this time period. Occupation is again indicated by 330 dummy variables, while education is indicated by 4 dummy variables (based on the same educational levels used in Table 4.1). Thus, the net occupational effect in Figure 4.2 refers to the R-squareds estimated by subtracting the R-squareds of the regression model with 4 educational dummy variables from the R-squared's of the regression model with 330 dummy occupational dummy variables in addition to 4 educational dummy variables (i.e., *Net Occupational Effect* $= R^2_{edu,occ} - R^2_{edu}$). The net education effect is calculated in the same way by subtracting the R-squareds of the model with 330 occupational dummy variables from the R-squareds of the model with both occupation and education dummies (i.e., *Net Educational Effect* $= R^2_{edu,occ} - R^2_{occ}$).

Not surprisingly, the incremental R-squareds are larger for occupation than for education, given the fewer degrees of freedom used in measuring the latter. However, the incremental R-squareds for occupation are clearly declining systematically in Figure 4.2, while the incremental R-squareds for education are slightly increasing over this time period. This same basic pattern is obvious for male workers separately, female workers separately, or for both genders combined.

In the meantime, occupation and industry are closely intertwined. Thus, it is possible that this declining explanatory power of occupation is the mere reflection of changing industrial mix. To check this possibility, I ran additional models that including three-digit industry dummies (about 300 industries) in addition to educational dummy variables and occupational dummy variables. Table 4.2 shows that even after controlling for industries, the same pattern of declining explanatory power of occupation is evident. Net of educational dummies, the incremental R-squared's of about 300 industry dummy variables have declined more than 50 percent for this period (from .1369 for 1983-1985 to .0601 for 2000-2002). This decline, however, does not fully account for the decline of incremental R-squared's of occupational variables. After controlling for education and industry variables, R-squared's of 330 occupational dummy variables was down 27.4 percent in 2000-2002 comparing to the R-squared for 1983-1985 (from .0930 for 1983-1985 to .0675 for 2000-2002).

In sum, the increase in within-occupational wage inequality is especially apparent after controlling for education and it is also evident even after controlling for industry. In other words, the effect of occupation, which represents one structural component of inequality, has a declining impact on wage inequality for this period. That is, the effects of occupation-specific skills are declining, while the effects of general skills are growing.

For explanatory purposes, I consider some additional statistics that provide a general description of the relation between wage inequality and occupational structure from 1983 to 2002. Table 4.3 shows the mean, standard deviation, and coefficient of variation of the socioeconomic index (SEI) scores for the labor force from 1983 to 2002. The SEI scores are based on the three-

Table 4.2: Incremental R-squared for Occupation, Industry, and Education in Regression Models of Individual Wage

	1983-1985	1991-1993	2000-2002
R^2_{edu} [a]	.1230	.1734	.1807
$R^2_{edu,ind}$ [b]	.2599	.2747	.2408
$R^2_{edu,ind,occ}$ [c]	.3529	.3600	.3083
Incremental R^2 of Industry			
$R^2_{edu,ind} - R^2_{edu}$	.1369	.1013	.0601
Percent Change from 1983-1985	n.a.	-26.0	-56.1
Incremental R^2 of Occupation			
$R^2_{edu,ind,occ} - R^2_{edu,ind}$	.0930	.0853	.0675
Percent Change from 1983-1985	n.a.	-8.3	-27.4

Notes: (a) R-squared of 5 educational dummy variables on hourly wage.
(b) R-squared of around 300 industrial dummy variables and 5 educational dummy variables on hourly wage. Each year has slightly different number of industries.
(c) R-squared of 330 occupational dummy variables in addition to 5 educational dummy variables and 300 industrial dummy variables on hourly wage.

digit occupation of the labor force for 331 occupations in the CPS-MORG over this time period. I estimated SEI following the method of Nakao and Treas (1994).[4] Nakao and Treas's (1994) SEI equation can be written as $SEI_j = 9.24 + .64(EDU_j) + .31(INCOME_j)$ where EDU_j refers to the percent of workers of college or more educated of occupation j and $INCOME_j$ refers to the percent of workers who earn more than 15,000 dollars a year in occupation j. In my calculation of SEI, I used the mean hourly wage instead of the percent of workers earning 15,000 dollars a year. Thus, my SEI is not exactly congruent with Nakao and Treas' SEI, but the SEI shown in Table 4.3

[4] Hauser and Warren (1997) also applied Nakao and Treas' method in their paper of the socioeconomic index.

Table 4.3: Descriptive Statistics for Socioeconomic Index for the Labor Force Employed in 331 Occupations, 1983-85 to 2000-02

Year	Mean	Standard Deviation	Coefficient of Variation
1983-1985	46.45	17.69	.3809
1984-1986	46.60	17.69	.3796
1985-1987	46.77	17.68	.3779
1986-1988	46.95	17.68	.3766
1987-1989	47.11	17.71	.3759
1988-1990	47.27	17.75	.3755
1989-1991	47.42	17.78	.3550
1990-1992	47.59	17.78	.3736
1991-1993	47.75	17.79	.3727
1992-1994	47.88	17.83	.3724
1993-1995	48.03	17.91	.3728
1994-1996	48.19	17.99	.3733
1995-1997	48.35	18.04	.3731
1996-1998	48.54	18.07	.3722
1997-1999	48.79	18.09	.3708
1998-2000	49.00	18.10	.3694
1999-2001	49.23	18.11	.3678
2000-2002	49.39	18.09	.3663
Total	47.85	17.87	.3735

Source: Author's own calculations using pooled CPS Merged Rotation Group (MORG) files. Statistics are based on three-year moving averages.
Note: Aged 18-65 employed workers only. Top coding is adjusted using the log normal distribution imputation method.

should be very similar to Nakao and Treas' SEI, given workers' hourly wages and their annual incomes are highly correlated.

The results in Table 4.3 indicate that, from 1983 to 2002, the mean SEI score increased from 46.45 to 49.39, while the standard deviation increased only slightly from 17.69 to 18.09. Inequality in the SEI scores, as measured by the coefficient of variation (i.e., the standard deviation divided by the mean), declined significantly from .3809 to .3663 over this time period.

As was discussed above, three-digit occupations are often implicitly assumed to be relatively homogeneous groups of workers with similar socioeconomic attainments (Grusky and Sørensen 1998; Weeden 2002; Grusky 2005). Based on the Durkheimian tradition, Grusky (2005) developed his theory that occupations represent *gemeinschaftlich* communities that are "destined to emerge at the site of production and shape individual values, life chances, and lifestyles" (55). He went on to say that since occupations work as a modern institution of closure and rent-extraction, occupations become the elementary unit of skill-based exploitation (74). Furthermore, because this exploitation is skill-based, Grusky argues, "inter-occupational differentials in earnings are typically regarded as acceptable, whereas intra-occupational differentials are closely scrutinized and are sometimes taken as evidence of discrimination" (75). According to Grusky's theory, it is hard to justify intra-occupational inequality, which should decline with the social development of anti-discriminatory movement. Indeed, he noted that "anti-discrimination legislation seeks to outlaw intra-occupational disparities in wages, whereas comparable worth legislation seeks to prohibit entrenched inter-occupational disparities"(75). Therefore, if inequality increases in a modern society, it would more likely be in the form of between-occupational rather than within-occupational inequality.

The results in Table 4.3 suggest, however, that the SEI scores of three-digit occupations do not accurately indicate the trend in aggregate wage inequality. As was previously discussed and as is evident in Figure 4.1, wage inequality has significantly increased in recent decades. However, Table 4.3

shows that, by contrast, *inequality in occupational SEI has actually declined.* Therefore, three-digit occupational SEI scores do not accurately predict increasing wage inequality over this time period because wages and SEI scores have opposing trends. This conclusion is generally consistent with my interpretation of Table 4.1. Sociologists' preoccupation with occupation perhaps helps to explain why they have not paid sufficient attention to increasing inequality; in terms of occupational status, inequality has actually not increased.

4.2 Decomposition Analysis

To estimate how much of the increase in inequality can be accounted for by inter-occupational inequality, I decompose diverse inequality indexes into between-occupational and within-occupational inequalities. Figure 4.4 shows the trends of decomposed Theil indexes with their combined total inequality index. The trend of total inequality of the Theil index in Figure 4.4 is congruent with the trend of the Gini index in Figure 4.1. The Theil was .166 in 1983-1985 and .198 in 2000-2002, which represents a 19.4 percent increase of inequality for this period. In Figure 4.4, then, both within-occupational inequality and between-occupational inequality show upward trends when total inequality is decomposed into within and between occupational inequality. Throughout the given period, within-occupational inequality dominates between-occupational inequality. The trend of within-occupational inequality determines the trend of total inequality. Between-occupational inequality does not have much of an effect on the trend of total inequality.

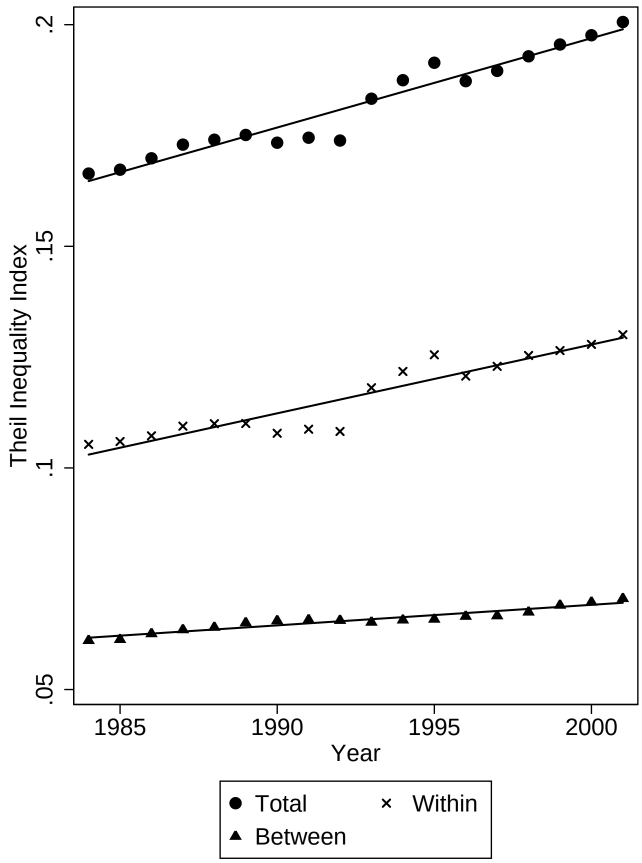

Figure 4.4: Theil Index of Wage Inequality from 1983-1985 to 2000-2002

Table 4.4: Hourly Wage Inequality: Between- and Within- Occupational Inequality[a]

	MLD[b]	Theil	HSCV[c]	AKI(.5)[d]	AKI(1)[d]	AKI(2)[d]
1983-1985						
Total	.16095	.16551	.21423	.07968	.15418	.29397
Between[e]	.06222	.06019	.06136	.02922	.05645	.10549
Within	.09873	.10532	.15287	.05046	.09773	.18848
% Within	(.613)	(.636)	(.714)	(.633)	(.634)	(.641)
1991-1993						
Total	.16881	.17385	.22942	.08360	.16147	.30572
Between	.06781	.06562	.06699	.03179	.06127	.11345
Within	.10100	.10823	.16243	.05181	.10020	.19227
% Within	(.598)	(.623)	(.708)	(.620)	(.621)	(.629)
2000-2002						
Total	.18426	.19762	.28461	.09394	.17778	.33017
Between	.07168	.06974	.07151	.03302	.06170	.10890
Within	.11258	.12788	.21310	.06092	.11608	.22127
% Within	(.611)	(.647)	(.749)	(.648)	(.653)	(.670)
% Change between 1991-93 and 2000-02						
Total	.09152	.13673	.24056	.12368	.10101	.07998
Between	.05707	.06279	.06747	.03869	.00702	-.04012
Within	.11465	.18156	.31195	.17583	.15848	.15083
% Within	(.750)	(.827)	(.918)	(.881)	(.974)	(1.186)
% Change between 1983-85 and 2000-02						
Total	.14483	.19401	.32853	.17900	.15301	.12314
Between	.15204	.15866	.16542	.13005	.09300	.03233
Within	.14028	.21420	.39400	.20729	.18776	.17397
% Within	(.594)	(.703)	(.856)	(.734)	(.778)	(.906)

Sources: Author's own calculation using pooled CPS Merged Outgoing Rotation Group (MORG) files. Aged 18-65 employed workers only. Top coding problem is adjusted using the log normal distribution imputation method. Less than 50 cents an hour after the adjustment to 2002 constant dollar using CPI-X is trimmed.

[b] Mean Logarithmic Deviation

[c] half the square of the coefficient of variation

[d] Atkinson Index. Numbers in parenthesis are inequality aversion parameters.

[e] Three digit occupational code is used. Total number of occupations is 331. Calculation using two digit occupational code basically produces the same results.

Table 4.4 shows the levels of wage inequality in 1983-1985, 1991-1993, and 2000-2002 for MLD, the Theil index, HSCV, and the Atkinson index, with three different values of the inequality aversion parameter (i.e., 0.5, 1.0 and 2.0). Consistent with the results for the Gini index, as shown above in Figure 4.1, all of these other measures also indicate increases in wage inequality across this time period. For example, Table 4.4 shows that HSCV increased from .2142 in 1983-1985 to .2846 in 2000-2002 (an increase of 33 percent). In addition to the general trend of inequality, Table 4.4 shows the decomposition of each inequality measure into between- and within-occupational inequalities using the 331 three-digit occupational categories (except for the Gini index which cannot be uniquely decomposed). The results shown in Table 4.4 indicate that for each of the inequality measures, in either 1983-1985, 1991-1993, or 2000-2002, within-occupational inequality is clearly greater than between-occupational inequality.[5] For example, in 1983-1985, the within-occupational component for the Theil index is .1053 while its between-occupational component is .0602 which together equal the (overall) value for the Theil index of .1655. As is also shown in Table 4.4, these numbers imply that 64 percent of the wage inequality in 1983-1985, according to the Theil index, is within occupations.

Table 4.4 furthermore shows the decomposition in terms of the increase in inequality for each measure between 1983-1985 and 2000-2002. For each measure, the bottom row of Table 4.4 shows that most of the increase in in-

[5]Previous studies (Jenkins 1999; NRC 1999) also find that there is more inequality within occupations than between occupations.

equality over this time period has occurred within the 331 occupations. The lowest figure is for MLD, indicating that 59 percent of the increase in inequality was within occupations. The highest figure is for the Atkinson index, with ε=2.0, indicating that 91 percent of the increase in inequality was occurring within occupations. During the 1990's within-occupational inequality grew even faster. The MLD shows that 75 percent of the increase occurred within-occupation, which is the lowest of all inequality indexes used. For the Atkinson index, where ε=2.0, the entire increase in inequality is attributable to the rise of within-occupational inequality during the 1990s. Between-occupational inequality measured by Atkinson (ε=2.0) has decreased by 4 percent, while the total inequality has increased by 8 percent. Thus, the 15 percent increase in within-occupational inequality just offsets the decrease in between-occupational inequality.

Diverse inequality indexes reported in Table 4.4 allow us to infer at which parts of the wage distribution within-occupational inequality grows faster. As discussed in Chapter 3.3, among Entrophy inequality indexes, HSCV is more sensitive to transfers at the upper end of the distribution, MLD is more sensitive to transfers at the lower end of the distribution, while Theil is evenly sensitive to all parts of the distribution. The amount of the growth of total inequality is the greatest for HSCV and the lowest for MLD. Furthermore, HSCV shows greater growth of the share of within-occupational inequality than MLD. That is, inequality grows faster at the upper end of the wage distribution where within-occupational inequality grows faster. Thus, the fact

Table 4.5: Proportion of Within-Occupational Inequality in Total Inequality

	MLD	Theil	HSCV	AKI(.5)	AKI(1)	AKI(2)
High School Graduate or less						
1983-1985	.670	.687	.743	.680	.675	.668
1991-1993	.693	.711	.769	.702	.696	.688
2000-2002	.723	.745	.811	.738	.735	.728
College Graduate or more						
1983-1985	.742	.756	.806	.748	.741	.730
1991-1993	.738	.758	.820	.748	.737	.720
2000-2002	.783	.806	.866	.796	.787	.770

that HSCV shows more relative growth of within-occupational inequality indicates that heterogeneity among workers with the same occupation is larger within high-income occupations. The increase of heterogeneity of wages among workers with the same occupation implies that occupations have become less gemeinschaftlish, especially among high-wage occupations. Atkinson indexes, which are based on social welfare theory, also show similar trends. As the inequality aversion parameter increases, Atkinson indexes become more sensitive to the upper end of the wage distribution. As shown on the last row of Table 4.4, as the inequality aversion parameter increases, so do the percents of inequality Change, due to the increase of within-occupation inequality.

It is evident in Table 4.4 that most of the increase in wage inequality from 1983-1985 to 2000-2002 has occurred within occupations. This trend, however, is not uniform for both the 1980's and the 1990's. As seen in Table 4.4, compared to 1983-1985, the proportion of within-occupational inequality decreased in 1991-1993. For example, the proportion of within-occupational inequality, as shown by a Theil of .636 for 1983-1985, drops to .623 for 1991-1993.

This decrease is consistent across all measures. Does this finding imply that the 1980's can be characterized as a period of growing between-occupational inequality and the 1990s as a period of growing within-occupational inequality? The results shown in Table 4.5 show that this may not be likely. When broken down by educational level, every inequality measure among workers with a high school degree or less demonstrates that within-occupational inequality grew faster than between-occupational inequality throughout both the 1980's and the 1990's, resulting in a growing share of within-occupational inequality. For Theil, the proportion of within is up to .711 in 1991-1993 from .687 in 1983-1985 and up again to .745 in 2000-2002. Among highly educated workers, the trends look rather mixed. What is clear is that inequality measures do not unanimously decline during the 1980s, as shown in Table 4.4. These findings are consistent with what we found in Figure 4.3 and Figure 4.2. The trends of the explanatory power of occupation seem mixed for the 1980's and 1990's at first, but when we control for education, the explanatory power of occupation, which is measured by either R-squareds or portions of between-occupational inequality, is falling continuously for these two decades.

These descriptive results indicate that, even at the detailed level of 331 occupational categories, wages are becoming less closely associated with occupation. Although wage inequality has been systematically and significantly growing, this increase is not at all operating through increasing inequality in the distribution of occupational status. Rather, most of the increase in wage inequality has occurred within occupations. Although most of the wage inequality was already within-occupational in 1983-1985, the percentage that is within-occupational has continued to grow, as inequality has increased over this time period.[6] Thus, as a bivariate association, wages are becoming increasingly decoupled from occupation.

4.3 Summary and Discussion

In sum, the findings of bivariate associations indicate that occupations are becoming less directly associated with wages, even when using a large number (i.e., 331) of detailed occupational categories, as suggested by the "disaggregate structuration" approach. From 1983 to 2002, the between-occupational variance declined, while the within-occupational variance increased to approximately three-fourths of the total variance. In terms of the decomposition of measures of inequality, five out of the six measures show an increase in the proportion of wage inequality that is within occupations (i.e., to about 65 percent or 75 percent) over this time period. Furthermore, all of the measures indicate that most of the increase in wage growth over this time period was within occupations. These results show that increasing within-occupational wage inequality is generally consistent with the basic conclusion of Table 4.3, which indicates that inequality in occupational status has actually not increased over this period (despite increases in wage inequality of 12 percent to 33 percent, according to the results in Table 4.4).

[6]The only exception is MLD for which the percentage within declined very slightly over this time period.

These findings provide some implications for "disaggregate structuration." As noted earlier, Grusky and Sørensen (1998:1191) claim that detailed occupations are, among other things, "positional sources of exploitation and inequality." My results indicate, however, that most of the wage inequality is within detailed occupational categories and that most of the growth in wage inequality has been within them as well. In other words, most wage inequality cannot be directly explained by detailed occupations, and occupations are increasingly becoming decoupled from wages. These findings therefore do not support the strong version of the "disaggregate structuration" view.

I suggested earlier that a weaker form of "disaggregate structuration" assumes that occupations may still be seen as fundamental if they remain a useful unit of analysis in explaining wage inequality, even if statistically there is more variance in wages within rather than between detailed occupations. Evaluating this weaker form of "disaggregate structuration" is more a matter of opinion regarding what constitutes being "useful," but I suggest that the explanatory power resulting from the use of detailed occupations as the unit of analysis in predicting wage inequality is far from conclusive. While I do not doubt that occupations have and will continue to serve important roles in both descriptive and analytical studies of social inequality and stratification, my results nonetheless do not support taking this usefulness to its logical extreme by postulating that detailed occupations represent the only important feature of the class structure and that they override the need to theoretically incorporate other, perhaps equally important, labor market variables.

Chapter 5

WITHIN-OCCUPATIONAL INEQUALITY

5.1 Changes of Mean Wage and Wage Inequality by Occupation

Before estimating causes of growing inequality, we need to see if there is enough variation in changes of inequality across occupations. If within-occupational inequality increases (or decreases) equally in every occupation, then different characteristics of different occupations are not very useful in explaining the growth of within-occupational-inequality. Previous studies find that within all age groups, all cohorts, both genders, and even all industrial sectors, within-group inequalities grew in the last couple of decades. Thus, different group characteristics within these categories do not provide much insight about what causes the rise of inequality.

Table 5.1 shows the cross-tabulation of changes in the mean wage and in wage inequality by occupation. In order to construct this table, I estimate a simple regression model, $INEQ_{jt} = \beta_{0j} + \beta_{1j} YEAR_t + \varepsilon_{jt}$, where $INEQ_{jt}$ refers to the Gini index of occupation j at time t, β_{0j} refers to the baseline Gini index of occupation j in 1983-1985, β_{1j} refers to yearly change in inequality over time, $YEAR$ refers to time, and ε_{jt} refers to the error term.

In Table 5.1, decreases in inequality represent the number of cases where the slope coefficient $\hat{\beta}_{1j}$ is negative and statistically significant at α=.05, while increases in inequality represent the number of cases where the slope coefficient is positive and statistically significant. No change in inequality is seen where $\hat{\beta}_{1j}$ is not statistically significant at α=.05. Changes in the mean wage by occupation were ascertained in a similar manner using the same simple regression except that, in this case, mean wage serves as the dependent variable. Table 5.1 thus reports the results of 331 regression models using within-occupational Gini indexes as dependent variables and another 331 regression models using occupational mean wages as dependent variables.

The cross-tabulations shown in Table 5.1 indicate significant variation across three-digit occupations in the patterns of annual change in mean wage and in wage inequality over this time period. One common pattern is no change in mean wage but an increase in wage inequality (i.e., 47 occupations, which employed 25 percent of all workers in the sample in 2002). Another 43 occupations (employing 17 percent of all workers) experienced an increase in

Table 5.1: Changes of Average Wage and Inequality Within Occupations

		Mean Wage[b]			Total
		Decrease	No Change	Increase	
Inequality[c]					
	Decrease	38	24	5	67
		(.123)	(.096)	(.011)	(.229)
	No Change	49	63	34	146
		(.103)	(.088)	(.100)	(.291)
	Increase	28	47	43	118
		(.059)	(.254)	(.167)	(.480)
Total		115	134	82	331
		(.285)	(.438)	(.278)	(1.000)

[a] Source: Author's own calculation using pooled CPS Merged Outgoing Rotation Group (MORG) files. Same as Table 4.3. Numbers in the tables are number of occupational categories. Numbers in parenthesis are share of workers in 2002.
[b] Mean hourly wage
[c] Gini index

mean wage as well as an increase in wage inequality. In terms of the number of occupations, the most common pattern is no change in either mean wage or in wage inequality (i.e., 63 occupations), although these occupations employed only 9 percent of workers. Employing 23 percent of workers, a total of 67 occupations experienced a decline in wage inequality, of which 38 also experienced a decline in mean wage. On the other hand, another 48 percent of workers, a total 118 occupations, underwent an increase in wage, of which 43 occupations also experienced an increase of mean wage. In sum, Table 5.1 shows that occupations vary significantly in terms of the variation and patterns of changes in mean wages and in wage inequality over this time period. The sources of these differences merit more detailed multivariate analysis.

Figure 5.1 shows associations between changes of mean wages and changes of inequalities between 1983-1985 and 2000-2002 by one digit occupation (8

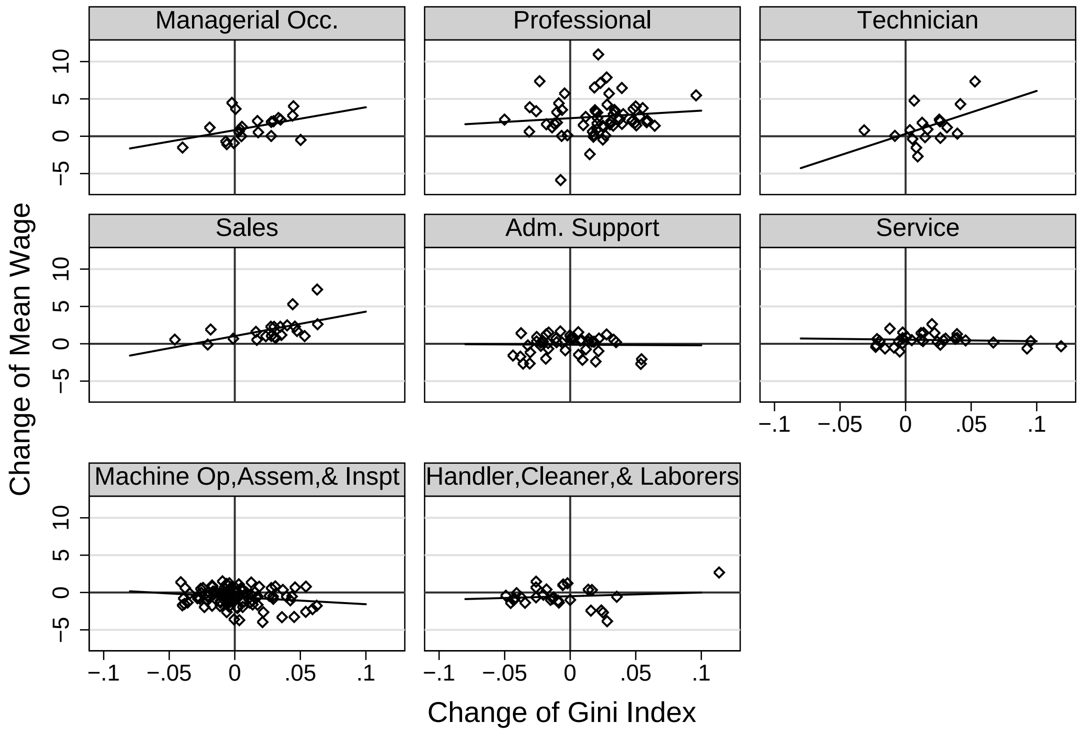

Figure 5.1: Change of Hourly Wage Inequality between 1983-85 and 2000-02

categories). Each dot in Figure 5.1 represents one occupation of 331 detailed occupational categories. The x-axis scales the change of the within-occupational Gini index between 1983-1985 and 2000-2002, and the Y-axis scales the change of the dollar amount of mean wages (2002 constant dollars). For example, the middle graph on the first row shows the associations of changes of mean wage and inequality among professional occupations. The majority of the dots are located in the right upper corner of the graph, indicating that in most professional jobs both mean wages and inequality grew during this period. The graph on the right graph on the second row shows the pattern of association within service occupations. Many service jobs experienced an increase in within-occupational inequality, but their mean wages do not change significantly. Summarizing Figure 5.1, managerial, professional, technical, and sales occupations seem to show positive associations between mean wages and inequality, while the other occupations appear to exhibit no clear associational pattern.

If we break down Table 5.1 into these broad occupational categories,[1] there are more interesting findings. Among 81 managerial and professional occupations, 46 occupations show an increase in inequality, and only 6 occupations show a decrease in inequality. Among those 46 occupations, the mean wages of 23 occupations increase, and the mean wages of 18 occupations do not show a significant change. Thus, it seems that both mean wages and inequality have increased in managerial and professional occupations. If we distinguish between managerial and professional occupations, however, we find that this positive association between mean wage and inequality is found only for professional jobs. Among executive administrative and managerial occupations, inequality increases in most occupations, while their mean wages do not go up at the same time.

Technical occupations also experience the similar pattern as executive administrative and managerial occupations. Administrative support occupations seem to have experienced reduced inequality but at the cost of a de-

[1]See Appendix Table C.1 for detail information.

creased mean wage. Seventeen occupational categories out of 47 show decreased mean wages, and 18 occupations show decreased inequalities. Unlike technical occupations, service occupations tend to show increased inequality with the increase of mean wage, which is a similar pattern observed in professional occupations.

Precision production and craft jobs seem to undergo the decrease of mean wages and the increase of inequalities. Thirty-one out of sixty-four occupations within these categories show a decrease in mean wages, while only nine occupations show a decrease in inequality. Operators, fabricators, and laborers also show downward equalization, similar to administrative support occupations. In these job categories, both the mean wage and inequality have decreased.

In sum, we can classify occupations into three broad groups according to their patterns of association between changes of inequality and mean wage. The first is upward polarization. Professional, sales, and service occupations are likely to show increased inequality with a higher mean wage. The second is polarization without changes of mean wage. Executive, administration and managerial workers, technicians, and precision production and crafts workers tend to experience increased inequality, which is not necessarily accompanied by an increase in the mean wage. The third pattern is downward equalization. Administrative support workers and low skilled laborers are likely to show lowered mean wages with decreased levels of inequality. In sum, although overall inequality has increased in the last two decades, there are substantially large variations in the changes in within-occupational inequality and mean wage across occupations. Understanding the factors causing such differences will merit sociological investigating in the studies of growing inequality.

5.2 Causes of Within-Occupational Inequality

5.2.1 Descriptive Analysis

Table 5.2 and Table 5.3 show changes of descriptive statistics between 1983-1985 and 2000-2002. The former table shows changes of demographic and social variables for this period among 'inequality-growing occupations' (118 occupations out of 331 detail occupations) and 'inequality-declining occupations' (67 occupations). Inequality growing or declining occupations are determined according to the results of a regression model used for Table 5.1. Table 5.3 displays changes in demographic and social variables for the same period by 'high-inequality occupations' (44 occupations) and 'low-inequality occupations' (49 occupations). High-inequality occupations refer to the occupations in which a group mean of within-occupational Gini across time is higher than one standard deviation above the grand mean of Gini (the grand mean of Gini is .2471 and the standard deviation is .0477), and low-inequality occupations denote the occupations where a group mean of Gini is lower than one standard deviation below the grand mean. That is, I classified occupations by longitudinal directions of inequality changes in Table 5.2 and divided occupations by cross-sectional amounts of inequality in Table 5.3.

Table 5.2: Descriptive Statistics by Inequality Growing and Inequality Declining Occupations

	Among Occupations with Decreased Inequality (67 Occupations)			Among Occupations with Increased Inequality (118 Occupations)		
Variable	1983-85	2000-02	Change	1983-85	2000-02	Change
Female	.3974	.4252	+.0278	.5201	.5184	−.0017
	(.3232)	(.3151)		(.3289)	(.2722)	
Black	.1382	.1488	+.0106	.0737	.0939	+.0202
	(.0666)	(.0525)		(.0459)	(.0448)	
Hispanics	.0777	.1660	+.0883	.0435	.0729	+.0294
	(.0324)	(.0807)		(.0289)	(.0445)	
Other Races	.0226	.0387	+.0161	.0273	.0518	+.0245
	(.0086)	(.0177)		(.0188)	(.0356)	
BA+	.0690	.0937	+.0247	.3504	.4331	+.0827
	(.1024)	(.1309)		(.2940)	(.2827)	
Edu. Div.	.6381	.6378	−.0003	.6412	.6391	−.0021
	(.0333)	(.0316)		(.0951)	(.1076)	
South	.3458	.3633	+.0175	.3248	.3456	+.0208
	(.0453)	(.0357)		(.0508)	(.0368)	
Public Sector	.1249	.1109	−.0140	.2334	.2126	−.0208
	(.1773)	(.1851)		(.2899)	(.2860)	
Part Time	.1993	.1609	−.0384	.1448	.1209	−.0239
	(.1570)	(.1222)		(.1602)	(.1217)	
Union	.2622	.1530	−.1092	.2097	.1594	−.0503
	(.1184)	(.0851)		(.2200)	(.1944)	
Manufacturing	.3296	.2487	−.0809	.2073	.1534	−.0539
	(.3022)	(.2923)		(.2618)	(.2163)	

Table 5.3: Descriptive Statistics by Occupations with High Level and Low Level Inequality

	Among Occupations with High Inequality Level (44 Occupations)			Among Occupations with Low Inequality Level (49 Occupations)		
Variable	1983-85	2000-02	Change	1983-85	2000-02	Change
Female	.3898	.4470	+.0572	.6347	.6392	+.0045
	(.2080)	(.1706)		(.3513)	(.3095)	
Black	.0612	.0778	+.0166	.1282	.1403	+.0121
	(.0670)	(.0284)		(.0717)	(.0577)	
Hispanics	.0364	.0717	+.0353	.0700	.1408	+.0708
	(.0209)	(.0509)		(.0394)	(.1010)	
Other Races	.0221	.0448	+.0227	.0349	.0595	+.0246
	(.0169)	(.0266)		(.0186)	(.0217)	
BA+	.4001	.4519	+.0518	.0981	.1446	+.0465
	(.2016)	(.1957)		(.1565)	(.1958)	
Edu. Div.	.6960	.6819	−.0141	.6146	.6149	+.0003
	(.0980)	(.1173)		(.0373)	(.0532)	
South	.3352	.3504	+.0152	.3476	.3520	+.0044
	(.0417)	(.0330)		(.0890)	(.0590)	
Public Sector	.0962	.0826	−.0136	.1338	.1178	−.0160
	(.1523)	(.1281)		(.1972)	(.1996)	
Part Time	.1352	.1069	−.0283	.2618	.2224	−.0394
	(.1700)	(.1030)		(.1938)	(.1357)	
Union	.0820	.0620	−.0200	.2599	.1659	−.0940
	(.0817)	(.0772)		(.2183)	(.1718)	
Manufacturing	.1733	.1482	−.0251	.2344	.1467	−.0877
	(.1656)	(.1496)		(.3812)	(.3133)	

There are several notable differences between inequality-growing occupations and inequality-declining occupations. First of all, the proportion of female workers is up among inequality-declining occupations for this period while it is down among inequality-growing occupations. This result casts doubt about a hypothesis that female labor market participation increases inequality. The proportion of Hispanic workers increases more in inequality-declining occupations (8.8 percent point) than in inequality-growing occupations (2.9 percent point). Other demographic characteristics seem to change similarly for both occupational groups in Table 5.2.

Regarding educational variables, inequality-growing occupations consist of more educated workers than inequality-declining occupations. 35 percent of workers of inequality-growing occupations have a bachelor degree or more in 1983-1985, although only 6.9 percent of workers of inequality-declining occupations have the same level of education. Furthermore, over this time period, inequality-growing occupations gain an even greater percentage of workers with a bachelor degree or more than inequality-declining occupations. Thus, the educational gap between inequality-growing occupations and inequality-declining occupations has widened. Both occupational groups lose similar amounts of educational diversity for this period.

Another visible difference can be found in the change of union rates. While union rates drop in both occupational groups, the amount of drop is twice as big among inequality-declining occupations than among inequality-growing occupations. This result does not seem to be consistent with Hypothesis 3-A. A bigger decrease of union rates does not appear to yield a bigger growth of inequality. The pattern of change within the manufacturing sector is also not congruent with my expectation. The proportion of the manufacturing sector has decreased more among inequality-declining occupations than among inequality-growing occupations.

Comparison between occupations with high inequality levels and occupations with low inequality levels in Table 5.3 gives us some interesting insights. The proportion female has increased substantially more among high-inequality occupations (5.7 percent point) than among low-inequality occupations (.5 percent point) between 1983-1985 and 2000-2002. Coupled with the fact that % female grows more in inequality-declining occupations in Table 5.2, the finding in Table 5.3 implies that more female workers may decrease inequality rather than increases it.

The amount of changes of % highly educated workers is similar both in high-inequality occupations and in low-inequality occupations. The educational diversity of high-inequality occupations falls by .0141 points, while it does not change among low-inequality occupations. This difference of changes of educational diversity may simply reflect the fact that % BA+ is already high enough for high-inequality occupations in 1983-1985; thus, the increase of % BA+ makes educational diversity for high-inequality occupations smaller, mathematically.

The decline of % union is substantially larger among low-inequality occupations. Considering that inequality-declining occupations lose more %

union in Table 5.2, it is plausible that low-inequality occupations become lower-inequality because of the decline of unions. To test what I found in the descriptive statistics using multivariate analysis, I estimate multi-level growth models.

5.2.2 Multivariate Analysis: Multilevel Growth Models

Table 5.4 shows the estimates of the multi-level growth models of the occupation-specific Gini index (which is multiplied by 100).[2] The results for the Baseline Model (i.e., equation 7, which does not include any substantive predictors) indicate that, across occupations, on average, wage inequality increased by .0491 points annually. This finding is generally consistent with the earlier results for the Gini index, as in Figure 4.1 (which is directly based on the entire sample of workers, however, without any occupations). The additional results that are obtained for the Baseline Model are the variations in the intercepts and slopes across the occupations. As reported in Table 5.4, the variance of the slopes across the occupations for the Baseline Model is .0286. Thus, within two standard deviations, the slopes range from $-.2891$ to .3873 (i.e., $.0491 \pm 2 \times \sqrt{.0286}$). Regarding the intercepts (i.e., the initial values of the Gini index in 1983-1985), the range is from 14.19 to 33.63, within two standard deviations (i.e., $23.9101 \pm 2 \times \sqrt{23.6162}$). The multi-level growth model, which can explain both the fixed structural component and the stochastic random component, is thus appropriate to employ given this variability in intercepts

[2] I also estimated these models using the different inequality indices discussed above and obtained similar results to those reported in Table 5.4, which is based on the Gini index.

Table 5.4: Models of Inequality Change over Time

	Base Model (Weight On)	Model 1 (Weight Off)	Model 2 (Weight On)[a]	Model 3 (Wt+Interact)
Intercept	23.9101***	16.1591***	16.6108***	16.3396***
Year	.0491***	-.0321	-.0489	-.0479
Slope Change by the Change of Proportion				
$\texttt{Female}_{jt}$		-.0219*	-.0470***	-.0483***
$\texttt{Black}_{jt}$		-.0201	-.0131	-.0141
$\texttt{Hisp}_{jt}$		.0169	.0022	.0029
$\texttt{Others}_{jt}$		-.0249	-.0237	-.0231
$\texttt{South}_{jt}$		.0536***	.0592***	.0600***
$\texttt{BA+}_{jt}$		-.0026	.0056	.0066
$\texttt{Edu.Div}_{jt}$		.0114	.0078	.0072
$\texttt{Public}_{jt}$		-.0241*	-.0535***	-.0532***
$\texttt{PartTime}_{jt}$		.0395***	.0131	.0410***
$\texttt{Union}_{jt}$		.0373***	.0294**	.0319***
$\texttt{Manuf}_{jt}$		-.0007	-.0079	-.0050
$\texttt{PartTime}_{jt} \times \texttt{Sales}_{j}$				-.0589**
$\texttt{PartTime}_{jt} \times \texttt{Service}_{j}$				-.0645***
Yearly Slope Change of Group Mean				
$\texttt{YEAR}_{t} \times \overline{\texttt{BA+}}_{j.}$		.0022***	.0023***	.0024***
$\texttt{YEAR}_{t} \times \overline{\texttt{Edu.Div}}_{j.}$		.0004	.0006	.0006
$\texttt{YEAR}_{t} \times \overline{\texttt{Public}}_{j.}$		-.0012*	-.0012*	-.0011*
$\texttt{YEAR}_{t} \times \overline{\texttt{PartTime}}_{j.}$		-.0009	-.0008	-.0010
$\texttt{YEAR}_{t} \times \overline{\texttt{Union}}_{j.}$		.0037***	.0036***	.0036***
$\texttt{YEAR}_{t} \times \overline{\texttt{Manuf}}_{j.}$		-.0010**	-.0011**	-.0010**
Effect of Group Mean				
$\overline{\texttt{Female}}_{j.}$		-.0293*	-.0032	-.0059
$\overline{\texttt{Black}}_{j.}$		-.0136	-.0220	-.0185
$\overline{\texttt{Hispanic}}_{j.}$		.0287	.0455	.0370
$\overline{\texttt{Others}}_{j.}$		-.2150*	-.2226*	-.2213*
$\overline{\texttt{South}}_{j.}$		-.0462	-.0575†	-.0609†
$\overline{\texttt{BA+}}_{j.}$		.0795***	.0700***	.0648***
$\overline{\texttt{Edu.Div}}_{j.}$		.1285***	.1288***	.1344***
$\overline{\texttt{Public}}_{j.}$		.0054	.0345*	.0342*
$\overline{\texttt{PartTime}}_{j.}$		.0696**	.0932***	.1147***
$\overline{\texttt{Union}}_{j.}$		-.1001***	-.0905***	-.0957***

Continued on next page

Table 5.4, cont.

	Base Model (Weight On)	Model 1 (Weight Off)	Model 2 (Weight On)^a	Model 3 (Wt+Interact)
			Continued from previous page	
$\overline{\texttt{Manuf}}_{j.}$		-.0122	-.0033	-.0057
σ^2_{int}	23.6162***	16.3954***	16.3422***	15.5909***
$\sigma_{int,t}$	-.2207***	-.2942***	-.2577***	-.2352***
σ^2_t	.0286***	.0233***	.0218***	.0207***
$\sigma_{toep(2)}$	.0010***	.8176***	.0009***	.0009***
σ^2_e	.0022***	1.9646***	.0022***	.0022***
r^2_{int} ^{b}		.3336	.3080	.3398
r^2_t ^{c}		.2862	.2370	.2755
-2LL	21746.1	21433.1	19752.5	19502.0
AIC	21760.1	21503.1	19762.5	19576.0
BIC	21786.7	21636.1	19781.5	19716.7

Note: (a) Weight variable is share of occupations at given years.
(b) Pseudo-R^2 (PRE) calculated by $(\sigma^2_{int,BaseModel} - \sigma^2_{int,FullModel})/\sigma^2_{int,BaseModel})$
(c) Pseudo-R^2 (PRE) calculated by $(\sigma^2_{t,BaseModel} - \sigma^2_{t,FullModel})/\sigma^2_{t,BaseModel})$
$^\dagger < .10$, $^* < .05$, $^{**} < .01$, $^{***} < .001$

and slopes.

Model 2 in Table 5.4 shows the results of the estimation of the equation 3.11.[3] An increase in the proportion female in an occupation (i.e., an increase of 1 percentage point) reduces growth in wage inequality (as measured by the Gini index) in that occupation by .0470, net of the other variables. This net effect is statistically significant at the .001 level and is obtained from Model 2, which also controls for several occupation-specific group means (which are defined as being constant over this time period). Thus, this estimated effect

[3]In the estimation of my growth models, I weigh each occupation by the proportion of the total sample of workers that is employed in the particular occupation. Unweighted results are available upon request from the author, although the unweighted results are generally very similar to the weighted results that I report.

is net of the overall average proportion of female workers in an occupation and therefore indicates that occupations that experienced increases in female workers actually had less inequality growth over this time period. This finding is inconsistent with Hypothesis 1-A, which predicts that increases in female employment would increase the growth of wage inequality.[4]

Although not shown in Table 5.4, I estimated another specification that included a quadratic term for the proportion female. The coefficient for this term was positive, indicating that the negative effect of the proportion female declines as the proportion increases. Using this model, I calculated the net effect of an increase of 1 percentage point in female employment for occupations where the proportion female is 90 percent and for occupations where the proportion female is 10 percent. In both cases, the net effects are still negative and are thus consistent with the basic result given by Model 2 in Table 5.4.

Another statistically significant result in Model 2 in Table 5.4 is the net effect of employment in the public sector. A 1 percentage point increase in public sector employment in an occupation reduces growth in within-occupational inequality by .0535, net of the other variables. Furthermore, the interaction between year and public sector employment is statistically significant in Model 2, indicating that inequality in the public sector is declining (after controlling for the other variables) over this time period. This interaction coefficient indicates that within-occupational wage inequality decreases by .0012 per year without changing the proportion of public sector employment.

[4]Cancian and Reed (1999) similarly find that the increase in female labor force participation has reduced household income inequality.

In contrast to public sector employment, employment in manufacturing does not have a direct net effect on growth in within-occupational inequality, according to the results for Model 2. The coefficient for manufacturing is not statistically significant. This finding is inconsistent with Hypothesis 2-A, which predicts that increases in manufacturing employment reduce growth in wage inequality. Also noteworthy is that there is no statistically significant net effect of the mean level of manufacturing employment, indicating that, net of the other variables, occupations with more manufacturing employment are not more equal during this time period. Although the interaction between year and the mean level of manufacturing employment is statistically significant, this negative effect indicates a temporal reduction in the level of inequality within the manufacturing sector, which has not been the major concern of the deindustrialization argument.

The net effect of unionized employment is a statistically significant predictor of growth in within-occupational inequality. A 1 percentage point increase in unionized employment increases growth in the occupation-specific Gini by .0294. This finding is inconsistent with Hypothesis 3-A, which predicts that increases in unionized employment reduce wage inequality. Furthermore, the coefficient for $\texttt{YEAR} \times \overline{\texttt{Union}}$ is statistically significant and positive, indicating that wage inequality within the unionized sector increased over this time period. Although the net effect of $\overline{\texttt{Union}}$ is statistically significant and negative, this result only shows that inequality tends to be lower in occupations where union membership is high for any given year.

Considering unions have long been viewed as an inequality reducing institution, this positive effect of unions is surprising. This finding surely needs further consideration. Unions can reduce inequality either by lowering the dispersion of earnings among their members or by increasing wages of less-skilled workers. On the other hand, unions can increase inequality by alienating non-union members and exclusively increasing union members' wages (monopoly rents). Only if the inequality reducing function of unions outweighs the inequality-enhancing function of unions can unions serve as an equalizing institution. Table 5.5 demonstrates that the inequality reducing function of unions has substantially weakened during this period. Inequality has grown faster among union members than among non-union members during this period. The Theil index gains .04403 (from .18642 to .21246) among union members, which is almost twice as large as the index among non-union members where the Theil index increases by .02604 (from .09092 to .13495). In both groups, within-occupational inequality dominates between-occupational inequality.[5]

Furthermore, unions fail to increase the wages of their members as much as non-union members. In every educational group, the amount of increase in the mean wage of union members for the given period is smaller than that of non-union members. The wage drop for the less than high school educated union workers is especially substantial ($3.19 per hour). Less educated union

[5]Additionally, it is worth mentioning that for non-union members, within-educational inequality does not increase as much as within-occupational inequality. Rather, between-educational inequality has grown faster among non-union members over this period.

Table 5.5: Change of Theil Inequality Index by Union and Non-union members of Private Sector

	Among Non-union Members			Among Union Members		
	1983-85	2000-02	Change	1983-85	2000-02	Change
Theil Inequality Index						
Theil	.18642	.21246	.02604	.09092	.13495	.04403
Within Occ.	.11185	.13338	.02153	.06355	.09815	.03460
Between Occ.	.07457	.07908	.00451	.02736	.03680	.00944
Within Edu.	.15136	.15526	.00389	.08725	.11921	.03195
Between Edu.	.03505	.05719	.02214	.00366	.01573	.01207
Less than High.	.12969	.09792	-.03177	.08456	.10045	.01589
High Sch.	.13922	.13144	-.00778	.08334	.09656	.01322
Some Col.	.16910	.16092	-.00818	.09747	.10026	.00279
BA	.16538	.17662	.01124	.13477	.19095	.05618
Grad.	.16007	.17716	.01709	.13496	.14281	.00785
MeanWage by Education						
Less than High.	10.1599	9.5230	-.6369	15.8919	12.7001	-3.1917
High Sch.	12.1974	12.6746	.4771	17.7863	16.3651	-1.4212
Some Col.	13.8975	14.5969	.6993	18.8358	18.1926	-.6431
BA	20.4240	23.2699	2.8458	21.4531	23.2692	1.8161
Grad.	25.0896	30.3405	5.2508	24.0326	26.4018	2.3692

members still earn more hourly wages than non-union members for 2000-2002, but the mean wage gap between union and non-union members has substantially narrowed. This implies that the spillover effect of unions likely did not take place. Benefits of being a union member have been cut, and thus employers receive much less pressure from unions to raise non-union members' wages to prevent unionization. What is worse for unions is that the decline of wages of less educated union members comes with an increase in within-group inequality. Among union members of both the less than high school educated and high school graduates, within-group inequalities have grown, while among non-union members, within-group inequalities for the same groups have decreased. Strikingly, among the less than high school educated, the Theil for union members is higher than the Theil for non-union members. It is no longer undoubtfably true that among union members the coefficients for education predicting wages is lower and the variance within the same educational groups is lower too (Freeman 1980). Rather, it seems that the norms in wage determination among unions is shifting towards an acceptance of more inequality among members (Mitchell 1985). In sum, the net effect of union membership on inequality is not negative but positive, mainly because of the increase in inequality among union members themselves.

Going back to multilevel models, the results in Table 5.4 provide some qualified support for Hypothesis 4-A that insecure employment relations, which are measured in terms of part-time employment, increase the growth in within-occupational inequality. Although the net effect of part-time employment is not statistically significant in Model 2, which is weighted by the share of occupation, it is highly significant in Model 1, which is unweighted. The coefficient of part-time is the only coefficient that is meaningfully altered by weighting. Thus, I investigate an additional specification that is shown as Model 3 in Table 5.4. Model 3 includes interaction terms between part-time employment and sales occupations and between part-time employment and service occupations.[6] In contrast to Model 2 and consistently with Model 1, the "main

[6] I also tested the effect of other interaction terms with part-time, but only two interaction terms introduced in Model 3 are significant.

effect" for part-time employment is highly positive and statistically significant in Model 3 after the addition of these two interaction terms.

These results for Model 3 in Table 5.4 show that outside of sales and service occupations, a 1 percentage point increase in part-time employment increases growth in wage inequality by .0410. In sales occupations, however, a 1 percentage point increase in part-time employment increases growth in inequality by $.0410 - .0589 = -.0179$. In service occupations, a 1 percentage point increase in part-time employment increases growth in inequality by $.0410 - .0645 = -.0235$. That is, in sales and service occupations, increases in part-employment lead to reductions in wage inequality. Union membership among sales and service workers is relatively rare, so increases in part-time employment in these occupations may serve to force down the wages of full-time sales and service workers (holding constant the other variables), resulting in reduced within-occupational inequality.

In sum, increases in part-time employment increase growth in within-occupational wage inequality in occupations other than sales and services. This finding supports Hypothesis 4-A, except for sales and service occupations. In terms of cross-sectional differences in occupational wage inequality, the net effect of the group mean for part-time employment is highly positive and statistically significant. This latter finding indicates that occupations with higher levels of part-time employment tend to be more unequal.

The net effects of the educational variables do not support Hypothesis 5-A, which is derived from the skill biased technological change (SBTC) view. In contrast to Hypothesis 5-A, the results for both Model 2 and Model 3 in Table 5.4 indicate that increases in the educational diversity index and in the proportion of workers with a college degree do not increase the growth of within-occupational wage inequality, as their coefficients are not statistically significant.[7] Contrary to much discussion in the economics literature, as mentioned earlier, increases in the dispersion in educational attainments do not appear to have a net effect on the growth in occupation-specific wage inequality. Furthermore, there is no additional net effect of changes in the proportion of workers who have at least a four-year college (i.e., B.A.) degree.

In addition, the coefficient for $\texttt{YEAR} \times \overline{\texttt{Edu.Div}}$ is not statistically significant, which is also contrary to the SBTC view. The latter contends that the return to having a college degree has increased in recent years, as highly skilled workers have become more valuable to employers. This argument implies that the average inequality in educational attainments should be increasing in its net effect over time, as the differential between the marginal revenue products of highly educated workers and poorly educated workers widens. This prediction is not borne out, however, because the coefficient for the interaction between year and the mean educational diversity index is not statistically significant in either Model 2 or Model 3 in Table 5.4.

The coefficient for $\texttt{YEAR} \times \overline{\texttt{BA+}}$ (i.e., the interaction between year and the mean proportion of college-educated workers) is statistically significant and

[7]Note that the removal of one of these two variables does not result in the other becoming statistically significant. That is, the lack of statistical significance for these two variables does not reflect multicollinearity.

positive, but this finding does not actually represent clear evidence in favor of the SBTC view. This coefficient is estimated net of the mean educational diversity index, which is my main indicator of variation in the skill levels of workers. The positive net effect of $\texttt{YEAR} \times \overline{\texttt{BA+}}$ is therefore more indicative of increasing wage inequality among college-educated workers, net of increases in the returns to education. This increasing wage inequality among college-educated workers is not of direct relevance, however, to the expectations of the SBTC view.[8]

To be sure, the net effects of the group means of the proportion of college-educated workers (i.e., $\overline{\texttt{BA+}}$) and of the educational diversity index (i.e., $\overline{\texttt{Edu.Div}}$) are highly positive and statistically significant. These net effects show that these two variables are important in predicting which occupations have greater inequality in a given year (i.e., in terms of a cross-section). Because these variables are constant over time, however, they cannot explain the growth in wage inequality, which is the main concern of the SBTC view. In sum, the SBTC view is not very useful in explaining the growth of within-occupational inequality, which accounts for most of the growth in inequality.

Regarding the hypothesis of organizational change, the results of Table 5.4 and Table 5.5 provide indirect evidence in favor of this hypothesis. This

[8]Additional evidence can be found in Table 5.5. The SBTC view implies that most of the growth in inequality will be attributable to the growth of between-educational inequality. Indeed, the wage gap between workers of different education levels has grown. The mean wages of less educated workers are down, while the mean wages of highly educated workers are up. In particular, among non-union members, 85 percent of the increase in Theil is due to between-education inequality. When it comes to union members, however, only 27.4 percent of the growth in Theil is due to between-education inequality. Thus, the legitimacy of SBTC is, at best, situationally dependent.

view implies that growing inequality is due to the change in necessary skill quality (Snower 1998; Lindbeck and Snower 1996, 2000). Proponents of this view argue that the college premium has risen in recent decades, not because the productivity of college educated workers at large has increased, but because the 'new economy' requires versatile ability across tasks. They further state that productivity is less dependent on specific tasks or jobs and more dependent on individuals' versatile ability. This view, therefore, predicts a decline in between-occupational inequality and a rise in within-occupational inequality. As seen above, the growth of within-occupational inequality is greater than the growth of between-occupational inequality.

According to the view of organizational change, college educated workers are more likely to have versatile ability. That is, the general demand for this group has risen, resulting in the growth of the mean wage for this group. But not all college educated workers have this ability, so this view predicts that, among college educated workers, inequality is likely to grow. As shown in Table 5.4, inequality has grown fast among equally educated high-skill workers (the significant coefficient of $\mathtt{YEAR} \times \overline{\mathtt{BA+}}$). The results of Table 5.5, showing that inequality grows faster among well educated workers, are also consistent with this view.

Compared to the Baseline Model, Table 5.4 shows that Model 3 explains 27.6 percent of the variance of the growth rate, while Model 2 explains 23.7 percent. The variance of the Baseline Model (i.e., .0286) is reduced in Model 3 (i.e., .0207). It is still statistically significant, however, indicating that there remains unexplained variation across the occupations. In terms of the model-fit test statistics, they are all significant, which indicates that Model 1 fits the data better than the Baseline Model and that Model 3 fits better than Model 1. Tests using AIC or BIC yield the same conclusions.

After controlling for the explanatory variables in Model 2 or Model 3, the coefficient for Year is not statistically significant (although it is highly significant in the Baseline Model). Thus, there is no net effect of Year on growth in wage inequality after accounting for changes in the independent variables and in their slopes over this time period.

Model 2 and Model 3 also explain a little more than 30 percent of the variation in the occupation-specific intercepts relative to the variation in the occupation-specific intercepts in the Baseline Model. In other words, around 70 percent of the variation is still left unexplained after controlling for race, gender, education, and industrial sectors in the models of inequality. That is, the majority of within-occupational inequality can not be regressed to these variables. Contrary to the assertion of the disaggregate structuration theorists, within-occupational heterogeneity does not disappear (nor is it reduced to a negligible quantity) after controlling for these 'other variables.'

It is also noteworthy that σ^t_{int} is significant and negative in all models of Table 5.4. This implies that the rate of inequality change for occupations with higher level of inequality is slower.

Table 5.6 shows how much variance in the growth rate can be explained by each variable. For example, when the education variables are excluded

Table 5.6: Explanatory Power of Predictors on the Variation of Growth

	Variation(σ_t^2)	Change of $\sigma_t^{2\text{a}}$	Proportion Explained[b]
Baseline Model[c]	.02860		
Full Model[d]	.02180		
If the following variables are excluded,			
Education	.02455	+.00275	.09615
Union[e]	.02441	+.00261	.09125
Sector	.02201	+.00021	.00734
Part Time	.02190	+.00010	.00349
Female	.02182	+.00002	.00069
Race	.02173	−.00007	−

Notes: (a) $\sigma_t^{2,RestrictedModel} - \sigma_t^{2,FullModel}$
(a) r^2 calculated by $(\sigma_t^{2,RestrictedModel} - \sigma_t^{2,FullModel})/\sigma_t^{2,BaseModel}$
(c) Baseline Model in Table 5.4.
(d) Full Model 2 in Table 5.4.
(e) Both pulbic sector and manufacturing sector.

from the full model, the variation of the growth rate becomes .02455, which is .00275 bigger than the variation of the growth rate of Model 2 in Table 5.4 that includes all variables. This difference is how much the variation improved by the introduction of education variables. Thus, r^2 (i.e., the proportion explained) due to education variables is .09615, which is obtained by dividing the difference of variation (.00275) by the variation of the Baseline Model (.02860). Other than education variables, another important variable that explains a large amount of variation is % union. When % union is excluded from the model, the variation of the growth rate jumps to .02441, which is .00261 more variation than the variation that can otherwise be explained by the full model. The proportion of variation explained by union membership is .09125. Therefore, education variables and union membership account for about two-thirds of the total variation of the growth rate improvement.

Other variables explain the reduction of variation by less than 1 percent. This is because either the variations over time of these predictors are small or their variations over time are not significantly associated with the change of inequality over time.

5.3 Summary and Discussion

The findings from descriptive statistics and multi-level growth analysis provide empirical evidence both supporting and refuting suggested hypotheses in regard to growing within-occupational inequality.

Disaggregate structuration. As discussed in Chapter 2.1.2, the disaggregate structuration view assumes homogeneity within an occupation. This view argues that via 'occupationalization,' an occupation becomes a more homogeneous group. The disaggregate structuration view, however, does not rule out the possibility of within-occupational heterogeneity. Within-occupational heterogeneity can be caused by demographic factors such as race and gender, and institutional elements such as union membership and industrial mix. Thus, these variables should explain most of the within-occupational inequality, so that the amount of total variation explained by these variables is substantially large and so that when these variables are controlled for, within-occupational inequality becomes negligibly small or disappears. According to Table 5.4, contrary to the expectation of the disaggregate structuration view, the amount of total variation explained by included explanatory variables is not large .

At maximum it is 27 percent in Model 3. Three-fourths of the total variation of within-occupational inequality across occupations is left unexplained by these variables. Therefore, even after controlling for demographic and institutional factors, there are remain significant amounts of within-occupational heterogeneity across occupations.

In terms of wages, the history of the last twenty years does not demonstrate the progress of occupationalization, which implies a reduction in heterogeneity within occupations. Unlike the expectation of the disaggregate structuration view, within-occupational inequality, namely, heterogeneity within occupations, is growing. Furthermore, this growing within-occupational inequality is not largely explained by other demographic or institutional variables. Contrary to the disaggregate structuration view, heterogeneity within occupations has grown. Thus, if anything has happened to occupations, it has been anti-occupationalization.

Hypothesis 1-A: The increase of % female in an occupation will increase within-occupational inequality. This is not supported. The % female increased in occupations where within-occupational inequality declined, while the % female decreased in occupations where inequality grew. This finding indicates that the increase of % female pulls down rather than raises inequality. The results of multivariate analysis (Table 5.4) also backs up this interpretation. A 1 percentage point increase of % female decreases the Theil index (multiplied by 100) by .0483. This finding is statistically significant at any conventional confidence level.

Peterson and Morgan (1995) reported that most of the gender wage gap is due to occupational segregation and that the within-job gender wage gap is small. That is, although female workers tend to have lower wages than their male counterparts, the difference is small. Therefore, more female workers do not necessarily lower male workers' wages at the lower end of wage distribution. Furthermore, female workers are not necessarily competing with male workers at the lower part of the wage distribution in an occupation. If the skill levels of female workers are competitive with male workers at the upper part of the wage distribution and if female workers are paid lower, then more female workers will put downward pressure on wages at the upper distribution, which, in turn, will decrease inequality.

Hypothesis 2-A: The decrease of the percent of workers in the manufacturing sector will increase within-occupational inequality. This is not supported. The changes in of % workers in the manufacturing sector do not affect the changes in inequality. Regardless of whether within-occupational inequality increases or decreases, the proportion of workers in the manufacturing sector in an occupation is decreased. If a decrease in the percent of workers in the manufacturing sectors boosts inequality, inequality-growing occupations should show at least bigger reductions in the percent of workers in manufacturing sectors. However, Table 5.2 shows that a decrease in the percentage of workers in the manufacturing sector is even larger within inequality-declining occupations. These findings do not support the 'deindustrialization' hypothesis.

This conclusion is consistent with the previous research done by Murphy and Welch (1993) and Juhn et al. (1993). Compositional changes of industrial mix, a decrease in the manufacturing sector and an increase in the service sector, do not seem to increase inequality. Furthermore, this finding provides evidence against Raffalovich (1993)'s argument. Raffalovich (1993) argues that without compositional changes of industries, a drop of average wages within manufacturing sectors could cause an increase in inequality. If that happens, occupations that have a greater proportion of workers in the manufacturing sector should show growth of inequality without changes in industrial mix. $\texttt{YEAR} \times \overline{\texttt{Manuf}}$ in Table 5.4 represents yearly inequality change without changes of % workers in the manufacturing sector. Raffalovich's argument implies that the coefficient of this variable should be positive. As shown in Table 5.4, however, the coefficient of $\texttt{YEAR} \times \overline{\texttt{Manuf}}$ is negative. That is, without changes in industrial mix, occupations where more workers work within the manufacturing sector do not show faster increases in inequality. At least in explaining changes of within-occupational inequality, which comprises the majority of recent inequality changes, the deindustrialization hypothesis does not seem to have much explanatory power.

Hypothesis 3-A: The decrease in the percent of union members will increase within-occupational inequality. This is not supported. The most striking result of my findings is that the effect of union membership on inequality is not negative, but positive. The increase in the percent of union membership by 1 percentage point in an occupation is likely to increase the Theil (multiplied by

100) by about .03. Furthermore, inequality grows faster among union members themselves. The growth rates of inequality among union members are higher than they are among non-union members. Although where unionization is higher inequality in a given year is lower, longitudinally, greater union membership seems to have brought about more inequality over the last two decades.

This result connotes that the function of unions on inequality in American society has fundamentally changed during the last several decades. Contrary to Freeman and Medoff's (1984) conclusion, 'what unions do' is no longer 'reducing inequality among union members' nor 'reducing inequality by boosting solidarity among equally skilled workers.' Rather, what unions mainly do is pursue monopoly rents for their own interests. The monopoly effect of unions seems to be greater than the spillover effect of unions. Mitchell (1985) argues that the norms of unions regarding wage determination are shifting toward two-tier wage plans, which increase (or at least do not decrease) wages of current union members at the cost of wages of newcomers. That is, unions become less resistant to inequality among union workers themselves. Thus, unions function as a barrier (i.e., social closure) against non-union members within the same occupation (Weeden 2002). The increase of unionization, therefore, will not reverse the current trend of growing inequality unless unions change their attitude. Indeed, the results of Table 5.4 show that an increase in the percentage of union membership would likely bring about more inequality (the coefficient of `Union` is positive), and among union members, inequality grows faster (the coefficient of $\texttt{YEAR} \times \overline{\texttt{Union}}$ is positive). The question is whether the changes of union norms are caused by attitudinal changes among union members/leaders. If so there is the possibility that they can be changed again by reinforced union activities. However,if these changes are caused by deeper structural transfers beyond the attitudes of union members, they are not likely to be reversed.

Acemoglu, Aghion, and Vilolante (2001) explained deunionization and the declining inequality-reducing effect of unions as phenomena mediated by changes of skill. That is, because of the widening productivity differentials between skilled and unskilled workers, the relative advantage of joining unions for skilled workers drops, and productivity changes increase the competitive market return for skilled workers and further weaken their incentives to join the unionized sector(231). "As the more productive employees face improved outside opportunities, wage compression becomes harder to sustain, and these workers quit unions and cause deunionization" (251). Western (1995) also found, in a comparison of eighteen advanced capitalist countries, that deunionization is a result of fundamental structural changes in the economy. He states that unions lacked the institutional resources to resist the decline; thus revitalization of unions is unlikely.

Regarding the relation between unionization and occupationalization, my result seems to support Grusky's (2005) argument that unions and occupational associations are competing institutions. When the unionization rate is down, within-occupational inequality is also declining; thus, homogeneity in an occupation is strengthened. While the unionization rate among blue collar workers is declining, the alternative occupational association does not seem to be emerging. As Grusky himself admits, blue collar occupations are examples of incomplete occupationalization.

In sum, within-occupational inequality is growing, not mainly because of deunionization, but because of the shift of unions towards a monopoly institution. Furthermore, the inequality-increasing effect of unions shown in Table 5.4 is neither by chance nor a temporary phenomenon, but rather evidence of a fundamentally altered function of unions in our society.

Hypothesis 4-A: The increase of part-time workers will increase inequality. This hypothesis is supported. The results in Table 5.4 provide supporting evidence for Hypothesis 4-A that insecure employment relations, which are measured in terms of part-time employment, increase the growth in within-occupational inequality. A one percentage point increase in part-time workers increases Theil by .0410. This positive effect of part-time workers, however, is not uniform across occupations. Among sales and service occupations, the net effects of part-time workers are negative. That is, more part-time workers decrease inequality in these occupations. It seems that increases in part-time employment in these occupations may serve to force down the wages of full-time sales and service workers, resulting in reduced within-occupational inequality.

Although the coefficient for part-time is positive, we can not blame the change of % part-time workers for the growing inequality. The proportion of part-time workers has been reduced by 2.6 percent during this period. McCall (2000) warned that the growth of insecure labor employment could bring about higher levels of inequality. While this warning itself is legitimate, when part-time workers, which are a form of insecure employment relations, have not increased over the last two decades, we may not need to take her warning too seriously. I want to note, however, that I did not study all forms of insecure employment. To investigate the trend of insecure employment contracts and their impacts, other forms of insecure employment relations should be closely examined in other studies.

Hypothesis 5-A: Wage inequality will increase in occupations that experience increases in the variability of educational attainments. This is not supported. Contrary to the SBTC view, a unit increase of educational diversity ($\texttt{Edu.Div}$) does not increase within-occupational inequality. Neither does the increase of the proportion of workers with a college degree. Furthermore, the coefficient for $\texttt{YEAR} \times \overline{\texttt{Edu.Div}}$ is not statistically significant, which is also contrary to the SBTC view. Although $\texttt{YEAR} \times \overline{\texttt{Edu.Div}}$ is significant and positive, this variable does not indicate a growth of inequality due to skill biased technological change. Rather, the positive coefficient of $\texttt{YEAR} \times \overline{\texttt{Edu.Div}}$ bespeaks the growth of wage inequality among college-educated workers themselves.

These findings cast doubt on the strength of the SBTC argument that has been popular in economics (e.g., Murphy and Welch 1997; Juhn et al. 1993). Although explaining the rise of wage inequality as the result of rise in returns to skill, Juhn et al. (1993) also observed the majority of inequality growth happened within education-experience group. While Juhn et al. asserted that the rise of return to skill was driven by the heightened skill demand, they did not propose anything about what kind of skill demand has been increased. Others argue that computers raise the demand of college educated workers, thus, in turn, the wages of skilled workers (e.g., Autor, Katz, and Krueger 1998), but the introduction of computer itself does not account for a major portion of inequality growth (e.g., Autor, Levy, and Murnane 2002). Rather, organizational and human resources factors seems to strongly mediate the impact of the changing economy (e.g., Black and Lynch 2001; Fernandez 2001; Autor, Levy, and Murnane 2002).

I want to note, however, that my tests of the SBTC as well as deindustrialization thesis, union effects, and other hypothesis are obviously doing so in the context of taking occupational structure as a given. The cases where the SBTC or deindustrialization operates by changing occupational structure, or where they operate in part via occupation as an intervening variable are not fully analyzed in my research. It is possible that these hypothesis could have a little more explanatory power in other contexts. I will indirectly examine that possibility in the next chapter in which the effects on occupational mean wage are tested. I leave the full scrutiny of this possibility for future researches.

Hypothesis 6-A: Within-occupational inequality would grow faster in high skill jobs and in service jobs. This hypothesis is supported. Although there is no variable in my data that measures organizational change directly, the patterns of growing inequality are consistent with what this view prognosticates. While the SBTC view predicts the growth of between-occupational inequality and has no clearly expected impact on within-occupational inequality, the organizational change hypothesis anticipates lowered occupational boundaries and thus a bigger growth of within-occupational inequality (in a weak form) or a decline of between-occupational inequality (in a strong form). This view assumes that materialistic bases for equal pay for equal work are eroding (Walter and Snellman 2004; Snower 1998) and predicts growing inequality for equal work (i.e., growing within-occupational inequality). This view also predicts the faster growth of within-group inequality for college educated workers than for less educated workers.

Indeed, between-occupational inequality has grown not as much as within-occupational inequality over the last two decades. As shown in Table 4.4, both between- and within-occupational inequality have been increasing between 1983-1985 and 2000-2002. Thus, although the strong form of the organizational change view is not supported, the weak form of this hypothesis is borne out by empirical data. Furthermore, the coefficient of $\texttt{YEAR} \times \overline{\texttt{BA+}}$, which represents the changes of within-group inequality among college educated workers, is highly significant and positive, while $\texttt{YEAR} \times \overline{\texttt{Edu.Div}}$, which the SBTC view predicts to be a positive coefficient, is not significant.

The organizational change hypothesis also anticipates that inequality will grow faster in occupations where workers need to meet customers face-to-face. Figure 5.1 shows that inequalities of most sales and service jobs have increased substantially, while inequalities of manual laborer jobs, which entail limited customer contacts, have been reduced in many cases.

Autor, Levy, and Murnane (2002) reported in their study of in-depth interviews at a bank that, rather than technological changes themselves, reorganization of tasks due to such changes lead to changes in productivity. Thus, organizational changes seem to be related to relocations of workers across firms. High-wage workers are more likely to be concentrated in certain establishments (Kremer and Maskin 1996), and according to Dunne et al. (2004), the between-plant component of wage dispersion accounts for almost the entire increase of hourly wage dispersion from 1975 to 1992 in the U.S. manufacturing sectors. That is, inequality is growing due to organizational changes, which are occurring at firm levels. Once again, organizations (firms) seem to serve as an intermediary between relocation of human capital and wage dispersion.

Chapter 6

BETWEEN-OCCUPATIONAL INEQUALITY

6.1 Causes of Between-Occupational Inequality

Between-occupational inequality accounts for about 29.7 percent of the increase of Theil from 1983-1985 to 2000-2002. In this section, I investigate the determinants of growing between-occupational inequality. To this end, factors regulating changes of mean wages of occupations are estimated. By doing this, we can indirectly estimate the sources of changing between-occupational inequality, since between-occupational inequality is a weighted sum of occupational mean wages.

6.1.1 Descriptive Analysis

As shown in Table 6.1, the occupational mean wage (2002 constant dollars) has stayed the same between 1983-1985 and 1991-1993 and has increased by 1.6 dollars an hour between 1991-1993 and 2000-2002. Table 6.2 and Table 6.3 show relevant descriptive statistics. Table 6.2 exhibits the changes of demographic, educational, and institutional variables in 'mean-wage-declining occupations' (115 occupations out of 331 detail occupations) and in 'mean-wage-growing occupations' (82 occupations). Whether an occupation is mean wage growing or declining is determined by the results of a regression model used for Table 5.1. The definitions of high-wage occupations and low-wage occupations for Table 6.3 are consistent with the definitions for Table 5.3.

In Table 6.2, mean-wage-declining occupations show a substantial gain of % female, while mean-wage-growing occupations have no change of % female. As expected, more female workers puts downward pressure on the wages of male workers in the same occupation, resulting in the decline of the mean wage of that occupation. By the way, Table 6.3 demonstrates that occupations that gain more female workers are high-wage occupations. These findings imply that the growth of female labor market participation will pull down the wages of high-income jobs, thus bringing about a reduction of between-occupational inequality.

Another noteworthy difference between mean-wage-growing and mean-wage declining occupations is the changes of % college educated workers. The proportion of college educated workers was up more in mean-wage-growing

Table 6.1: Descriptive Statistics for Change of Mean Wage of 331 Occupations, 1983-85 to 2000-02

		Total	1983-1985	1991-1993	2000-2002
Meanwage	Mean	15.508	15.136	15.155	16.720
	(sd. dev.)	(5.741)	(5.344)	(5.591)	(6.403)
	Min	5.46	5.84	5.52	6.19
	Max	45.89	45.89	39.69	43.19
Sample Size (n)		5958	331	331	331

occupations than in mean-wage-declining occupations (Table 6.2). And high-wage occupations have seen larger increases in % college educated workers than have low-wage occupations (Table 6.3). Thus, it is reasonable to induce that the increment of college educated workers for the given period may be attributable to the rise of between-occupational inequality. This induction is congruent with the SBTC view. Regarding educational diversity, substantial differences between occupational groups are observed neither in Table 6.2 or in Table 6.3.

The proportion of part-time workers is down in mean-wage-growing occupations, while it is stable in mean-wage-declining occupations. Also, the proportion of part-time workers is decreasing among low-wage occupations, while it is increasing in high-wage occupations. The change of proportion of part-time workers for this period therefore seems to be conducive to the narrowing of the between-occupational wage dispersion.

Both % union and % manufacturing sectors are down substantially more in mean-wage-declining occupations than in mean-wage-growing occupations. The of % union has especially decreased more among low-wage occupations than among high-wage occupations, so that the decline of % union may be

Table 6.2: Descriptive Statistics by Mean Wage Growing and Mean Wage Declining Occupations

	Among Occupations with Decreased Mean Wage (115 Occupations)			Among Occupations with Increased Mean Wage (82 Occupations)		
Variable	1983-85	2000-02	Change	1983-85	2000-02	Change
Female	.2777	.3426	+.0649	.6586	.6625	+.0039
	(.2391)	(.2718)		(.2902)	(.2646)	
Black	.1269	.1377	+.0108	.1157	.1230	+.0073
	(.0643)	(.0618)		(.0783)	(.0735)	
Hispanics	.0764	.1554	+.0790	.0563	.1116	+.0553
	(.0364)	(.0862)		(.0389)	(.0932)	
Other Races	.0239	.0413	+.0174	.0292	.0490	+.0198
	(.0110)	(.0205)		(.0177)	(.0296)	
BA+	.0965	.1226	+.0261	.3186	.3774	+.0588
	(.1498)	(.1640)		(.3447)	(.3461)	
Edu. Div.	.6391	.6330	−.0061	.6210	.6098	−.0112
	(.0374)	(.0332)		(.0993)	(.1235)	
South	.3344	.3537	+.0193	.3318	.3446	+.0128
	(.0608)	(.0486)		(.0562)	(.0419)	
Public Sector	.1323	.1172	−.0151	.2709	.2494	−.0215
	(.1845)	(.1848)		(.3020)	(.2956)	
Part Time	.1134	.1047	−.0087	.2830	.2163	−.0667
	(.1325)	(.1078)		(.1818)	(.1349)	
Union	.3443	.2036	−.1407	.1961	.1726	−.0235
	(.1664)	(.1409)		(.2055)	(.1926)	
Manufacturing	.5326	.4381	−.0945	.0444	.0302	−.0142
	(.3515)	(.3696)		(.1097)	(.0794)	

Table 6.3: Change of Percent of Workers Among High-Income Jobs and Low-Income Jobs

	High-Wage Occupations (59 Occupations)			Low-Wage Occupations (39 Occupations)		
Variable	1983-85	2000-02	Change	1983-85	2000-02	Change
Female	.3005	.3957	+.0952	.6793	.6393	−.0400
	(.1476)	(.1661)		(.2592)	(.2437)	
Black	.0473	.0737	+.0264	.1517	.1538	+.0021
	(.0221)	(.0243)		(.0865)	(.0812)	
Hispanics	.0273	.0498	+.0225	.0896	.1991	+.1095
	(.0080)	(.0124)		(.0463)	(.1096)	
Other Races	.0315	.0637	+.0322	.0362	.0574	+.0212
	(.0232)	(.0457)		(.0153)	(.0237)	
BA+	.5793	.6224	+.0431	.0500	.0670	+.0170
	(.2065)	(.1872)		(.0341)	(.0393)	
Edu. Div.	.6580	.6387	−.0193	.6458	.6562	+.0104
	(.1459)	(.1552)		(.0387)	(.0265)	
South	.3091	.3350	+.0259	.3521	.3461	−.0060
	(.0413)	(.0338)		(.0592)	(.0338)	
Public Sector	.2263	.1801	−.0462	.0833	.0664	−.0169
	(.2571)	(.2342)		(.1148)	(.0992)	
Part Time	.0601	.0642	+.0041	.4085	.3163	−.0922
	(.0758)	(.0707)		(.1651)	(.1226)	
Union	.1222	.0851	−.0371	.1318	.0788	−.0530
	(.1194)	(.1030)		(.0890)	(.0499)	
Manufacturing	.2767	.2035	−.0732	.0818	.0381	−.0437
	(.2194)	(.1747)		(.2346)	(.1508)	

contributing to the widening between-occupational wage gap. Contrary to % union, the proportion of manufacturing sectors diminished more among high-wage occupations than among low-wage occupations; thus, whether the change of % manufacturing sector causes the rise of inequality or not can not be easily induced from this findings. Multivariate analysis may be required.

The changes of the % race variables do not substantially differ between mean-wage-growing and mean-wage-declining occupations. Neither the change of % south nor the change of % public sector shows notable difference between the two occupational categories.

6.1.2 Multivariate Analysis: Multilevel Growth Models

Table 6.4 shows the results for the multi-level growth models of mean wage, as shown by equation 3.12. Although not a direct decomposition, the findings in Table 6.4 provide some indirect evidence about the sources of between-occupational wage inequality because the latter reflects variation between occupations in their mean wages. In regard to the Baseline Model, the effect of year is not statistically significant, indicating that there is no increase in the occupation-specific mean wage over this time period.

According to Full Model 2 in Table 6.4, a 1 percentage point increase in female employment in an occupation reduces growth in the mean wage by .0293 dollars. In Model 2, an interaction term is added to indicate female employment in high-wage occupations (i.e., occupations where the mean wage is more than 1 standard deviation above the grand mean). The results for

Table 6.4: Models of Mean Wage Change over Time

	Base Model (Weight On)	Full Model 1 (Weight Off)	Full Model 2 (Weight On)[a]	Full Model 3 (Wt+Interact)
Intercept	16.1214***	13.2158***	13.4359***	13.0746***
Year	-.0033	.3412***	.3432***	.3517***
		Slope Change by the Change of Proportion		
$\texttt{Female}_{jt}$		-.0263***	-.0293***	-.0205*
$\texttt{Black}_{jt}$		-.0255***	-.0098	-.0135*
$\texttt{Hisp}_{jt}$		.0033	.0167**	.0147*
$\texttt{Others}_{jt}$		.0039***	.0538***	.0510***
$\texttt{South}_{jt}$		.0050	-.0001	.0011
$\texttt{BA+}_{jt}$		.0724***	.0736***	.0749***
$\texttt{Edu.Div}_{jt}$		-.0058	.0085	.0088
$\texttt{Public}_{jt}$		-.0468***	-.0409***	-.0541***
$\texttt{PartTime}_{jt}$		-.0071	-.0181***	-.0265***
$\texttt{Union}_{jt}$		.0759***	.0816***	.0847***
$\texttt{Manuf}_{jt}$		.0202***	.0201***	.0188***
$\texttt{Female}_{jt} \times \texttt{HighWage}_j$				-.0406***
$\texttt{PartTime}_{jt} \times \texttt{HighWage}_j$				.0696***
$\texttt{Public}_{jt} \times \texttt{LowWage}_j$				.0666***
$\texttt{Union}_{jt} \times \texttt{LowWage}_j$				-.0441**
		Yearly Slope Change of Group Mean		
$\texttt{YEAR}_t \times \overline{\texttt{BA+}}_{j.}$		.0010***	.0012***	.0012***
$\texttt{YEAR}_t \times \overline{\texttt{Edu.Div}}_{j.}$		-.0048***	-.0049***	-.0050***
$\texttt{YEAR}_t \times \overline{\texttt{Public}}_{j.}$		-.0002	-.0003	-.0003
$\texttt{YEAR}_t \times \overline{\texttt{PartTime}}_{j.}$		-.0001	-.0003	-.0005
$\texttt{YEAR}_t \times \overline{\texttt{Union}}_{j.}$		-.0012**	-.0011*	-.0011**
$\texttt{YEAR}_t \times \overline{\texttt{Manuf}}_{j.}$		-.0006**	-.0007***	-.0007***
		Effect of Group Mean		
$\overline{\texttt{Female}}_{j.}$		-.0061	-.0022	-.0085
$\overline{\texttt{Black}}_{j.}$		-.0903**	-.1086***	-.1006***
$\overline{\texttt{Hispanic}}_{j.}$		-.1592***	-.1767***	-.1659***
$\overline{\texttt{Others}}_{j.}$		.0162	-.0541	-.0615
$\overline{\texttt{South}}_{j.}$		.0105	.0146	.0128
$\overline{\texttt{BA+}}_{j.}$		.0578***	.0546***	.0627***
$\overline{\texttt{Edu.Div}}_{j.}$		.0460*	.0320	.0374

Continued on next page

Table 6.4, cont.

	Base Model (Weight On)	Full Model 1 (Weight Off)	Full Model 2 (Weight On)^a	Full Model 3 (Wt+Interact)
			Continued from previous page	
$\overline{\texttt{Public}}_{j.}$		.0264*	.0206†	.0290**
$\overline{\texttt{PartTime}}_{j.}$		-.0656***	-.0536***	-.0583***
$\overline{\texttt{Union}}_{j.}$		-.0031	-.0101	-.0125
$\overline{\texttt{Manuf}}_{j.}$		-.0160*	-.0153†	-.0151†
σ^2_{int}	30.9396***	7.6519***	7.6116***	8.0224***
$\sigma_{int,t}$	-.0549*	-.1555***	-.1317***	-.1208***
σ^2_t	.0187***	.0093***	.0067***	.0061***
$\sigma_{toep(2)}$	.0003***	.1951***	.0003***	.0003***
σ^2_e	.0007***	.4292***	.0006***	.0006***
r^2_{int} ^{b}		.7618	.7540	.7407
r^2_t ^{c}		.5753	.6417	.6738
-2LL	13609.2	12225.5	11904.9	11870.7
AIC	13623.2	12295.5	11941.9	11880.7
BIC	13649.8	12428.5	11933.9	11899.7

Note: (a) Weight variable is share of occupations at given years.
(b) Pseudo-R^2 (PRE) calculated by $(\sigma^2_{int,BaseModel} - \sigma^2_{int,FullModel})/\sigma^2_{int,BaseModel})$
(c) Pseudo-R^2 (PRE) calculated by $(\sigma^2_{t,BaseModel} - \sigma^2_{t,FullModel})/\sigma^2_{t,BaseModel})$
† < .10, * < .05, ** < .01, *** < .001

Full Model 3 shows that the coefficient for $\texttt{Female} \times \texttt{HighWage}$ is negative and significant. (The interaction for female employment and low-wage occupations was not statistically significant and thus deleted from the model.) For high-wage occupations, a 1 percentage point increase in female employment therefore reduces growth in the mean wage by .0611 dollars (i.e., .0205 + .0406). I thus conclude that increasing female employment tends to decrease between-occupational inequality because the mean wages of high-wage occupations are brought down more than are the mean wages of non-high-wage occupations. This conclusion is the opposite, however, of the prediction of

Hypothesis 1-B.

By contrast, the mean wage tends to increase in occupations that experience an increase in manufacturing employment. The results for Full Model 3 in Table 6.4 show that a 1 percentage point increase in manufacturing employment increases the growth in mean wage by .0188 dollars. In general, manufacturing employment has traditionally provided higher paying jobs for workers without a college degree (e.g., laborers and semi-skilled blue-collar workers) who would otherwise have few desirable job opportunities. Therefore, it is most likely that declining employment in the manufacturing sector contributes to growing between-occupational inequality by increasing the number of workers with wages below the overall mean. This result is consistent with Hypothesis 2-B, which is derived from the deindustrialization view.

Another interesting result in Table 6.4 is the statistically significant and negative net effect of the interaction between year and the mean of manufacturing employment. This finding indicates that, over this time period, the mean wage for manufacturing workers has been declining net of other changes (i.e., in unionization, female employment, education, part-time employment, and public sector employment). Although not formally hypothesized in my discussion, this decline in the mean wage of manufacturing workers may reflect increasing foreign trade and global competition, particularly within developing countries (e.g., China), where the wages for manufacturing workers are considerably lower.

The results for public sector employment indicate that a 1 percentage point increase in public sector employment in non-low-wage occupations, decreases the mean wage by .0541 dollars, as is evident in Full Model 3 of Table 6.4. In occupations that are not low-wage, private sector workers tend to have higher wages than public sector workers. Full Model 3 also includes, however, a statistically significant interaction effect for $\texttt{Public} \times \texttt{LowWage}$. This result implies that in low-wage occupations, a 1 percentage point increase in public sector employment increases the mean wage by .0541 + .0666 = .0125 dollars. Thus, for low-wage occupations, the net effect of public sector employment is opposite of that for non-low-wage occupations. These findings suggest that privatization (i.e., reductions in public sector employment) will increase between-occupational inequality because the mean wages of workers in low-wage occupations will be reduced while the wages of higher-wage workers will be increased.

Regarding the effect of unionization, the results for Model 2 in Table 6.4 indicate that a 1 percentage point increase in union membership in a non-low-wage occupation will increase its mean wage by .0847 dollars. In low-wage occupations, a 1 percentage point increase in union membership will increase mean wages by .0847 + (.0441) = .0406 dollars. To the extent that unionization tends to most benefit the wages of blue-collar workers, who would otherwise typically have few desirable alternative employment prospects, I interpret these results as supporting Hypothesis 3-B, that reductions in unionization increase between-occupational inequality.

The net effects of part-time employment also vary depending on an interaction, as is shown in Full Model 3 of Table 6.4. In occupations that are not high wage, a 1 percentage point increase in part-time employment reduces the growth in mean wage by .0265 dollars, whereas in high-wage occupations, a 1 percentage point increase in part-time employment increases the growth in mean wage by .0265 + .0696 = .0431 dollars. These results suggest that contingent work in high-wage occupations often refers to specialized, high skilled jobs that command wage premiums, as was discussed by Hipple and Stewart (1996). By contrast, in occupations that are not high wage, increased part-time employment tends to reduce mean wages. These opposing trends imply that increasing part-time employment increases between-occupational inequality as was proposed by Hypothesis 4-B.

In terms of temporal changes in occupation-specific mean wages, the results in Table 6.4 provide greater support for the SBTC view. A 1 percentage point increase in college-educated workers increases the mean wage by .0749 dollars in Model 2. Thus, increases in the educational level of an occupation increase its mean wage. Furthermore, the interaction between year and the average proportion of workers who are college educated is positive and statistically significant in Table 6.4. This interaction coefficient indicates an increasing return to the educational attainment of college-educated workers over this time period and therefore directly supports the SBTC view and Hypothesis 5-B. This widening wage gap by educational level probably increases between-occupational inequality.

Multivariate analysis of Table 6.4 does not provide direct evidence to support Hypothesis 6-B. Descriptive statistics of Table 4.1, however, offer a valuable support of Hypothesis 6-B. the explanatory power of occupations has diminished by 30 percent among college or more educated workers while it is down by 26 percent among high school or less educated workers. That is, the occupational wage difference among highly educated workers has been reduced more than it has among less educated workers.

These models do fairly well in explaining changes in occupation-specific mean wages. As shown in Table 6.4, Full Model 3 explains 74.1 percent of the variance of the intercepts across occupations and 67.4 percent of the variance of the slopes. Chi-square test statistics indicate that Full Model 3 is statistically significant relative to Full Model 2 and the Baseline Model. Thus, changes of occupational mean wage over time for this period are well explained by the predictors included in the models of Table 6.4. These results are contradictory to the disaggregate structuration view that predicts R-squareds for these models of mean wages to be relatively low.

Table 6.5 shows how much variation in the mean-wage growth rate can be accounted for by each variable. Similar to what was discovered in Table 5.6 of the variation of the inequality growth rate, education variables and unionization are the two most powerful variables in explaining the variation of mean-wage growth rate as well. Unlike in the variation of the inequality growth rate, however, industrial sector variables and percent female also play significant roles in explaining the variation of the mean-wage growth rate. When education variables are excluded from the model, the variation of slopes

Table 6.5: Explanatory Power of Predictors on the Variation of Growth

Excluded Time-Variant Predictor	Variation(σ_t^2)	Change of $\sigma_t^{2\text{a}}$	Proportion Explained[b]
Baseline Model[c]	.02190		
Full Model[d]	.00671		
If the following variables are excluded,			
Education	.01051	+.00380	.17351
Union	.01021	+.00350	.15981
Sector[e]	.00815	+.00144	.06575
Part Time	.00653	−.00018	−
Female	.00706	+.00035	.01598
Race	.00665	−.00006	−

Notes: (a) $\sigma_t^{2,RestrictedModel} - \sigma_t^{2,FullModel}$
(b) r^2 calculated by $(\sigma_t^{2,RestrictedModel} - \sigma_t^{2,FullModel})/\sigma_t^{2,BaseModel}$
(c) Baseline Model in Table 6.4.
(d) Full Model 2 in Table 6.4
(e) Both pulbic sector and manufacturing sector.

is increased to .01051, which is a .00380 increase from .00671 of the full model. Thus, education variables account for 17.4 percent (.00380/.02190) of the total variation of mean-wage slopes. If we omit % union from the predictors, the variation of slopes is up by .00350. This accounts for 15.9 percent of the total variation.

The change of % public sector and % manufacturing sector combined explains 6.6 percent of the total variation. When we leave them out of the model, the variation of slopes increases by .00144. Also, the changes of % female account for 1.6 percent of the total variation of slopes. If we run a model without % female, the variation of slopes goes up from .00671 to .00706.

6.1.3 Counterfactual Analysis

Although informative, Table 6.4 does not provide direct estimates of the effects of independent variables on between-occupational inequality. To overcome this shortcoming, I estimate the counterfactual between-occupational inequalities from the predicted occupational mean wages. Occupational mean wages for 1983-1985 and 2000-2002 are estimated using the coefficients of Full Model 2 in Table 6.4, and between-occupational Gini indexes are then calculated using those estimated occupational mean wages. In Table 6.6, the estimated between-occupational Gini for 1983-1985 is .18422, and it is .19608 for 2000-2002, which is a .01186 point increase. The between-occupational Gini using actually observed occupational mean-wage is .16969 for 1983-1985 and .21391 for 2000-2002. Thus, the predicted Gini indexes reflects the actual trend of growing between-occupational inequality, although the estimated Gini indexes are a little smaller than actual Gini indexes.

In order to examine the effect of each predictor on between-occupational inequality, the between-occupational Gini indexes are estimated with the condition that only the individual predictor changes between 1983-1985 and 2000-2002 while all the other predictors are fixed to the 1983-1985 figures. The middle row of Table 6.6 shows the results. The results of Table 6.6 are congruent with what we inferred from Table 6.4. The changes of % female reduce the between-occupational inequality for the given period by .00800. The increases of part time workers are conducive to the growth of between-occupational inequality, and the declines in manufacturing sectors cause the rise of between-

Table 6.6: Counterfactual Analysis of Between-Occupational Inequality

	Predicted Between-Occupational Gini	Predicted Change from 1983-1985
Predicted Gini in 1983-1985	.18422	
(Actual Gini in 1983-1985)	(.16969)	
What if only the following variable changes, 1983-1985 and 2000-2002		
Female	.17622	−.00800
BA+	.19469	+.01047
Union	.19531	+.01109
Part Time	.18764	+.00342
Public Sector	.18328	−.00094
Manufacturing	.18617	+.00195
Predicted Gini in 2000-2002	.19608	+.01186
(Actual Gini in 2000-2002)	(.21391)	(+.01583)

Notes: Actual Gini in parenthesis are calculated with the observed occupational mean wages, not estimated mean wages using Model 2.

occupational inequality, as expected.

The changes of % BA+ and % union are the two biggest predictors. The amount of the effects of the two are similar. The changes of % BA+ for this period cause an increase of .01047 in the between-occupational Gini inequality. The changes in unionization bring about a growth in the Gini inequality by .01109. Thus, education variables and unionization are the two most inequality growth inducing variables in regards to both within-occupational and between-occupational inequalities.

The only unexpected result in Table 6.4 is the effect of public sector. The reduction in % public sector for this time period does not increase between-occupational inequality but instead decreases it. This may be partially because % public sector is reduced more among high-wage occupations than among low-wage occupations. A more reasonable cause, however, may be that I applied the coefficients of Full Model 2 instead of the coefficients of Full Model 3. That is, the interaction effects of % public sector and high-wage occupations are not reflected. Indeed, when interaction effects are included, the changes of public sector turn out to increase the between-occupational inequality for this period. In sum, except for the change of % female, all other hypothesized variables are contributing to the rise of between-occupational inequality.

6.2 Summary and Discussion

The results of multivariate analyses presented above provide empirical evidence and counter-evidence for the hypotheses on growing between-occupational inequality.

Disaggregate structuration. According to this view, with the progress of occupationalization, increases or decreases in occupational mean wage will be achieved by diverse kinds of occupation-specific actions rather than by the results of changes of other social and economic elements such as race, gender, or industrial composition. Therefore, the total variation in the changes of occupational mean wage over time explained by other variables (i.e., R-squared for models of the changes of occupational mean wages) should be small.

The R-squared of Table 6.4 is .75 for the variation across occupation-specific intercepts and .64 for the variation over time. The majority of variation can be explained by demographic and institutional variables. That is, the changes in occupational mean wages are a function of gender, race, general skill (education), and institutional factors such as unionization and industrial mix. The assumption of disaggregate structuration is not supported again for the models of mean wage, as it is not supported for the models of within-occupational inequality.

Hypothesis 1-B: The increase of % female will cause the rise of between-occupational inequality. This is not supported. Contrary to the expectation, the increase of % female is likely to decrease the between-occupational inequality. The increase of % female in an occupation tends to decrease the mean wage of that occupation. The negative interaction effect of female and high-wage occupations indicates that the increase of female would pull down the wages further for high-wage occupations relative to non-high-wage occupations. The answer to the question of whether the increase in % female would bring about the growth/reduction of between-occupational inequality depends on among which occupations the female labor force increases more during this period.

Juhn and Murphy (1997) report that since the late 1970's wives of high-earning husbands have entered into labor markets more than have wives of low- or middle-earning husbands and that the skill levels of these wives are competitive with high-skilled male workers. Maxwell (1990) also find that increased female labor force participation reduces the income share of the top quintile. Congruent with my result, Juhn and Kim (1999) state that, since the 1980's, female participation has contributed more at higher-skill job categories. The uniqueness of the female labor force participation since the 1980's is not its augmented quantity but its compositional change, specifically the increase in the proportion high-skilled. Juhn and Kim (1999) also state that college-educated women have substituted for college-educated men, indicating that the increased labor supply has not increased wage inequality among male workers in the last two decades.

Similar to the results for within-occupational inequality, the results for between-occupational inequality also show that the increase of female labor force participation does not increase inequality but that it decrease inequality. Before moving to the next topic, I want to caution the reader not to conclude that this association between female participation and inequality can necessarily be applied to the causal study of increasing household inequality. Household income is a joint distribution of male and female earners. Thus, although female participation decreases individual inequality, the same factor could bring about an increase in household inequality due to the associated mating (Maxwell 1990; Hyslop 2001; Alderson and Nielsen 2002).

Hypothesis 2-B: The decrease in employment in the manufacturing sector will increase the between-occupational inequality. This hypothesis is marginally supported. Contrary to the results for within-occupational inequality, the decline of the manufacturing sector explains a portion of the rise in between-occupational inequality for this time period. The amount of inequality increase due to the decline of the manufacturing sector, however, is marginal. Out of a total of .0119 increase in the Gini between 1983-1985 and 2000-2002, only at best can .0020 be accounted for by the decline of the manufacturing sector (Table 6.6).

This finding is consistent with the results of economic studies (e.g., Gittleman 1994; Juhn 1999; Danziger and Gottschalk 1993). The majority of inequality growth has occurred within industries rather than between industries (Gittleman 1994). And changes of between-industrial inequality is mainly due to employment shifts within industries, not to deindustrialization (Raffalovich 1993). In almost all industries, college-educated workers have been increasing, and this within-industrial change of occupational mix accounts for more than 80 percent of the occupational changes (Danziger and Gottschalk 1993). The reduction in the demand for middle skilled male workers in all industries contributes more to the growth of inequality than does the decline in employment in the manufacturing sector (Juhn 1999). That is, the compositional change effect does not provide a tangible explanation either for within-occupational inequality or for between-occupational inequality.

Hypothesis 3-B: The decline of % union will increase between-occupational inequality. This hypothesis is supported. Decreased union density is strongly correlated with the reduction of occupational mean wage. A 1 percentage point decrease of union density is likely to lower the occupational mean wage by .09 dollars. Union density is down by only 2 percent among occupations with increased mean wages, but it is down by 14 percent among occupations with decreased mean wages. Furthermore, union density has diminished more among low-wage occupations. The significantly negative effect of the interaction variable of union density and low-wage occupations implies that if union density declines equally across occupations, union density will decrease between-occupational inequality rather than increase it. In total, for the given period, the decrease of union membership is estimated to cause a .011 point increase in the between-occupational Gini.

Hypothesis 4-B: The increase of % part-time workers will bring about the rise of between-occupational inequality. Supported. The effects of part-time workers are conditional on the type of occupations. High-wage occupations gain mean wages with the increase of part-time workers, while non-high-wage occupations lose mean wages. That is, high-skilled workers actually earn more in contingent labor arrangements (Hipple and Stewart 1996; Polivka 1996). The total effect of the change of part-time workers on between-occupational inequality, however, is not large, since part-time workers have decreased during this time period. Furthermore, reduction rate is higher among low-wage occupations. Indeed, insecure employment relations have a strong potential to drive up inequality if contingent labor arrangements rise. A cross-sectional study comparing U.S. counties by McCall (2000) shows the same possibility.

Hypothesis 5-B: The increase of % college educated workers will increase between-occupational inequality. Supported. Contrary to the results of within-occupational inequality, the SBTC view is well supported in explaining between-occupational inequality. The higher the % college-educated in an occupation, the higher the mean wage of that occupation. Considering that % college-educated is higher among high-wage occupations in any give time and that the growth of college-educated workers is also bigger among high-wage occupations, it is apparent that the positive coefficients of `BA+` will bring forth an increase in between-occupational inequality. Counterfactual analysis of Table 6.6 confirms these reasonings.

Hypothesis 6-B: Among highly-educated workers between-occupational inequality decrease faster. Not supported. Both highly-educated workers and less-educated workers show a decline in the portion of between-occupational inequality (Table 4.1). Although the amount of decline is bigger for the college or more educated in Table 4.1 than for the high school or less educated, the difference does not seem to be substantially wide. That is, occupational barriers become lower than before regardless of the level of educational attainment.

If the organizational change view is not wrong, there could be two possible explanations as to why Hypothesis 6-B is not supported in my analysis. First, there is the possibility of a 'flooring effect.' Jobs for less educated workers are most likely to be low-wage jobs. Thus, the decreased demand for these jobs lowers the wages of jobs that have wages well above the minimum wage to near minimum wage yet does not change the wages of jobs whose wage rates are already near the minimum wage. The distribution of mean wages therefore becomes narrower. A second possible explanation is that organizational changes are likely to equally affect both well-educated and less-educated workers. In other words, organizational changes require versatile multi-tasking ability among low-skilled workers as well as among high-skilled workers, so that workers with these abilities earn more.

Although the proportion of between-occupational inequality grows for both less-educated and highly-educated workers, the growth for less-educated workers is due to the decline of between-occupational inequality. For highly-educated workers, by contrast, the growth is due to the increase of within-occupational inequality. Within-occupational inequality for less-skilled workers was .0912 during 1983-1985, and it stays at a similar level of .0974 during 2000-2002 (7 percent increase), while between-occupational inequality has decreased from .0416 for 1983-1985 to .0334 for 2000-2002 (20 percent decline). For highly-educated workers, within-occupational inequality has grown substantially, as it increases to .1403 in 2000-2002 from .1112 during 1983-1985 (26 percent increase). However, between-occupational inequality is down by only 6 percent (from .0359 to .0338). That is, no significant growth of within-occupational inequality is observed for less-skilled workers during this period. Therefore, considering the results of the inequality decomposition, the first scenario is more likely.

Chapter 7

CONCLUSION

7.1 Summary of Findings

The foregoing results provide considerable new insight into the role of occupation as a mediating structure in the growth of wage inequality in recent decades. In terms of a bivariate association, my findings indicate that occupations are becoming less directly associated with wages, even when using a large number (i.e., 331) of detailed occupational categories, as suggested by the "disaggregate structuration" approach. From 1983 to 2002, the between-occupational variance declined while the within-occupational variance increased to approximately three-fourths of the total variance. In terms of the decomposition of measures of inequality, five out of the six measures show an increase in the proportion of wage inequality within occupations (i.e., to about 65 percent or 75 percent) over this time period. Furthermore, all of the measures indicate that most of the increase in wage growth over this time period was within occupations. These results show that increasing within-occupational wage inequality is generally consistent with the basic conclusion of Table 4.3, that inequality in occupational status has actually not increased over this period (despite increases in wage inequality of 12 percent to 33 percent, according to the results in Table 4.4).

In terms of the multivariate analysis of growing wage inequality within occupations, my multi-level growth model reveals some unexpected results. Contrary to hypothesized predictions, the growth of wage inequality within occupations was actually reduced by the employment of women, increased by a larger unionized work force, and unaffected by reductions in manufacturing employment or by changes in the distribution of education. Increased part-time employment did increase the growth of wage inequality but only outside of sales and service occupations. Perhaps the least surprising finding is that public-sector employment reduces wage inequality.

The hypothesized predictions were somewhat more evident in regard to the growth in mean wages and between-occupational inequality. As expected, the growth in mean wages and between-occupational inequality was decreased by reductions in manufacturing employment and by increased unionization. Increased part-time employment increased between-occupational inequality by increasing mean wages in high-wage occupations and by reducing mean wages elsewhere. Increasing returns to education were also evident, as mean wages increased faster in occupations with more college graduates and in occupations with more growth in the employment of college graduates. Although the decrease in between-occupational inequality due to increases in female employment was not formally hypothesized, in retrospect, this finding is certainly reasonable, given the large negative effect on the growth in mean wages that results from increased female employment in high-wage occupations. As for privatization, it clearly increases between-occupational wage inequality.

7.2 Implications for Disaggregate Structuration

As noted earlier, Grusky and Sørensen (1998:1191) claim that detailed occupations are, among other things, "positional sources of exploitation and inequality." My results indicate, however, that most wage inequality is within detailed occupational categories and that most of the growth in wage inequality has been within them as well. In other words, most wage inequality cannot be directly explained by detailed occupations, these detailed occupations are increasingly becoming decoupled from wages. Occupation-specific skills become less determinant of wages, while general skills increase their influence.

The argument that occupations become classes through 'occupationalization' is not supported in multivariate analysis. Demographic, educational, and institutional variables could not account for the within-occupational variation, while the same variables cannot explain most changes in occupational mean wages over time. That is, an occupation does not turn out to be a homogeneous community net of 'other variables,' and occupational mean wages, which are a clear occupational common interest, are not explained by occupational activities themselves but instead by 'other variables.' These findings, therefore, do not support the strong version of the "disaggregate structuration" view.

I suggested earlier that a weaker form of "disaggregate structuration" assumes that occupations may still be seen as fundamental if they are a useful unit of analysis for explaining wage inequality, even if statistically there is more variance in wages within rather than between detailed occupations. Evaluating this weaker form of "disaggregate structuration" is more a matter of opinion regarding what constitutes being "useful." I suggest that the explanatory power resulting from the use of detailed occupations as the unit of analysis in predicting wage inequality is far from conclusive.

Although my investigation has yielded some important findings about the net effects of various variables, these results do not provide unequivocal support for the view that occupations may be construed as the primary "positional sources of exploitation and inequality," to the exclusion of other aspects of class structure, because over three-quarters of the variation in the growth of within occupational inequality still remains statistically unexplained in my models. While I do not doubt that occupations have and will continue to serve important roles in both descriptive and analytical studies of social inequality and stratification, my results nonetheless do not support taking this usefulness to the logical extreme of postulating that detailed occupations represent the only important feature of the class structure and that they override the need to theoretically incorporate other, perhaps equally important, labor market variables.

7.3 Implications for Understanding the Sources of Growing Wage Inequality

Female. The educational attainment of female workers at the level of college or more and their labor market participation has reduced individual inequality in the last two decades. These findings signal that the effects of female labor force participation are much more complicated than we expected. Unlike Topel's (1994) assertion, highly educated female workers are not competing with low-skilled male workers; rather, they are substituting for their equally educated male counterparts (Juhn and Kim 1999). Thus, the influx of female workers is likely to put downward pressure on the wages of high-skilled male workers at the upper tail of the distribution. This inequality-reducing effect of female workers, however, cannot be assumed to extend to household/family inequality. The amount of household income increased by assortative mating may well exceed the amount of the diminished income of male counterparts (Maxwell 1990; Hyslop 2001).

Skill-Biased Technological Change. To be sure, my results do find some limited support for the SBTC view in that mean wages increased faster in occupations with more college graduates or with more growth in the employment of college graduates. Therefore, strictly speaking, my findings are not entirely inconsistent with the SBTC argument. As I have shown, however, most of the growth in wage inequality has been within occupations, and this latter phenomenon is not explained by the SBTC hypothesis, which emphasizes increasing returns to education.

These findings call into question the strength of the SBTC argument that has been popular in economics (e.g., Murphy and Welch 1997; Juhn et al. 1993). My findings may be more consistent with the argument of Fernandez (2001). In the context of a case study of a food processing plant, Fernandez argues that firm organization heavily mediates the relationship between the distribution of human capital and wage dispersion.[1] Although my data do not pertain to firms, Fernandez' (2001) argument refers the determination of the distribution of jobs (and hence occupations) as one of the processes by which organizations serve as an intermediary between human capital and wage dispersion. Consistent with that argument, my results may be interpreted as indicating that occupations represent a structural buffer between wages and the distribution of human capital among workers.

This latter interpretation is evident in the findings, reported above, which indicate that the educational diversity index and the proportion of college-educated workers in an occupation do not explain changes in within-occupational wage inequality. My analysis thus suggests that the institutional features of occupations serve as one of wedges between education and wages because within-occupational wage dispersion appears to be relatively unaffected

[1]More systematic and precise empirical evidence for this general view is provided by Hedstöm's (1991) analysis of a large sample of firms in the Swedish manufacturing sector.

by the within-occupational distribution of education. Although my investigation has not fully uncovered all of the relevant institutional processes, it does at least imply that the SBTC perspective is at best only a limited and partial explanation of growing wage inequality.

Furthermore, the lack of an effect of the distribution of schooling on within-occupational wage inequality suggests that sociologists need to revisit the classic concern in the labor market literature regarding the mechanism by which schooling affects wages. If the effect derives from a competitive labor market for human capital (as is assumed in the SBTC argument), then its theoretical and policy implications regarding inequality are quite different from those that follow if education serves primarily as a screening or rationing device for a relatively small number of "good jobs" (Thurow 1975; Sørensen 1977; Sørensen and Kalleberg 1981; Sakamoto and Powers 1995; Collins 1979). While these two different processes are not mutually exclusive, the effectiveness of altering the distribution of education to reduce wage inequality is diminished to the extent that the screening role of schooling is larger (Jencks et al. 1972). This disconnection between changes in the distributions of schooling and wages is precisely what is observed in my results for within-occupational inequality but which is unexpected according to the general human capital theory of income distribution (Becker and Chiswick 1966).

Unions. My findings suggest a major change in the relationship between unions and labor market inequality. As noted above, the traditional view has been that unions tend to increase equality due to reduced wage dispersion within the unionized sector (relative to the non-unionized sector), increased wages for workers with lower skill levels, and improved wages in the non-union sector due to spillover effects. However, using a more multivariate and systematic model of the growth in wage inequality for a longer time period, my results indicate that, given the current level of unionization, increases in unionization actually increase wage inequality within an occupation[2], and that inequality within the union sector has been growing. Although in the cross-section, occupations with more unionized workers tend to have greater wage equality, increases in unionization lead to increases in within-occupational wage inequality. Increases in unionization do, to some extent, reduce between-occupational inequality, as is expected by the traditional view, but between-occupational inequality is relatively small and is declining over time.

These results suggest the increasing significance of the monopolistic or social closure perspective discussed by Weeden (2002) and by Freeman and Medoff (1984). According to this view, unions work as a barrier against non-union members in an occupation, so the net effect of unionization is to raise inequality. Rather than having a large spillover effect, the more an occupation becomes unionized, the more unequal the occupation becomes. The increasing

[2]In order to assess whether there is a non-linearity in the effect of unionization (depending upon the current level of unionization in the occupation) that could result in the effect becoming negative, I estimated another multi-level model that included an interaction between highly unionized occupations and $\texttt{YEAR} \times \overline{\texttt{Union}}$. A highly unionized occupation is defined as one with a unionization level of more than 51.2 percent (i.e., two standard deviations above the mean level). The results indicate that the coefficient for this interaction term is not statistically significant at the .05 level. Furthermore, although negative, the estimated coefficient is still less than the positive coefficient for the "main effect," indicating that the net effect of increases in unionization is still positive, even in occupations with high levels of unionization.

inequality within the unionized sector over time further suggests that unions are losing their power to set universal wage standards among the broad ranks of its members. The latter trend may reflect declining union membership and political influence. In sum, my results suggest that unions in the U.S. labor market have arrived at a new era. They have gone from being the great equalizer to a weak but monopolistic institution that struggles to increase wages whenever it can, and in doing so, leads to greater inequality in a period when most less-educated workers are not unionized and when their wages are being diminished.

Before moving to the next discussion, I would like to note that the effect of industry which is closely correlated with the distribution of occupations in American economy is not fully investigated in this study. I have limited my research on the effect of % manufacturing sector. Although an important subject, this is above the scope of this study and needs a bigger data which contains enough sample of each occupation in different industries. I leave this topic for a future research.

7.4 Further Implications Regarding Inequality in the "New Economy"

The "New Economy" is a term that has been used to refer to the U.S. economy since 1980, when inequality, as I have shown, began substantially increasing. There is some debate as to exactly what characteristics underlie and define the “New Economy” (e.g., Hollister 2004). Most accounts often include, however, such changes as heightened market competition due to improvements in information and transportation, increasing application of computer and other advanced production technologies, reduced internal labor markets and greater inter-firm mobility, “lean and mean” firm organization (i.e., flatter managerial hierarchies), declining unions, rising globalization and international competition, and downsizing and outsourcing (e.g., Cappelli 1999; Kalleberg 2001; Hollister 2004; Levine et al. 2002; McCall 2000; Neumark 2001; Osterman 1999).

The implications of the “New Economy” for traditional thinking about occupations and “disaggregate structuration” have not been addressed in the sociological literature. Given my results about the limited capacity of detailed occupations to explain the growth in wage inequality, I propose the hypothesis that firms and organizations are becoming more important in determining labor market outcomes. Firms have become more heterogeneous, and occupational boundaries have become increasingly blurred in the “New Economy.” Wage inequality is increasingly less dependent upon an individual’s measured occupational category and more dependent upon the firm in which one is employed, as well as in one’s bargaining power within the firm.

As discussed by Lindbeck and Snower (1996, 2000), many firms have moved from Tayloristic to holistic organizational structures during the period of the “New Economy.” Tayloristic firms are organized around the principle of promoting the specialization of labor that is “micro-managed” by a steep hierarchy of managerial control. This organizational approach assumes the traditional economic model of a fixed technology with highly specialized labor that is concerned with cost minimization in the context of a stable market environment with known factor costs and well-defined consumer demand functions. A worker's productivity is supposed to be strictly determined by the successful execution of the specific job tasks that the worker is hired to perform. Employers are supposed to set the worker's wage equal to the market rate for persons who carry out those specific job tasks. A worker's productivity is closely aligned with the particular job that the worker is assigned to perform.

By contrast, holistic firms arise due to heightened market competition derived from product or production innovations, the use of computerized information and communication systems by the firm, the changing demands of consumers, who often directly communicate their concerns to the firm, and ever evolving production technologies. Holistic firms are characterized by a flatter management structure, greater production flexibility, more individualistic treatment of employees, team work and job rotation, multi-tasking over occupational or divisional boundaries, and the involvement of employees in decision making. In a holistic firm, productivities are enhanced by making greater use of workers' information about the production system, reducing management costs, and by promoting workers' understanding of the broader production process (Black and Lynch 2001; Krafcik 1988; Lindbeck and Snower 2000; Pfeiffer 1994). Because a worker's tasks are not limited to one division of the firm, a worker's productivity is judged broadly, as technology develops and changes. Workers' wages are based on assessments of a worker's productive efforts in comprehensive terms rather than in a strictly determined bureaucratic manner based on the execution of a narrow range of job tasks.

Holistic firms remind us of Japanese labor markets. Although changing recently, Japanese workers in large firms experience an extensive job rotation. Their wages are associated primarily with their ranks in firms, not with jobs (Sakamoto and Powers 1995:225). Firm-specific work skills are another crucial component determining their wages (Sørensen and Kalleberg 1981). Because of high employment security and wages not depending on job titles, Japanese workers do not fear from technological changes, thus the Japanese employment system is more conducive to the introduction of new technology (Sakamoto and Powers 1995:226). Regarding growing inequality, I want to recall Dunne et al.'s (2004) finding that virtually the entire increase in overall dispersion in hourly wage is accounted for by the between-plant components. One crucial difference of holistic firms of New Economy from Japanese firms might be that Japanese firms do not try to associate individual worker's wage with her individual productivity, while holistic firms strongly do.

In contrast to traditional human capital theory, the theory of holistic organizations assumes that the college premium arises not so much because college graduates are learning particular work skills that are demanded by the labor market but because colleges are serving to screen and certify workers' aptitudes regarding versatility, the ability to learn, communication and social skills, general analytical capacities, and creativity. For this reason, the role of educational attainment in a labor market of holistic organizations reflects a screening process mentioned above. Human capital theory is still also relevant, however, to the extent that schools augment students' basic abilities relating to the aptitudes mentioned above.

Given the rise of holistic organizations, occupational distinctions have become obscured, and within-group inequality has increased because workers of a given category (e.g., educational, occupational, industrial) have varying abilities in regard to versatility, multi-tasking, communication, creativity, capacity to learn new skills, and other characteristics that are not well measured. Furthermore, organizations may vary in the extent that they reward these sorts of skills or provide individuals with the opportunities for utilizing them. In short, the structural bases for a close association between equal pay for equal work are eroded by holistic organizational change. The decline of centralized bargaining among unions and growing wage inequality within the unionized sector is simply a reflection of this change.

7.5 Conclusion

Writing before the 1980's, an eminent economist once remarked that the distribution of income in the U.S. has changed so little that studying it is like "watching the grass grow" (Aaron 1978:17). By contrast, the post-1980 experience might be characterized as a time-elapsed film that shows grass spurting up by leaps and bounds within a few seconds. This phenomenon of rapidly increasing inequality (or at least aspects of it) has been referred to by economists as the "Great U-Turn" (Harrison and Bluestone 1988) and the "quiet depression" (Levy 1987). On the other hand, as noted by Morris and Western (1999:624), "if you had been reading only the flagship journals in sociology, you probably would not know about these trends. Sociologists have been strangely and remarkably silent on this issue."

In order to improve the sociological understanding of wage inequality, I have investigated the role of occupational structure and how it mediates the effects of other relevant labor market variables. My results have shown that the effects of education and manufacturing have been somewhat overemphasized, at least after taking occupation as a given, and that part-time employment, privatization, and even unions lead to increased growth in wage inequality. However, rather than increasing wage inequality, the rising employment of women appears to reduce inequality. Future research on wage inequality should build upon these findings in order to explicate them more fully.

Meanwhile, the direct correlation between wages and occupations appears to be declining, even when the latter are investigated at the detailed three-digit level. As increasingly more of the variance in wages is within occupations, sociologists need to develop broader theories to better understand the causes of growing wage inequality. Although occupational structure is certainly one of these causes, my results imply that sociologists should not overlook other labor market variables and aspects of the class structure.

Appendix A

Occupation Recode Table

Table A.1: Occupation Recode Codebook

Occupations	CPS Code before 1992	CPS Code from 1992
Administrators and officials, public administration	5	5
Administrators, protective services	6	6
Financial managers	7	7
Personnel and labor relations managers	8	8
Purchasing managers	9	9
Managers, marketing, advertising, and public relations	13	13
Administrators, education and related fields	14	14
Managers, medicine and health	15	15
Managers, properties and real estate	16	18
Funeral directors	18, 19	19
Other Managers, service organizations, administrators, and legislators n.e.c.	3, 4, 17, 22	3, 4, 17, 21, 22
Accountants and auditors	23	23
Underwriters	24	24
Other financial officers	25	25
Management analysts	26	26

Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
		Continued from previous page
Personnel, training, and labor relations specialists	27	27
Buyers, wholesale and retail trade except farm products	29	29
Purchasing agents and buyers, n.e.c.	33	33
Construction inspectors	35	35
Inspectors and compliance officers, except construction	36	36
Management related occupations, n.e.c.	28, 34, 37	28, 34, 37
Architects	43	43
Aerospace	44	44
Metallurgical and materials	45	45
Chemical	48	48
Civil	53	53
Electrical and electronic	55	55
Industrial	56	56
Mechanical	57	57
Engineers, n.e.c.	46, 47, 49, 54, 58, 59	46, 47, 49, 54, 58, 59
Computer systems analysts and scientists	64	64
Operations and systems researchers and analysts	65	65
Mathematical scientists, n.e.c.	66-68	66-68
Chemists, except biochemists	73	73
Geologists and geodesists	75	75
Physical scientists, n.e.c.	69, 74, 76	69, 74, 76
Agricultural and food scientists	77	77
Biological and life scientists	78	78
Forestry and conservation scientists	79	79
Medical scientists	83	83
Physicians	84	84
Health diagnosing practitioners, n.e.c.	85-89	85-89
Registered nurses	95	95
Pharmacists	96	96
Dietitians	97	97
Respiratory therapists	98	98
Occupational therapists	99	99
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
		Continued from previous page
Physical therapists	103	103
Speech therapists	104	104
Therapists, n.e.c.	105	105
Physicians' assistants	106	106
Natural science teachers, n.e.c.	113-117	113-117
Social science teachers, n.e.c.	118-126	118-126
Other teachers, postsecondary, n.e.c.	127-153	127-153
Postsecondary teachers, subject not specified	154	154
Teachers, prekindergarten and kindergarten	155	155
Teachers, elementary school	156	156
Teachers, secondary school	157	157
Teachers, special education	158	158
Teachers, n.e.c.	159	159
Counselors, Educational and Vocational	163	163
Librarians	164	164
Economists	166	166
Psychologists	167	167
Surveyors, Urban Planners, Other social scientists, n.e.c.	63, 165, 168, 169, 173	63, 165, 168, 169, 173
Social workers	174	174
Recreation workers	175	175
Clergy	176	176
Religious workers, n.e.c.	177	177
Lawyers and Judges	178	178
Technical writers	184	184
Designers	185	185
Musicians and composers	186	186
Actors and directors	187	187
Painters, sculptors, craft-artists, and artist printmakers	188	188
Photographers	189	189
Artists, authors, dancers, performers, and related workers, n.e.c.	183, 193, 194	183, 193, 194
Editors and reporters	195	195
Public relations specialists	197	197
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
		Continued from previous page
Announcers	198	198
Athletes	199	199
Clinical laboratory technologists and technicians	203	203
Dental hygienists	204	204
Radiologic technicians	206	206
Licensed practical nurses	207	207
Health technologists and technicians, n.e.c.	205, 208	205, 208
Electrical and electronic technicians	213	213
Engineering technicians, n.e.c.	214-216	214-216
Drafting occupations	217	217
Surveying and mapping technicians	218	218
Biological technicians	223	223
Chemical technicians	224	224
Science technicians, n.e.c.	225	225
Airplane pilots and navigators	226	226
Air traffic controllers	227	227
Computer programmers	229	229
Legal assistants	234	234
Technicians, n.e.c.	228, 233, 235	228, 233, 235
Supervisors and Proprietors, Sales Occupations	243	243
Insurance sales occupations	253	253
Real estate sales occupations	254	254
Securities and financial services sales occupations	255	255
Advertising and related sales occupations	256	256
Sales occupations, other business services	257	257
Sales engineers	258	258
Sales representatives, mining, manufacturing, and wholesale	259	259
Sales workers, motor vehicles and boats	263	263
Sales workers, apparel	264	264
Sales workers, shoes	265	265
Sales workers, furniture and home furnishings	266	266
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
		Continued from previous page
Sales workers, radio, TV, hi-fi, and appliances	267	267
Sales workers, hardware and building supplies	268	268
Sales workers, parts	269	269
Sales workers, other commodities	274	274
Sales counter clerks	275	275
Cashiers	276	276
Street and door-to-door sales workers	277	277
News vendors	278	278
Demonstrators, promoters and models, sales	283	283
Auctioneers, and other sales support occupations, n.e.c.	284, 285	284, 285
Supervisors, general office	303	303
Supervisors, financial records processing	305	305
Supervisors, distribution, scheduling, and adjusting clerks	307	307
Computer operators	308	308
Secretaries	313	313
Stenographers	314	314
Typists	315	315
Interviewers	316	316
Hotel clerks	317	317
Transportation ticket and reservation agents	318	318
Receptionists	319	319
Information clerks, n.e.c.	323	323
Order clerks	327	327
Personnel clerks, except payroll and timekeeping	328	328
Library clerks	329	329
File clerks	335	335
Records clerks	336	336
Bookkeepers, accounting, and auditing clerks	337	337
Payroll and timekeeping clerks	338	338
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
	Continued from previous page	
Billing clerks	339	339
Cost and rate clerks	343	343
Billing, posting, and calculating machine operators	344	344
Duplicating machine operators	345	345
Office machine operators, n.e.c.	325, 326, 346, 347	325, 326, 346, 347
Computer and communications equipment operators, n.e.c. and other peripheral equipment operators, n.e.c.	304, 306, 348, 349, 353	304, 306, 348, 353
Postal clerks, except mail carriers	354	354
Mail carriers, postal service	355	355
Mail clerks, except postal service	356	356
Messengers	357	357
Dispatchers	359	359
Production coordinators	363	363
Traffic, shipping, and receiving clerks	364	364
Stock and inventory clerks	365	365
Meter readers	366	366
Weighers, measurers, checkers, and samplers	368, 369	368
Expediters	373	373
Material recording, scheduling, and distributing clerks, n.e.c.	374	374
Insurance adjusters, examiners, and investigators	375	375
Investigators and adjusters, except insurance	376	376
Eligibility clerks, social welfare	377	377
Bill and account collectors	378	378
General office clerks	379	379
Bank tellers	383	383
Data-entry keyers	385	385
Statistical clerks	386	386
Teachers' aides	387	387
Administrative support occupations, n.e.c.	384, 389	384, 389
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
		Continued from previous page
Private household cleaners and servants	403-407	403-407
Supervisors, firefighting and fire prevention occupations	413	413
Supervisors, police and detectives	414	414
Supervisors, guards	415	415
Fire inspection, fire fighting, and fire prevention occupations	416, 417	416, 417
Police and detectives, public service	418	418
Sheriffs, bailiffs, and other law enforcement officers	423	423
Correctional institution officers	424	424
Crossing guards	425	425
Guards and police, except public service	426	426
Protective service occupations, n.e.c.	427	427
Supervisors, food preparation and service occupations	433	433
Bartenders	434	434
Waiters and waitresses	435	435
Cooks	436, 437	436
Food counter, fountain and related occupations	438	438
Kitchen workers, food preparation	439	439
Waiters'/waitresses' assistants	443	443
Miscellaneous food preparation occupations	444	444
Dental assistants	445	445
Health aides, except nursing	446	446
Nursing aides, orderlies, and attendants	447	447
Supervisors, cleaning and building service workers	448	448
Maids and housemen	449	449
Elevator operators and janitors and cleaners	453, 454	453, 454
Pest control occupations	455	455
Supervisors, personal service occupations	456	456
Hairdressers and cosmetologists	458	458
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
	Continued from previous page	
Attendants, amusement and recreation facilities	459	459
Public transportation attendants	463	463
Welfare service aides	465	465
Early childhood teacher's assistants	467	467
Child care workers, n.e.c.	468	468
Personal service occupations, n.e.c.	457, 461, 462, 464, 466, 469	457, 461, 462, 464, 466, 469
Farm workers	473-479	473-479
Supervisors, related agricultural occupations	485	485
Groundskeepers and gardeners, except farm	486	486
Animal caretakers, except farm	487	487
Other agriculture related workers	483, 484, 488, 489	483, 484, 488, 489
Forestry, fishing, and hunting related workers	494-499	494-499
Supervisors, mechanics and repairers	503	503
Automobile mechanics	505	505
Bus, truck, and stationary engine mechanics	507	507
Aircraft engine mechanics	508	508
Small engine repairers	509	509
Automobile body and related repairers	514	514
Heavy equipment mechanics	516	516
Farm equipment mechanics	517	517
Industrial machinery repairers	518	518
Electronic repairers, communications and industrial equipment	523	523
Data processing equipment repairers	525	525
Household appliance and power tool repairers	526	526
Telephone line installers and repairers	527	527
Telephone installers and repairers	529	529
Miscellaneous electrical and electronic equipment repairers	533	533

Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
	Continued from previous page	
Heating, air conditioning, and refrigeration mechanics	534	534
Office machine repairers	538	538
Millwrights	544	544
Specified mechanics and repairers, n.e.c.	506, 515, 519, 535, 536, 539, 543, 547	506, 515, 519, 535, 536, 539, 543, 547
Not specified mechanics and repairers"	549	549
Supervisors, electricians and power transmission installers	555	555
Supervisors, construction, n.e.c.	558	558
Brickmasons and stonemasons	553, 563, 564	553, 563, 564
Tile setters, hard and soft	565	565
Carpet installers	566	566
Carpenters	554, 567, 569	554, 567, 569
Drywall installers	573	573
Electricians	575	575
Electrician apprentices	576	576
Electrical power installers and repairers	577	577
Painters, construction and maintenance	556, 579	556, 579
Plasterers	584	584
Plumbers, pipefitters, and steamfitters	557, 585, 587	557, 585, 587
Concrete and terrazzo finishers	588	588
Glaziers	589	589
Insulation workers	593	593
Roofers	595	595
Sheetmetal duct installers	596	596
Structural metal workers	597	597
Construction trades, n.e.c.	583, 594, 598, 599	583, 594, 598, 599
Supervisors, extractive occupations	613	613
Drillers, oil well	614	614
Mining machine operators	616	616
Mining occupations, n.e.c.	617	617
Tool and die makers	634, 635	634, 635
Machinists	637, 639	637, 639
Boilermakers	643	643
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
	Continued from previous page	
Precious stones and metals workers (Jewelers)	647	647
Sheet metal workers	653, 654	653, 654
Cabinet makers and bench carpenters	657	657
Dressmakers	666	666
Upholsterers	668	668
Optical goods workers	677	677
Dental laboratory and medical appliance technicians	678	678
Electrical and electronic equipment assemblers	683	683
Butchers and meat cutters	686	686
Bakers	687	687
Food batchmakers	688	688
Inspectors, testers, and graders	689	689
Other Miscellaneous workers	615, 628, 636, 644-646, 649, 655, 656, 658, 659, 667, 669, 673-676, 679, 684, 693	615, 628, 636, 644-646, 649, 655, 656, 658, 659, 667, 669, 673-676, 679, 684, 693
Water and sewage treatment plant operators	694	694
Power plant operators	695	695
Stationary engineers	696	696
Miscellaneous plant and system operators	699	699
Lathe and turning machine operators	704	704
Punching and stamping press machine operators	706	706
Grinding, abrading, buffing, and polishing machine operators	709	709
Miscellaneous metal, plastic, stone, and glass working machine operators	715	715
Molding and casting machine operators	719	719
Sawing machine operators	727	727
Miscellaneous woodworking machine operators	733	733
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
		Continued from previous page
Printing press operators	734	734
Photoengravers and lithographers	735	735
Miscellaneous printing machine operators	737	737
Winding and twisting machine operators	738	738
Knitting, looping, taping, and weaving machine operators	739	739
Textile sewing machine operators	744	744
Pressing machine operators	747	747
Laundering and dry cleaning machine operators	748	748
Miscellaneous textile machine operators	749	749
Packaging and filling machine operators	754	754
Extruding and forming machine operators	755	755
Mixing and blending machine operators	756	756
Separating, filtering, and clarifying machine operators	757	757
Painting and paint spraying machine operators	759	759
Furnace, kiln, and oven operators, except food	766	766
Crushing and grinding machine operators	768	768
Slicing and cutting machine operators	769	769
Photographic process machine operators	774	774
Miscellaneous machine operators, n.e.c.	777	777
Machine operators, not specified	779	779
Other Mischellaneous machine workers	703, 705, 707, 708, 713, 714, 717, 723-726, 728, 729, 736, 743, 745, 753, 758, 763-765, 773	703, 705, 707, 708, 713, 714, 717, 723-726, 728, 729, 736, 743, 745, 753, 758, 763-765, 773
Welders and cutters	783	783
Assemblers	785	785
Miscellaneous hand working occupations	794, 795	795
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
		Continued from previous page
Production inspectors, checkers, and examiners	796	796
Production testers	797	797
Other hand working occupations & other production testers	784, 786, 787, 789, 793, 798	784, 786, 787, 789, 793, 798
Graders and sorters, except agricultural	799	799
Supervisors, motor vehicle operators and Motor transportation occupations, n.e.c.	803, 814	803, 814
Truck drivers	804, 805	804
Driver-sales workers	806	806
Bus drivers	808	808
Taxicab drivers and chauffeurs	809	809
Parking lot attendants	813	813
Railroad conductors and yardmasters	823	823
Locomotive operating occupations	824	824
Operating engineers	844	844
Other transp. & material moving occupations	825, 826, 828, 829, 833, 834, 843, 845, 848	825, 826, 828, 829, 833, 834, 843, 845, 848
Crane and tower operators	849	849
Excavating and loading machine operators	853	853
Grader, dozer, and scraper operators	855	855
Industrial truck and tractor equipment operators	856	856
Miscellaneous material moving equipment operators	859	859
Construction laborers	869	869
Other handlers,equipment cleaners,helpers,laborers	864-868, 873, 874	864-868, 873, 874
Garbage collectors	875	875
Stock handlers and baggers	877	877
Machine feeders and offbearers	878	878
Freight, stock, and material handlers, n.e.c.	876, 883	876, 883
Garage and service station related occupations	885	885
		Continued on next page

Occupations	CPS Code before 1992	CPS Code from 1992
	Continued from previous page	
Vehicle washers and equipment cleaners	887	887
Hand packers and packagers	888	888
Laborers, except construction	889	889

Appendix B

Descriptive Statistics Tables

Table B.1: Descriptive Statistics for Socioeconomic Index for the Labor Force Employed in 331 Occupations, 1983-85 to 2000-02

		Total	1983-1985	2000-2002
Meanwage	Mean	15.508	15.136	16.720
	(sd. dev.)	(5.741)	(5.344)	(6.403)
	Min	5.46	5.84	6.19
	Max	45.89	45.89	43.19
Female	Mean	.477	.464	.483
	(sd. dev.)	(.312)	(.329)	(.299)
	Min	0	0	0
	Max	1	1	0.99
Black	Mean	.112	.105	.118
	(sd. dev.)	(.063)	(.067)	(.062)
	Min	0	0	0.01
	Max	0.42	0.38	0.34
Hispanic	Mean	.088	.060	.060
	(sd. dev.)	(.063)	(.037)	.060 (.062)
	Min	0	0	0.01
	Max	0.64	0.32	0.64

Continued on next page

		Total	1983-1985	2000-2002
				Continued from previous page
Other race	Mean	.035	.026	.047
	(sd. dev.)	(.022)	(.016)	(.029)
	Min	0	0	0
	Max	0.29	0.12	0.19
South	Mean	.344	.335	.350
	(sd. dev.)	(.048)	(.057)	(.042)
	Min	0.12	0.16	0.13
	Max	0.96	0.92	0.96
Lee than High School	Mean	.116	.153	.094
	(sd. dev.)	(.125)	(.143)	(.111)
	Min	0	0	0
	Max	0.66	0.55	0.66
High School Graduate	Mean	.356	.381	.325
	(sd. dev.)	(.168)	(.158)	(.172)
	Min	0	0	0
	Max	0.69	0.67	0.67
Some College	Mean	.279	.248	.300
	(sd. dev.)	(.118)	(.104)	(.125)
	Min	0	0	0
	Max	0.77	0.59	0.76
BA +	Mean	.248	.218	.282
	(sd. dev.)	(.271)	(.263)	(.281)
	Min	0	0	0
	Max	1	1	1
Educational Diversity	Mean	.640	.642	.639
	(sd. dev.)	(.073)	(.070)	(.079)
	Min	0.09	0.17	0.11
	Max	0.78	0.78	0.77
Public Sector	Mean	.171	.176	.163
	(sd. dev.)	(.234)	(.232)	(.233)
				Continued on next page

Continued from previous page

		Total	1983-1985	2000-2002
	Min	0	0	0
	Max	1	0.99	1
Part Timer	Mean	.153	.165	.136
	(sd. dev.)	(.146)	(.164)	(.123)
	Min	0	0	0
	Max	0.94	0.94	0.78
Unionization	Mean	.182	.225	.152
	(sd. dev.)	(.165)	(.181)	(.150)
	Min	0	0	0.01
	Max	0.94	0.89	0.87
Manufacturing Sector	Mean	.247	.281 .215	
	(sd. dev.)	(.303)	(.317)	(.290)
	Min	0	0	0
	Max	1	1	1
Sample Size (n)		5958	331	331

Table B.2: Correlation Coefficients Matrix

	Gini	Age	Female	Black	Hisp.	Other	BA+	Edu.Div.	South	Public	PartTime	Union
Age	.0380	1.0000										
	(.0033)											
Female	.0260	-.0596	1.0000									
	(.0448)	(.0000)										
Black	-.2297	-.0200	.2370	1.0000								
	(.0000)	(.1219)	(.0000)									
Hispanic	-.1517	-.2093	-.0563	.2922	1.0000							
	(.0000)	(.0000)	(.0000)	(.0000)								
Other Races	.0456	.0195	.1656	-.0199	.1039	1.0000						
	(.0004)	(.1330)	(.0000)	(.1250)	(.0000)							
BA+	.3920	.2764	.1428	-.3861	-.4750	.2787	1.0000					
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)						
Edu.Div.	.1548	-.1229	.1134	.0843	.0401	-.1250	-.1947	1.0000				
	(.0000)	(.0000)	(.0000)	(.0000)	(.0020)	(.0000)	(.0000)					
South	-.1043	.0347	-.1806	.2332	.0862	-.2068	-.2166	-.0309	1.0000			
	(.0000)	(.0074)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0171)				
Public	-.0043	.3236	.0938	.0894	-.2620	-.0244	.3493	-.1069	-.0703	1.0000		
	(.7379)	(.0000)	(.0000)	(.0000)	(.0000)	(.0601)	(.0000)	(.0000)	(.0000)			
Part Time	.1925	-.3202	.5692	.1800	.0646	.0676	-.0553	.1207	-.1824	.0388	1.0000	
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0027)		
Union	-.2782	.2803	-.3259	.1435	-.0782	-.2705	-.1731	-.2112	.0274	.3947	-.2794	1.0000
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0346)	(.0000)	(.0000)	
Manuf	-.2507	.0118	-.4686	-.0555	.2050	-.0895	-.3099	-.0912	.2236	-.3817	-.4442	.1760
	(.0000)	(.3632)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)

Table B.3: Correlation Coefficients Matrix of Percent Changes Over Time

	Gini	Age	Female	Black	Hisp.	Other	BA+	Edu.Div.	South	Public	PartTime	Union
Age	.0239	1.0000										
	(.0647)											
Female	.0317	.0895	1.0000									
	(.0145)	(.0000)										
Black	-.0303	.0886	.0651	1.0000								
	(.0192)	(.0000)	(.0000)									
Hispanic	-.0229	.1108	-.1039	-.1545	1.0000							
	(.0777)	(.0000)	(.0000)	(.0000)								
Other Races	.0305	.0842	.0190	.1009	.1026	1.0000						
	(.0187)	(.0000)	(.1433)	(.0000)	(.0000)							
BA+	.0849	.0063	.0202	.0198	-.0142	.1990	1.0000					
	(.0000)	(.6252)	(.1198)	(.1273)	(.2728)	(.0000)						
Edu.Div.	-.0318	-.2323	-.1375	-.0125	.0953	.0534	.0222	1.0000				
	(.0142)	(.0000)	(.0000)	(.3343)	(.0000)	(.0000)	(.0868)					
South	.1323	.0559	.0667	.2062	-.0942	.0431	-.0144	-.0442	1.0000			
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0009)	(.2661)	(.0006)				
Public	-.0963	-.0528	-.1856	.1971	-.0218	.0358	.0487	.1708	-.1145	1.0000		
	(.0000)	(.0000)	(.0000)	(.0000)	(.0921)	(.0057)	(.0002)	(.0000)	(.0000)			
Part Time	.0657	-.1659	.1634	.0052	-.2899	-.0016	.0739	-.0125	-.0431	.0153	1.0000	
	(.0000)	(.0000)	(.0000)	(.6900)	(.0000)	(.9003)	(.0000)	(.3351)	(.0009)	(.2377)		
Union	.1175	-.0932	.0789	-.0651	-.2467	-.1417	.1694	.0270	-.1427	.0090	.0234	1.0000
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0375)	(.0000)	(.4883)	(.0715)	
Manuf	.0931	-.0302	-.2031	-.0725	-.0221	-.1858	-.1204	.0306	-.1077	-.0760	-.0876	.1066
	(.0000)	(.0199)	(.0000)	(.0000)	(.0881)	(.0000)	(.0000)	(.0182)	(.0000)	(.0000)	(.0000)	(.0000)

Note: Percent point changes from year 1983-85.

Appendix C

Inequality and Mean Wage

Table C.1: Changes of Inequality and Mean Wage by Occupation

		Mean Wage			Total
	Inequality	Decrease	No Change	Increase	
(1) Managerial and Professional					
	Decrease	2	2	2	6
	No Change	4	16	9	29
	Increase	5	18	23	46
	Total	11	36	34	81
(1-a) Executive Administration, Managerial Occupations Only					
	Decrease	1	2	1	4
	No Change	3	2	1	6
	Increase	2	7	2	11
	Total	6	11	4	21
(1-b) Professional Only					
	Decrease	1	0	1	2
	No Change	1	14	8	23
	Increase	3	11	21	35
	Total	5	25	30	60

Continued on next page

Inequality	Mean Wage: Decrease	No Change	Increase	Total
Continued from previous page				
(2) Technical, Sales, and Administrative Support				
Decrease	9	11	2	22
No Change	9	18	8	35
Increase	4	13	12	29
Total	22	42	22	86
(2-a) Sales Only				
Decrease	1	2	0	3
No Change	0	4	3	7
Increase	0	7	5	12
Total	1	13	8	22
(2-b) Technicians Only				
Decrease	0	1	0	1
No Change	3	5	1	9
Increase	1	1	5	7
Total	4	7	6	17
(2-c) Administrative Support Only				
Decrease	8	8	2	18
No Change	6	9	4	19
Increase	3	5	2	10
Total	17	22	8	47
(3) Services				
Decrease	4	2	0	6
No Change	3	2	8	13
Increase	3	5	7	15
Total	10	9	15	34
Continued on next page				

	Inequality	Mean Wage: Decrease	Mean Wage: No Change	Mean Wage: Increase	Total
				Continued from previous page	
(4) Precision Production, Craft					
	Decrease	5	4	0	9
	No Change	15	17	4	36
	Increase	11	8	0	19
	Total	31	29	4	64
(5) Operators, Fabricators, and Laborers					
	Decrease	18	3	1	22
	No Change	18	9	2	29
	Increase	5	3	1	9
	Total	41	15	4	60

Note: Numbers in Table are numbers of occupations.

Bibliography

Aaron, Henry J. 1978. *Politics and the Professors*. Washington, D.C.: The Brookings Institution.

Acemoglu, Daron, Philippe Aghion, and Giovanni L. Vilolante. 2001. "Deunionization, Technical Change and Inequality." *Carnegie-Rochester Conference Series on Public Policy* 55:229–264.

Alderson, Arthur S. and François Nielsen. 2002. "Globalization and the Great U-Turn Income Inequality Trends in 16 OECD Countries." *American Journal of Sociology* 107:1244–1299.

Allison, Paul D. 1978. "Measures of Inequality." *American Sociological Review* 43:865–880.

Atkinson, Anthony. 1999. "Is Rising Income Inequality Inevitable? A Crique of the Transatlantic Consensus." In *WIDER Annual Lecture*. The University of Oslo.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *The Quarterly Journal of Economics* pp. 1169–1213.

Autor, David H., Frank Levy, and Richard J. Murnane. 2002. "Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank." *Industrial and Labor Relations Review* 55:432–47.

Beck, Nathaniel. 2001. "Time-Series-Cross-Section Data: What Have We Learned in the Past Few Years." *Annual Review of Political Science* 4:271–293.

Becker, Gary S. and Barry R. Chiswick. 1966. "Education and the Distribution of Earnings." *American Economic Review* 56:358–69.

Belous, Richard S. 1989. *The Contingent Economy: The Growth of the Temporary, Part-Time and Subcontracted Workforce*. Washington: National Planning Association.

Bernhardt, Annette, Martin Morris, Mark S. Handcock, and Marc A. Scott. 2001. *Economic Mobility in the New American Labor Market*. New York, NY: Russell Sage Foundation.

Bernstein, Jared and Lawrence Mishel. 1997. "Has wage inequality stopped growing?" *Monthly Labor Review* 120:3–16.

Black, Sandra E. and Lisa M. Lynch. 2001. "How to Compete: The Impact of Workplace Practices and Information Technology on Productivity." *The Review of Economics and Statistics* 83:434–45.

Blau, Peter and Otis Dudley Duncan. 1967. *The American Occupational Structure*. The Free Press.

Bloomquist, Leonard and Gene F. Summers. 1982. "Organization of Production and Community Income Distribution." *American Sociological Review* 47:325–338.

Bluestone, Barry and Bennett Harrison. 1988. *The Great U-Turn: Corporate Restructuring and the Polarizing of America*. New York, NY: Basic Books.

Borjas, George J., Richard B Freeman, and Lawrence Katz. 1996. "Searching for the Effect of Immigration on the Labor Market." *American Economic Review* 86:246–251.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt. 2002. "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence." *The Quarterly Journal of Economics* 117:339–76.

Brynjolfsson, Erik, Lorin M. Hitt, and Shinkyu Yang. 2002. "Intangible Assets: Computers and Organizational Capital." *Brookings Papers on Economic Activity* 2002:137–98.

Cancian, Maria and Deborah Reed. 1999. "The Impact of Wives' Earnings on Income Inequality: Issues and Estimates." *Demography* 36:173–184.

Cappelli, Peter. 1999. *The New Deal at Work: Mananging the Market-Driven Workforce*. Boston, MA: Harvard Business School Press.

Card, David and John E. DiNardo. 2002. “Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles.” *Journal of Labor Economics* 20:733–783.

Caroli, Eve and John Van Reenen. 2001. “Skill-Biased Organizational Change? Evidence From a Panel of British and French Establishments.” *The Quarterly Journal of Economics* 116:1449–92.

Collins, Randall. 1979. *The Credential Society: A Historical Sociology of Education and Stratification*. New York: Academic Press.

Coulter, Philip B. 1989. *Measuring Inequality*. Boulder: Westview Press.

Cowell, Frank A. 1995. *Measuring Inequality*. LSE Handbooks in Economics Series. London: Prentice Hall, 2nd edition.

Danziger, Sheldon and Peter Gottschalk (eds.). 1993. *Uneven Tide: Rising Inequality In America*. New York: Russell Sage Foundation.

Davis, Kingsley and Wilbert Moore. 1984. “Some Principles of Stratification.” In *Social Stratification in Sociological Perspective: Class, Race and Gender*, edited by David B. Grusky, pp. 55–64. Westview Press.

Dinardo, John and Thomas Lemieux. 1997. “Diverging Male Wage Inequality in the United States and Canada, 1981-1988 :Do Institutions Explain the Difference?” *Industrial and Labor Relations Review* 50:629–651.

DiPrete, Thomas A. and Patricia A. McManus. 1996. “Institutions, Technical Change, and Diverging Life Chances: Earnings Mobility in the United States and Germany.” *American Journal of Sociology* 102:34–79.

Dooley, Martin and Peter Gottschalk. 1982. “Does a Younger Male Labor Force Mean Growing Earnings Inequality.” *Monthly Labor Review* 105:42–45.

Dooley, Martin and Peter Gottschalk. 1985. “”The Increasing Proportion of Men with Low Earnings in the United States.” *Demography* 22:25–34.

Dunne, Timothy, Lucia Foster, John Haltiwanger, and Kenneth R. Troske. 2004. “Wage and Productivity Dispersion in United States Manufacturing: The Role of Computer Investment.” *Journal of Labor Economics* 22:397–429.

Eliason, Scott R. 1995. "An Extension of the Sørensen-Kalleberg Theory of the Labor Market Matching and Attainment Processes." *American Sociological Review* 60:247–71.

England, Paula. 1992. *Comparable Worth: Theories and Evidence*. New York, NY: Aldine de Gruyter.

Erikson, Robert and John H. Goldthorpe. 1992. *The Constant Flux: A Study of Class Mobility in Industrial Societies*. Oxford: Oxford University Press.

Farber, Henry S. and Bruce Western. 2001. "Accounting for the Decline of Unions in the Private Sector, 1973-1998." *Journal of Labor Research* 22:459–85.

Farley, Reynolds. 1996. *The New American Reality: Who We Are, How We Got Here, Where We Are Going*. New York, NY: Russell Sage Foundation.

Featherman, David L. and Robert M. Hauser. 1978. *Opportunity and Change*. New York, NY: Academic Press.

Featherman, David L., F Lancaster Jones, and Robert M. Hauser. 1978. "Assumptions of Social Mobility Research in the U.S. : The Case of Occupational Status." *Social Science Research* 4:329–360.

Fernandez, Roberto M. 2001. "Skill-Biased Technological Change and Wage Inequality: Evidence from a Plant Retooling." *American Journal of Sociology* 107:273–320.

Firebaugh, Glenn and Brian Goesling. 2004. "Accounting for the Recent Decline in Global Income Inequality." *American Journal of Sociology* 110:283–312.

Freeman, Richard B. 1980. "Unionism and the Dispersion of Wages." *Industrial and Labor Relations Review* 34:3–23.

Freeman, Richard B. 1993. "How Much Has De-Unionization Contributed to the Rise in Male Earnings Inequality?" In *Uneven Tide: Rising Inequality In America*, edited by Sheldon Danziger and Peter Gottschalk, pp. 133–163. New York: Russell Sage Foundation.

Freeman, Richard B. and James L. Medoff. 1984. *What Do Unions Do?* NY: New York: Basic Books, Inc.

Gittleman, Maury. 1994. “Earnings in the 1980s: an Occupational Perspective.” *Monthly Labor Review* 117:16–27.

Goldthorpe, John H. 1987. *Social Mobility and Class Structure in Modern Britain*. Oxford: Clarendon Press, 2nd edition.

Gottschalk, Peter. 1997. “Inequality, Income Growth, and Mobility: The Basic Facts.” *Journal of Economic Perspectives* 11:21–40.

Gottschalk, Peter and Timothy M. Smeeding. 1997. “Cross-National Comparisons of Earnings and Income Inequality.” *Journal of Economic Literature* 35:633–687.

Granovetter, Mark. 1981. “Toward a Sociological Theory of Income Differences.” In *Sociological Perspectives on Labor Market*, edited by Ivar Berg, chapter 2. New York: Academic Press.

Grodsky, Eric and Devah Pager. 2001. “The Structure of Disadvantage: Individual and Occupational Determinants of the Black-White Wage Gap.” *American Sociological Review* 66:542–567.

Grusky, David B. 2001. “Introduction.” In *Social Stratification: Class, Race and Gender in Sociological Perspective*, edited by David B. Grusky, pp. 182–194, Boulder, CO. Westview Press.

Grusky, David B. 2005. “Foundations of a Neo-Durkheimian Class Analysis.” In *Approaches to Class Analysis*, edited by Erik O. Wright, pp. 51–81, New York, NY. Cambridge University Press.

Grusky, David B. and Robert M. Hauser. 1984. “Comparative Social Mobility Revisited: Models of Convergence and Divergence in Sixteen Countries.” *American Sociological Review* 49:19–38.

Grusky, David B. and Jesper B. Sørensen. 1998. “Can Class Analysis Be Salvaged?” *American Journal of Sociology* 103:1187–1234.

Grusky, David B. and Jesper B. Sørensen. 2001. “Are There Big Social Classes?” In *Social Stratification: Class, Race and Gender in Sociological Perspective*, edited by David B. Grusky, pp. 182–194, Boulder, CO. Westview Press.

Gustafsson, Björn and Mats Johansson. 1999. "In Search of Smoking Guns: What Makes Income Inequality Vary Over Time in Different Countries?" *American Sociological Review* 64:585–605.

Halaby, Charles N. 2004. "Panel Models in Sociological Research: Theory into Practice." *Annual Review of Sociology* 30:507–544.

Hall, Richard H. 1969. *Occupations and the Social Structure*. Englewood Cliffs, NJ: Prentice-Hall.

Harrison, Bennett and Barry Bluestone. 1988. *The Great U-Turn: Corporate Restructuring and the Polarizing of America*. New York: Basic Books.

Hauser, Robert M. and John Robert Warren. 1997. "Socioeconomic Indexes for Occupations: A Review, Update, and Critique." *Sociological Methodology* 27:177–298.

Hedstöm, Peter. 1991. "Organizational Differentiation and Earnings Dispersion." *American Journal of Sociology* 43:865–80.

Hedström, Peter and Richard Swedberg. 1985. "The Power of Working Class Organization and Inter-Industrial Wage Structure." *International Journal of Comparative Sociology* 26:90–99.

Hipple, Steward. 2001. "Cintingent Work in the late-1990s." *Monthly Labor Review* 124:3–27.

Hipple, Steven and Jay Stewart. 1996. "Earnings and Benefits of Contingent and Noncontingent Workers." *Monthly Labor Review* 119:22–45.

Hirsch, Barry T. and Edward J. Schumacher. 2001. "Private Sector Union Density and the Wage Premium: Past, Present, and Future." *Journal of Labor Research* 22:487–518.

Hodge, Robert W. 1981. "The Measurement of Occupational Status." *Social Science Research* 10:396–415.

Hollister, Matissa N. 2004. "Does Firm Size Matter Anymore? The New Economy and Firm Size Wage Effects." *American Sociological Review* 69:659–676.

Hout, Michael and Thomas DiPrete. 2006. "What Have We Learned? RC28s Contributions to Knowledge about Social Stratification." *Research in Social Stratification and Mobility* 2006:forthcoming.

Hyslop, Dean R. 2001. "Rising U.S. Earnings Inequality and Family Labor Supply: The Covariance Structure of Intrafamily Earnings." *American Economic Review* 91:755–777.

Jacobs, David. 1985. "Unequal Organizations or Unequal Attainments? An Empirical Comparison of Sectoral and Individualistic Explanations for Aggregate Inequality." *American Sociological Review* 50:166–80.

Jencks, Christoper, Marshall Smith, Henry Acland, Mary Jo Bane, David Cohen, Herbert Gintis, Barbara Heyns, and Stephan Michelson. 1972. *Inequality: A Reassessment of the Effect of Family and Schooling in America*. New York: Harper Colophon Books.

Jenkins, Stephen P. 1999. "INEQDECO: Stata module to calculate inequality indices with decomposition by subgroup." Statistical Software Components, Boston College Department of Economics. available at http://ideas.repec.org/c/boc/bocode/s366002.html.

Juhn, Chinhui. 1999. "Wage Inequality and Demand for Skill: Evidence from Five Decades." *Industrial and Labor Relations Review* 52:424–43.

Juhn, Chinhui and Dae Il Kim. 1999. "The Effects of Rising Female Labor Supply on Male Wages." *Journal of Labor Economics* 17:23–48.

Juhn, Chinhui and Kevin M. Murphy. 1997. "Wage Inequality and Family Labor-Supply." *Journal of Labor Economics* 15:72–97.

Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce. 1993. "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy* 101:410–442.

Kalleberg, Arne. 2001. "Farewell to Commitment? Changing Employmnet Relations and Laobr Markets in the United States." *Contemporary Sociology* 30:9–16.

Kalleberg, Arne L., Michael Wallace, and Robert P. Althauser. 1981. "Economic Segmentation, Worker Power, and Income Inequality." *American Journal of Sociology* 87:651–683.

Karoly, Lynn A. 1993. "The Trend in Inequality Among Families, Individuals, and Workers in the United States: A Twenty-Five Year Perspective." In *Uneven Tide: Rising Inequality In America*, edited by Sheldon Danziger and Peter Gottschalk, chapter 2, pp. 19–98. New York: Russell Sage Foundation.

Kelley, Jonathan and M.D.R. Evans. 1993. "The Legitimation of Inequality: Occupational Earnings in Nine Nations." *American Journal of Sociology* 99:75–125.

Kilbourne, Barbara-Stanek, Paula England, and George Farkas. 1994. "Returns to skill, compensating differentials, and gender bias: effects of occupational characteristics on the wages of white women and men." *American Journal of Sociology* 100:689–719.

Kittel, Bernhard and Hannes Winner. 2005. "How Reliable is Pooled Analysis in Political Economy?: The Globalization-Welfare State Nexus Revisited." *European Journal of Political Research* 44:269–293.

Krafcik, John. 1988. "Triumph of the Lean Production System." *Sloan Management Review* 30:41–52.

Kremer, Michael and Eric Maskin. 1996. "Wage Inequality and Segregation by Skill." NBER Working Papers 5718.

Krueger, Alan B. and Lawrence H. Summers. 1988. "Efficiency Wages and the Inter-industry Wage Structure." *Econometrica* 56:259–293.

Kuznets, Simon. 1955. "Economic Growth and Income Inequality." *American Economic Review* 45:1–28.

Lee, Cheol-Sung. 2004. "Income-Inequality, Democracy, and Public Secotr Size." *American Sociological Review* 70:158–181.

Lee, Cheol-Sung. 2005. "International Migration, Deindustrialization and Union Decline in 16 Affluent OECD Countries, 1962-1997." *Social Forces* 84:71–88.

Leicht, Kevin T. 1989. "On the Estimation of Union Threat Effects." *American Sociological Review* 54:1035–1047.

Levine, David I., Dale Belman, Gary Charness, Erica Groschen, and K.C.O'Shaughnessy. 2002. *How New is the "New Employment Contract"?* Kalamazoo, MI: Upjohn Institute.

Levy, Frank. 1987. *Dollars and Dreams: The Changing American Income Distribution*. New York, NY: Russell Sage Foundation.

Levy, Frank. 1998. *The New Dollars and Dreams: American Incomes and Economic Change*. New York, NY: Russell Sage Foundation.

Levy, Frank and Richard J. Murnane. 1992. "U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trend and Proposed Explanations." *Journal of Economic Literature* 30:1333–1381.

Lillard, Lee, James P. Smith, and Finis Welch. 1986. "What Do We Really Know about Wages? The Importance of Non-reporting and Census Imputation." *Journal of Political Economy* 94:489–506.

Lindbeck, Assar and Dennis J. Snower. 1996. "Reorganization of Firms and Labor Market Inequality." *American Economic Review* 86:315–321.

Lindbeck, Assar and Dennis J. Snower. 2000. "Multitask Learning and the Reorganization of Work: From Tayloristic to Holistic Organization." *Journal of Labor Economics* 18:353–376.

Lipset, Seymour Martin, Reinhard Bendix, and Hans L. Zetterberg. 1959. *Social Mobility in Industrial Society*. Berkeley, CA: University of California Press.

Lorence, Jon and Joel Nelson. 1993. "Industrial Restructuring and Metropolitan Earnings Inequality, 1970-1980." *Research in Social Stratification and Mobility* 12:145–184.

Maxwell, Nan L. 1990. "Changing Female Labor Force Participation: Influences on Income Inequality and Distribution." *Social Forces* 68:1251–1266.

McCall, Leslie. 2000. "Explaining Levels of Within-Group Wage Inequality in U.S. Labor Markets." *Demography* 37:415–430.

McCall, Leslie. 2001. "Sources of Racial Wage Inequality in Metropolitan Labor Markets: Racial, Ethnic, and Gender Differences." *American Sociological Review* 66:520–541.

Milanovic, Branko. 1994. "Determinants of Cross-Country Income Inequality: An "Augmented" Kuznets' Hypothesis." Policy Research Working Paper 1246, World Bank.

Mishel, Lawrence, Jared Bernstein, and John Schmitt. 1999. "Wage Inequality in the 1990s: Measurement and Trends." New York City. Allied Social Sciences Associations Meetings.

Mitchell, Daniel J.B. 1985. "Shifting Norms in Wage Determination." *Brookings Papers on Economic Activity* 1985:565–608.

Morgan, Stephen L. and William R. Morgan. 1998. "Education and Earnings in Nigeria, 1974-1992." *Research in Social Stratification and Mobility* 16:3–26.

Morris, Martina and Bruce Western. 1999. "Inequality in Earnings at the Close of the Twentieth Century." *Annual Review of Sociology* 25:623–657.

Murphy, Kevin and Finis Welch. 1997. "The Structure of Wages Revisited." *manuscript* .

Murphy, Kevin M. and Finis Welch. 1993. "Industrial Change and the Rising Importance of Skill." In *Uneven Tide: Rising Inequality In America*, edited by Sheldon Danziger and Peter Gottschalk, pp. 101–132. New York: Russell Sage Foundation.

Nakao, Keiko and Judith Treas. 1994. "Updating Occupational Prestige and Socioeconomic Scores: How the New Measures Measure up." *Sociological Methodology* 24:1–72.

Nelson, Joel I. and Jon Lorence. 1988. "Metropolitan Earnings Inequality and Service Sector Employment." *Social Forces* 67:492–511.

Neumark, David. 2001. *On the Job: Is Long-Term Employment a Thing of the Past?* New York: Russell Sage Foundation.

Nickell, Stephen and Richard Layard. 1999. "Labor Market Institutions and Economic Performance." *Handbook of Labor Economics* 3c:3029–3084.

Nielsen, François and Arthur S. Alderson. 1995. "Income Inequality, Development, and Dualism: Results from an Unbalanced Cross-National Panel." *American Sociological Review* 60:674–701.

Nielsen, François and Arthur S. Alderson. 1997. "The Kuznets Curve and the Greate U-Turn: Income Inequality in U.S. Counties. 1970 to 1990." *American Sociological Review* 62:12–33.

Osterman, Paul. 1999. *Securing Prosperity: The American Labor Market: How It Has Changed and What to Do About It*. Princeton, NJ: Princeton University Press.

Parkin, Frank. 1971. *Class Inequality and Political Order*. London: Paladin.

Peterson, Trond and Laurie A. Morgan. 1995. "Separate and Unequal: Occupation-Establishment Sex Segregation and the Gender Wage Gap." *American Journal of Sociology* 101:329–365.

Pfeiffer, Jeffrey. 1994. *Competitive Adavantage Through People*. Boston, MA: Harvard Business School Press.

Piketty, Thomas. 2003. "Income inequality in France, 1901-1998." *Journal of Political Economy* 111:1004–1042.

Piketty, Thomas. 2005. "Top Income Shares in the Long Run: an Overview." *Journal of the European economic association* 3-4:1–11.

Piketty, Thomas and Emmanuel Saez. 2003. "Income Inequality in the United States, 1913-1998." *The Quarterly Journal of Economics* 118:1–39.

Pindyck, Robert S. and Daniel L. Rubinfeld. 2001. *Microeconomics*. Upper Saddle River, NJ: Prentice-Hall.

Polivka, Anne E. 1996. "A Profile of Contingent Workers." *Monthly Labor Review* 119:10–21.

Raffalovich, Lawrence E. 1993. "Structural Sources of Change in Earnings Inequality: Evidence From the Current Population Survey, 1967-1981." *Research in Social Stratification and Mobility* 12:113–144.

Reskin, Barbara and Denise Bielby. 2005. "A Sociological Perspective on Gender and Career Outcomes." *Journal of Economic Perspectives* 19:71–86.

Sakamoto, Arthur. 1988. "Labor Market Structure, Human Capital, and Earnings Inequality in Metropolitan Areas." *Social Forces* 67:86–107.

Sakamoto, Arthur and David Powers. 1995. "Education and the Dual Labor Market for Japanese Men." *American Sociological Review* 60:222–246.

Sewell, William H., Archibald O. Haller, and Alejandro Portes. 1969. "The Educational and Early Occupational Attainment Process." *American Sociological Review* 34:82–92.

Smith, James P and Michael Ward. 1989. "Women in the Labor Market and in the Family." *Journal of Economic Perspectives* 3:9–23.

Snower, Dennis J. 1998. "Causes of Changing Earnings Inequality." In *Symposium: Income Inequality Issues and Policy Options*, Wyoming:Jackson Hole. the Federal Reserve Bank of Kansas City.

Sørensen, Aage. 1977. "The Structure of Inequality and the Process of Attainment." *American Sociological Review* 42:222–46.

Sørensen, Aage. 2000. "Towards a Sounder Basis for Class Analysis." *American Journal of Sociology* 105:1523–1558.

Sørensen, Aage and Arne Kalleberg. 1981. "An Outline of a Theory of the Matching of Persons to Jobs." In *Sociological Perspectives on Labor Markets*, edited by Ivar Berg, pp. 49–74, New York. Basic Books.

Sorokin, Pitirim A. 1959. *Social and Culturual Mobility*. New York, NY: The Free Press.

Thompson, Edward P. 1966. *Making of the English Working Class*. New York: Vintage Books.

Thurow, Lester C. 1975. *Generating Inequality: Mechanisms of Distribution in the U.S. Economy*. New York: Basic Books.

Tilly, Chris. 1991. "Reasons for the Continuing Growth of Part-time Employment." *Monthly Labor Review* 114:10–18.

Topel, Robert H. 1994. "Regional Labor Markets and the Determinants of Wage Inequality." *American Economic Review* 84:17–22.

Treiman, Donald. 1976. "A Standard Occupational Prestige Scale for Use with Historical Data." *The Journal of Interdisciplinary History* 7:283–304.

Tumin, Melvin. 1953. "Some Principles of Stratification: A Critical Analysis." *American Sociological Review* 18:387–394.

Walter, W. Powell and Kaisa Snellman. 2004. "The Knowledge Economy." *Annual Review of Sociology* 30:199–220.

Weeden, Kim A. 1998. "Revisiting Occupational Sex Segregation in the United States, 1910-1990: Results from a Log-Linear Approach." *Demography* 35:475–487.

Weeden, Kim A. 2002. "Why Do Some Occupations Pay More than Others? Social Closure and Earnings Inequality in the United States." *American Journal of Sociology* 108:55–101.

Weeden, Kim A. and David B. Grusky. 2005. "The Case for a New Class Map." *American Journal of Sociology* 111:141–212.

Western, Bruce. 1995. "A Comparative Study of Working-Class Disorganization: Union Decline in Eighteen Advanced Capitalist Countries." *American Sociological Review* 60:179–201.

Western, Bruce. 2002. "The Impact of Incarceration on Wage Mobility and Inequality." *American Sociological Review* 67:526–46.

Wilson, William. 1996. *When Work Disappers*. New York: Vintage Books.

Wong, Raymond. 2002. "Occupational Attainment in Eastern Europe Under Socialism." *Research in Social Stratification and Mobility* 19:191–230.

Wooldridge, Jeffrey M. 2004. "Fixed Effects and Related Estimators for Correlated Random Coefficient and Treatment Effect Panel Data Models." *manuscript* .

Wright, Eric Olin. 1984. "A General Framework for the Analysis of Class Structure." *Politics and Society* 13:383–397.

Wright, Erik Olin. 1997. *Class Counts: Comparative Studies in Class Analysis*. Cambridge: Cambridge University Press.

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Vita ===

Vita

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