Redesigning the Measure of Class: The American Class Structure Revisited

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Abstract

Relational class theory explains how inequality arises from positions in the social relations of production. However, relational measures of class are difficult to construct due to limited survey data. Consequently, occupations are often used to measure class, despite not directly capturing social relations at work. This study addresses the measurement gap using a *task-based class identification* framework that extracts class relations from task descriptions at the detailed occupational level. Using machine learning and large-scale survey data, it maps the American class structure in 2002 and 2020. It finds that while the aggregate class structure remains stable, substantial changes occurred within the non-managerial employee class. The share of proletarian workers declined by 8%, primarily due to occupation-level "upward" shifts of class stratum, as some occupations added new supervisory responsibilities. However, this shift is not linked to income gains, raising questions about how supervisory work should be conceptualized in delineating class boundaries.

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1 Introduction

Social class offers a theory that explains how economic and social relations in the workplace generate inequality. Although some argue that class has lost its relevance in shaping social outcomes (Pakulski and Waters 1996; Kingston 2000), empirical research has demonstrated a consistent and robust influence of class on life conditions and political attitudes (Wright 1979; Kalleberg and Griffin 1980; Wodtke 2017). Research has also shown that class-based inequality in both income and wealth is increasing in the U.S., underscoring the urgent need to examine how class structure has evolved in our society (Wolff and Zacharias 2013; Mohun 2016; Wodtke 2016).

Despite its importance, few sociological studies in the past two decades have examined the American class structure and class-based inequalities (the exceptions are Wodtke 2015, 2016, 2017). A major barrier to class research is the lack of high-quality, relational class measures in large-scale surveys. While class has a clear conceptual definition as a position in the social relations of production, its operationalization and measurement prove to be challenging. Existing studies have relied either on original surveys designed to measure class (Wright 1979, 1997; Kalleberg and Griffin 1980; Wright et al. 1982) or on public surveys that include limited class-relevant questions (Wodtke 2015, 2016, 2017). Both approaches have significant limitations. While original surveys offer the best data for class research, they require substantial resources for sustained collection, and questions on workplace relations are sometimes misinterpreted by respondents, leading to weak construct validity (Wright 1985; Marshall et al. 1988). The alternative strategy that uses the General Social Survey (GSS) to measure class considers only ownership and authority, omitting other critical class dimensions and resulting in a crude class typology. Moreover, both approaches rely on relatively small samples – typically 1,000 to 2,000 respondents per year – limiting the ability to analyze trends among minority groups or conduct robust statistical analysis on the effects of class (Kalleberg and Griffin 1980).

When data on class – measured in line with its relational definition – is lacking, *occupa-*

tion-based class schemas rise to prominence in stratification research because of occupational data's broad availability and improved quality (Barone, Hertel, and Smallenbroek 2022; York, Song and Xie 2024). Scholars have developed various schema to map occupations to class categories (Erikson and Goldthorpe 1992; Oesch 2008; Wolff and Zacharies 2013), and some even advocate for replacing the conventional class categories with detailed occupations as the new measure of class (Weeden and Grusky 2005, 2012). Both approaches have generated fruitful research that uncovers important variation across a wide range of outcomes at the occupational level, highlighting the significance of occupation in the stratification process.

However, a key limitation of occupation-based class research is that occupation and class are conceptually distinct aspects of work. The occupational system is a taxonomy of technical activities in a society, and thus refers to one's position in the *technical division of labor*. Class, on the other hand, refers to positions in the *social relations of production*, and is tied to the dominant modes of production determined by the economic structure (Marx 1976/1990; Carchedi 1977; Wright 1979). Just as individuals belonging to the same class can have different occupations, those in the same occupation can be in different classes. Carpenters, for example, while sharing the same occupational title and performing similar technical activities, can either be capitalists – if they own a firm and employ others – or workers – if they are employed by others and subject to the authority of the employers and managers (Wright 1979). Therefore, theories that treat occupation and class as equivalents – such as the "micro-class" theory proposed by Weeden and Grusky (2005, 2012) – imply an overhaul of the conceptual meaning of class, one that displaces its social and relational properties (Wright 1980; Goldthorpe 2002; Wodtke 2017).

Those who remain cognizant of the conceptual distinction between occupation and class argue that even though occupation is not a direct measure of class, the types of social relations tend to be highly correlated with occupation, and therefore occupation serves as an "adequate proxy" for class (Goldthorpe 2006:102). This type of research tends to first distinguish class by property ownership, and then uses occupations to identify class cate-

gories among employees (Featherman and Hauser 1978; Erikson and Goldthorpe 1992; Wolff and Zacharies 2013). However, such occupation-to-class mapping struggles to catch up with *dynamic* changes in the occupational system. Through technological change, new occupations emerge, old occupations disappear, and the task content of the same occupation can be transformed to the extent that it alters the social relations of production (i.e., *class*) of a given occupation (Gil-Hernández, Vidal and Torrejón Perez 2024). For example, recent developments in generative AI not only change the occupational structure by generating new and outdating old occupations (prompt engineers replacing graphic designers, for example), but also influence the tasks and therefore the class positions of existing occupations by altering the level of control one has over others and over their immediate production process (Kinder et al. 2024). The occupation-based class schema, for this reason, needs to be constantly revised to reflect changes in the occupational system. This challenge is affirmed by the transition from the EGP class schema to the more recent NS-SEC schema (Erikson and Goldthorpe 1992; Office for National Statistics 2005; Goldthorpe 2006). However, there is no standardized guidance on when and how to update the occupation-to-class mapping, leading to a lack of consistency and comparability between research done across time and space.

Given the lack of relational information and the dynamic nature of the occupational system, class scholars generally reject the use of occupation as a measure of class (Wright 1980; Wodtke 2017), leading to a divide between class and occupation research. On the one hand, the widespread availability of occupational data has made occupation-based class measures more commonly used than relational class measures (Barone et al. 2022). Recent studies have even leveraged occupation- and job-level skill requirement data to analyze shifts in skill premiums and how the U.S. employment structure has changed (Autor and Dorn 2013; Acemoglu and Autor 2011; Atalay et al. 2020; Zhang 2023). On the other hand, class scholars have struggled to incorporate such insights to understand how the class structure has shifted in our society because occupation and class are conceptually and empirically distinctive concepts, while stall on developing relational measures of class due to limited

survey data. As a result, the field has seen a divergence in knowledge production – with a growing body of scholarship on occupations, and a relative decline in empirical research on class.

This study aims to address both the measurement challenge and the intellectual disconnect between occupation and class research. The key theoretical argument of this study is the *dual nature* of the production process. Following Carchedi (1977), the paper stipulates that every production activity occupies a position in the *social* division of labor, which defines its position in the class structure, and a position in the *technical* division of labor, which defines its position in the occupational structure. Both the social and technical nature of the production activity can be derived from its *task content*.

Leveraging this conceptualization, this paper proposes a new *task-based class identification* framework that measures class relationally and dynamically. Using longitudinal occupational task description data and supervised machine learning models, this paper proposes a measure of class based on Wright's "contradictory class location" theory (1976, 1979) that conceptualizes class as positions in the three-dimensional relations of production consisting of control over money capital, control over the production process, and authority over others' labor power. By identifying these production relations in occupational task descriptions, the paper provides a relational and dynamic measure of class at the detailed occupation level, and matches the results to large scale surveys to examine changes in the class and occupational structure in the U.S. in the past two decades.

Analysis shows that the American class structure, broadly conceived, has been stable in the past two decades – a finding consistent with previous class research (Wodtke 2015; Wright 1997). However, the stability at the aggregate level belies dynamic shifts occurring between class strata. In particular, the share of the "proletarian worker" stratum – people who are excluded from any decision-making process, have little work autonomy, and no task authority – witnessed a significant decrease from 2002 to 2020. Decomposition analysis suggests that this shrinkage is driven by both occupational structural change (that proletarian occupations

are decreasing as a share of employment) and occupation-level class/stratum shifts (that proletarian occupations are given new supervisory tasks), leading a notable share of the proletarian workers to become *supervisors*.

However, statistical modeling that controls for the effect of institutionalized, disaggregate occupations suggests that such an upward shift from proletarian workers to supervisors is unlikely to accompany any wage gains. Nonetheless, the addition of supervisory tasks among proletarian workers raises important empirical and theoretical questions on how supervisory work is carried out, why the managerial class would give workers more supervisory responsibilities, and how task authority should be conceptualized in delineating class boundaries.

The *task-based class identification framework* unites the technical and social component of work by measuring class at the level of detailed occupation, and has two distinct advantages over existing approaches to studying class. First, by offering a standardized, text-based method to measure class, it overcomes limitations of previous survey-based class research such as cost barriers, weak construct validity, and limited sample sizes. It also allows the identification of detailed class strata within aggregate class without the need to rely on comprehensive class questionnaires. Second, this framework bridges class and occupation research by enabling analysis of both the social and technical dimensions of work, recognizing that work tasks embody elements of both. While the current study uses occupation-level task data, the framework can be easily extended to use job-level task information to understand how changes in class structure can be decomposed into shifts in the technical division of labor and the occupation- or job-level social relations of production. Overall, this framework opens new possibilities for future research to theorize and examine class and its intricate relationship to the occupational structure and technological change.

2 Literature Review

2.1 Class: A relational concept of the social division of labor

Class is a fundamental yet contested concept in sociology. Various theories of class have been developed following different intellectual lineage, including Marx, Weber, Durkheim, and Bourdieu (Wright 2005). This study follows the Marxist conceptualization of class that defines it as a relational concept that refers to positions in the social relations of production.

This relational perspective has been consistently adopted in Marxist class analysis (Carchedi 1977; Poulantzas 1978; Wright 1979; Wodkte 2016; Livingstone 2023), and one of the most influential analytical frameworks is the "contradictory class location" (CCL) theory developed by Wright (1976, 1979).[1] The thrust of the theory is that the social relations of production are multi-dimensional and give rise to "contradictory class locations" that occupy advantageous positions in some dimensions but not others. The CCL framework complicates the bi-polar class structure proposed by Marx (1976/1990), enabling empirical and theoretical examinations of the various types of middle classes that have emerged in advanced capitalism.

At its simplest form, Wright argues that the social relation of production can be decomposed to two dimensions: *ownership* of the means of production, and *authority* over others' labor power (Wright and Perrone 1977; Wright 1985:44). In this framework, the capitalist class has both ownership and authority whereas the working class has neither. The managerial class has authority delegated from the capitalist class, but not ownership. The owner-operator class has ownership of their own productive assets, but since they do not employ other workers, they have no authority. This framework has been operationalized by Wright and Perrone (1977), and Wodtke (2015, 2016, 2017) to study class structure and class-based inequalities.

[1] Wright developed a series of neo-Marxist theories of class, but this study mainly focus on the original "contradictory class location" schema developed in Wright's (1976, 1979) and Wright et al.'s (1982) earlier work, rather than later iterations (1985, 1997) because the later frameworks, by incorporating a "relation to scarce skills" dimension, rely on occupational titles in their measurement of class, thus susceptible to limitations of occupation-based measurement of class discussed in this paper (see Wright 1997:80-90).

While the two-dimensional model provides a straightforward categorization, the class schema falls short of differentiating the various types of managers and workers who are intuitively and empirically distinct in their relative control of the production process and of others' labor power (Wright 1985:45). As an improvement, Wright (1976, 1979) proposed to view the social relations of production as consisting of *three dimensions*: (1) control over money capital, (2) control over the production process, and (3) control over others' labor power. The three dimensions together describe the forms of domination and power imbalance encapsulated in capitalist relations of production.

Control over money capital refers to decision-making power over how to deploy financial resources for production, and how to allocate them across different usages, such as fixed capital, labor (wages), and investment. Control over the production process refers to decision-making power over how to deploy productive assets, including determining product specifications and the methods of production. Control over others' labor power refers to the capacity to exert authority in the production process, including the power to monitor workers, assign tasks, and impose rewards and sanctions to ensure discipline and compliance (Wright 1976, 1979).

By decomposing class into three dimensions, a set of class categories can be identified depending on the level of control one has along each dimension. In this specification, the *capitalist* class occupies the class location that has full control over all three dimensions, while the *proletariat* occupies the class location that has no control over any dimensions.

The rising middle classes, Wright argues, occupy "contradictory class locations" that have advantageous positions in some dimensions but not others. For example, *managers* are themselves employees but can have some control over investment and the production process depending on their specific position at work. They also tend to have authority over other workers. Depending on the levels of control they have, researchers can further identify managers of different levels.

Semi-autonomous employees are those positions that have no control of investment or

others' labor power, but retain a high level of autonomy at work, implying some control over their immediate production process. *Supervisors* do not have control of the first two dimensions, but they have a limited level of authority over other workers in monitoring their work.

Wright (1976, 1979) argues that these three class locations (managers, semi-autonomous employees, and supervisors) are "contradictory" in nature because they are delegated some capitalist functions but are ultimately subject to capitalist control. Therefore, they tend to have both antagonistic and aligning interests with the proletariat, leading to a contradiction in their identification at the workplace. However, the managerial class is more likely to identify with capitalist interests as compared to supervisors and semi-autonomous employees given the amount of power these classes have.

Lastly, in this class schema there is also the *owner-operator* (the petty bourgeoisie) class made up of self-employed producers who work for themselves but do not employ others. This class has control over both financial resources and the production process, but since does not control others' labor power by virtue of not having employees. Different from the three contradictory class locations, the structural location of the owner-operator class does not have contradictory interests. This CCL class schema is listed in Table 1.

[Table 1 About Here]

This CCL framework and its variants have led to a series of empirical examinations of the class structure both in the U.S. and across other advanced capitalist countries (Wright 1979; Wright and Singelmann 1982; Wright et al. 1982; Wright and Martin 1987; Marshall et al. 1988; Wright 1997; Wodtke 2015, 2016). Overall, these studies roughly agree on their estimate of the American class structure, with about 6 to 8% of the workforce in the capitalist class, 4 to 7% in the owner-operator class, 30 to 35% in the manager and supervisor classes, and 50 to 60% in the semi-autonomous and proletariat classes. The class structure has been quite stable over time. The latest estimates provided in Wodtke (2015, 2016) for the 2000s

have revealed some small changes but are still within the ranges estimated by Wright et al. 1982) in their study using the 1970s data.

However, existing methods to measure class have weaknesses that impede the development of a sustainable class research program. First, Wright's original class survey, while foundational to empirical class research, suffers from the problem of construct validity and requires substantial resources to sustain long-term data collection. Since class-related information is not available in large-scale surveys, Wright designed his original class surveys to directly ask the respondents' work situations, including their involvement in budget allocation, production-related policy-making, job autonomy, and workplace authority (Wright 1979: 241-7; Survey Research Center 1980; Wright et al. 1982). However, this method has been shown to generate anomalous results because respondents have not only "varying perceptions" of the key concepts asked in the class survey, but also contingent work circumstances that may not be typical (Marshall et al. 1988: 51). As Marshall et al. (1988) has discussed, under Wright's operationalization of class, it is possible that an office cleaner who can decide their work tasks and work pace may end up having more autonomy than a pilot whose work schedule and work content is highly structured.[2] When surveys also have limited sample sizes, such noise tend to be amplified, thus creating inaccurate estimates. As a result, it requires careful *post hoc* adjustment of the class identification strategies and produces *ranges* of class shares that sometimes vary greatly (Wright 1979; Wright et al. 1982), compromising the estimation precision of the empirical analysis.

Second, Wodtke's (2015, 2016) class analysis, while creatively leveraging employment status and the authority questions in the General Social Survey (GSS), only identifies four big classes with a limited number of class strata: proprietors (large and small), independent producers, managers (high and low-level), and workers. This operationalization of class

[2]For the curious readers, my task-based approach classifies "aircraft pilots and flight engineers" as semi-autonomous workers in 2002 and semi-autonomous supervisors in 2020, while "janitors and building cleaners" remain proletarian workers throughout. Compared to surveys, the task-based method avoids subjective interpretations of questions related to class dimensions and ensures a consistent evaluation of occupational task content.

misses the two other key dimensions of class, including control over money capital and control over the production process. In addition, without measures of work autonomy and different types of work authority, Wodtke's measure of class cannot identify class strata based on qualitatively different work conditions, thus lacking the important details needed to distinguish different types of managers and workers. In addition, both Wright and Wodtke's research have relied on surveys with relatively small samples (about 1 to 2,000 respondents for each survey year), making it difficult to make inferences about minority groups and obtain a stable estimate of the distribution of different classes within detailed occupations.

Fortunately, these methodological weaknesses can be addressed by the new framework proposed in this study. Before detailing the approach, I clarify the relationship between class and occupation, given the prominence of the latter concept in class and stratification research.

2.2 Occupation: A dynamic system of technical division of labor

While relational measures of class remain difficult to operationalize, *occupation* studies and *occupation*-based class analysis have gained prominence in stratification research (Barone et al. 2022). By leveraging the finer granularity of occupational categories, these studies produce better-fitting models that capture variations in life conditions (Weeden and Grusky 2005, 2012), clarify how specific occupations contribute to wage inequality (Mouw and Kalleberg 2010), and present the terrain of mobility in greater detail (Jarvis and Song 2017; Mouw, Kalleberg and Schultz 2024; York et al. 2024). While these contributions underscore the value of analyzing inequality at the occupational level, occupation remains conceptually distinct from class. Occupation does not measure the *social relations* embedded in production, and its *dynamic* nature makes occupation-based class schema problematic.

There are mainly two strands of occupation-based class research. The first group, often referred to as the "micro-class" or "decomposition of class" perspective, proposes a radical view that defines class as *disaggregate occupational groups* (Grusky and Sørensen 1998;

Grusky and Weeden 2001; Weeden and Grusky 2005, 2012). This perspective argues that the preferred definition of class should "[capture] as much of the variability in life conditions as possible," and since disaggregate occupational groups provide the "strongest possible signal of 'life conditions,'" they are the best measure for class (Weeden and Grusky 2005: 143-6). The original "micro-class" schema consists of 126 "deeply institutionalized" occupational groups (Weeden and Grusky 2005:142). To account for wider time and country range, Jonsson and colleagues (2009) later developed a 82-category micro-class schema that has been more commonly used by subsequent research (Jarvis and Song 2017; Cheng and Park 2020).

The second strand of research uses *aggregate* occupational groups to measure class, and is seen in both Marxist and non-Marxist class research (Featherman and Hauser 1978; Erikson and Goldthorpe 1992; Wolff and Zacharies 2013). These studies acknowledge that occupation and class are distinct concepts, and often consider property ownership (i.e., employer, self-employed, or employee) as an important dimension of class. But class is still identified through occupations (at least for the employees) because direct measures of class as conceptualized in their theories are often not available, and aggregate occupational groups provide the best approximation for class. For example, Goldthorpe theorizes class as arising from different types of labor contracts but relies on aggregate occupational groups as a measurement, arguing that occupations are "adequate proxy for those features of ... employment relations" central to his class theory (2006:102).

Despite the convenience of measuring class using occupations and the analytical power of occupational categories, occupation-based class analysis has two important limitations. First, occupational measures of class obscure the conceptual distinction between the two concepts. The concept of occupation refers to positions in the *technical division of labor*, whereas class refers to positions in the *social relations of production* (Wright 1979; Kalleberg and Griffin 1980). As a measurement, occupation aims to provide a taxonomy of positions that perform similar technical activities, require similar skills, and produce similar end products (Hauser and Warren 1997). In contrast, class aims to identify similar structural

locations in the multi-dimensional relations of production regardless of other features of work (Wright 1979). In short, occupation is not a measure of social relation.

However, when the "micro-class" perspective reconceptualizes class as occupation, it effectively eliminates the conceptual distinction between the two. The theory implies that class is adequately expressed through occupations and that they have no independent effects on life conditions. Yet numerous studies have shown that occupation and class are related, but nonetheless *distinct* sources of inequality (Kalleberg and Griffin 1980). People working in the same occupation can be in various class positions and vice versa (Wright and Martin 1987). In addition, class is a significant predictor of income, work fulfillment, political attitudes, and other life conditions even after controlling for occupations (Kalleberg and Griffin 1980; Halaby and Weakliem 1993; Wodtke 2017).

Second, even for those that recognize the conceptual distinction and carefully map occupations to class based on the typical social relations embedded in the occupation (Goldthorpe 2006), their method is still challenged by the *dynamic* nature of the occupational system. Technological change[3] constantly modifies the occupational structure by creating new occupations while outdating old ones. It also transforms the specific tasks people perform under the same occupational title, thus potentially changing the occupation's position in the social relations of production, i.e., the occupation's *class* (Carchedi 1977; Gil-Hernández et al. 2024). For example, computerization has fragmented design tasks for engineers, reducing their work autonomy (Armstrong et al. 2022). The introduction of "lean production" has reconfigured the tasks of production-line workers, requiring them to perform a wider range of tasks and engage in on-the-spot problem-solving – changes that may increase their workplace autonomy or authority (Thompson and McHugh 2009).

Because of this ongoing dynamic, the measurement of occupation reflects the efforts to capture the *current* state of technical division of labor and is constantly changing (Scopp 2003). This means that any occupation-based class schema is tied to the specific occupational

[3]Technological change not only refers to new technologies, but all forms of cost-saving, productivity-increasing techniques, for example, the globalization of capital.

system of that time, and the validity of the occupation-to-class mapping cannot be assumed to remain static over an indefinite period of time. Indeed, this is a known limitation as researchers have revised the occupation-based class schema to "catch up" with the evolving occupational structure (Office for National Statistics 2005; Goldthorpe 2016). However, there is no standardized procedure or guidance for when and how to update such mappings, and practitioners generally find such revisions challenging (Morgan 2017).

Therefore, while occupation describes a crucial dimension of a society's economic activities, it is conceptually distinct from class because occupation conveys insufficient information about the *relational* aspect of work. The occupational system's dynamic nature forms an additional challenge for using occupation to measure class, as occupational categories and their task content cannot be assumed to be time invariant, making longitudinal analysis based on an occupation-based class schema problematic.

2.3 Bridging the two concepts for class analysis

The conceptual distinction between class and occupation has created a divide in class research. On one hand, both aggregate and disaggregate occupational categories are widely used to approximate class, largely due to their availability in large-scale survey data and the desire to analyze stratification and inequality at a micro level. On the other hand, class scholars reject the use of occupation as a proxy for class, emphasizing its conceptual distinction. However, they still haven't developed adequate relational class measures that capture the complexities of the social relations of production.

The current debate presents an incompatibility between the relational and occupation-based measure of class. However, class and occupation are two lenses observing the same reality of the production process, with class focusing on the social asepct and occupation focusing on the technical. It follows that it is possible to identify both the technical content (the occupation) and the social content (the class) of labor by observing how it is conducted. This conceptualization is described explicitly in *On the Economic Identification of Social*

Class by Carchedi (1977:6):

> Since the capitalist production process is always both a technical process and a process which rests on definite production relations, it follows that a function has always a double content, i.e. a technical and a social content. ... A 'job account', then, i.e. technical description of a function, if sufficiently specified, should always provide us with enough information to judge about not only that function's technical content but also that function's social nature.

Carchedi's remark suggests that the dual nature of work makes it plausible to observe both class and occupation simultaneously by examining task content. Following this insight, this paper proposes a *task-based class identification* model that measures the social relation of an occupation by examining its task descriptions over time, thus providing a measure of class at the level of detailed occupations that allows both changes in occupational categories and the occupation-level class designation when the task content experiences class-relevant shifts. This measure enables not only macro-level analysis of class structural change, but also occupation-level analysis of how each occupation experiences class shifts, and how that relates to various micro-level outcomes.

3 Data and Method

3.1 The Task-Based Class Identification Framework: An Overview

Given that work contains both a technical and a social component, observing the content of the work allows us to derive both occupation and class. Ideally, researchers can observe a representative sample of jobs to identify their occupation and class positions. Yet given the difficulty of conducting such research at a large scale, alternative sources of data should be considered to study the structure of occupation and class. This study proposes a "*task-based class identification*" framework that uses longitudinal occupation-level task description data as a proxy for work content, and measures the *relational* component of these tasks to identify its class position over time. In this framework, the social division of labor is the

target measure while the technical division of labor is treated as given by the occupational title.[4] Meanwhile, the occupational structure can vary over time as new occupations emerge and existing occupations' tasks are revised. This task-based class information is then linked to nationally representative survey data which includes details about individuals' occupation and employment status, thus enabling analysis of both macro-level class structural change and occupation-level class shifts.

The workflow of this approach is illustrated in Figure 1. The process begins with training machine learning models to fine-tuned classifiers that identify tasks indicative of class-related powers. These classifiers are then applied to time-varying occupational task descriptions to score occupations on five binary class dimensions. The resulting data is stored in a master dataset containing the task-based class scores for each year-occupation observation. Finally, nationally representative microdata is used to identify individuals' classes based on employment information, survey year, occupational title, and the occupation's task-based class scores using a decision tree that will be discussed later. This method overcomes the limitations of previous class research, which either relies on surveys that cannot accurately measure class or uses a static mapping from occupation to class that cannot account for the dynamic, class-related changes in the occupational system.

[Figure 1 About Here]

3.2 Data

The study uses three data sources: ONET, CPS-ASEC, and OEWS. First, to train classifiers and obtain task-based class categories (steps 1 and 2 in Figure 1), this study uses the occupational task description data from the Occupational Information Network (ONET) database. Developed by the U.S. Department of Labor, ONET has extensive data for over 900 occupations, including tasks, work conditions, skill requirements, and worker characteristics.

[4]While it is possible to further distinguish positions in the technical division of labor using job titles and job-level task descriptions, such analysis is still limited by obtaining employment estimates at the job-level. Nonetheless, the proposed approach can be easily extended to use job-level task descriptions.

The task description data used in this study were sourced from ONET's annual release from 2003 to 2020.[5] Each ONET occupation includes 5 to 30 task statements summarizing the tasks performed, based on information provided by occupational specialists, job incumbents, census data, and online sources (Dierdorff and Norton 2011). On average, each occupational task description contains 183 words. In addition to task statements, ONET contains task-level metadata classifying tasks as "core" or "supplementary" with ratings for each task's importance and frequency. Each annual release may update task descriptions based on data collected from job incumbents and occupational analysts to reflect the changing content of occupations (Dierdorff and Norton 2011). On average, each occupation has three to four updates in task statements in the two decades of ONET releases. I downloaded the data from the ONET Resource Center and compiled it into a structured dataset containing occupational titles, task statements, and associated task-level metadata when available.

ONET serves as the primary resource of occupational information for job seekers, HR professionals, and academic researchers. It has been broadly used in sociological and economic research to analyze occupation-level characteristics and how they evolve over time. For example, economists have used ONET task data to study the impact of computerization and automation (Acemoglu et al. 2024; Acemoglu and Autor 2011). Similarly, research on occupational skill requirements and wage premiums uses ONET to analyze the changing skill content of occupations (Cheng, Chauhan, and Chintala 2019; Liu and Grusky 2013). Studies on mobility have also employed ONET to explore how occupational traits are transmitted intergenerationally (York et al. 2024). As an open access database, ONET provides the highest quality public information on occupational tasks.

Second, to estimate the class structure in the U.S. labor force, this study utilized the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC), accessed

[5]The 2003 ONET data are used to approximate the occupational task content for occupations in 2002. Although task descriptions are available in the 2002 ONET, the quality of these descriptions improved substantially in the 2003 release. To minimize the potential confounding effect of data quality on the observed changes in task content, I rely on the 2003 ONET data.

through IPUMS (Flood et al. 2024). ASEC provides information crucial for identifying an individual's class, including detailed occupational titles, employment status (self-employed or wage/salary worker), and the number of employees for self-employed individuals. By integrating this information with the task-based class scores identified using the occupational task description, an individual's class position can be determined (step 3 in Figure 1). The study utilizes the 2003 and 2021 ASEC data to estimate the class population for 2002 and 2020, respectively, as the key employment variables refer to the preceding calendar year. I restricted my analysis to those who worked last year and aged between 16 and 64. Military occupations are excluded from the sample.

Finally, the Occupational Employment and Wage Statistics (OEWS) is used to reconcile the differences in occupational titles between ONET and ASEC. OEWS is an annual survey of business establishments conducted by the U.S. Bureau of Labor Statistics since 2004. It provides employment estimates for the detailed SOC occupations, aligning closely with the titles included in the ONET database. While both ONET and OEWS use the standardized SOC occupational classification system containing over 900 occupational titles, ASEC uses census occupational codes with only 400 to 500 distinct occupations. Consequently, the task-based occupation class identified in step 2, Figure 1 cannot be directly merged with individual survey data in step 3, Figure 1, as some ASEC occupations are more aggregated than those in ONET. In such cases, class dimension scores for ASEC occupations are calculated as weighted averages of the ONET occupations' scores, using employment population data from OEWS as weights. This approach ensures a more accurate estimation of an individual's class category, even when the occupation is an aggregation of multiple ONET occupations (see Appendix A).

3.3 Measuring Class in Text Data (Step 1 and 2)

As discussed earlier, I use machine learning models to extract class information from occupational task descriptions. Based on Wright's conceptualization of class, there are three

dimensions of capitalist relations of production that define one's class: (1) control over money capital, (2) control over the production process, and (3) control over the labor power of others. Therefore, when approaching the text, machine learning models need to identify these relational class features from each occupation's task descriptions. To address this challenge, I developed a set of five classification models (classifiers), each designed to identify one particular relational class characteristic.

Specifically, I operationalized the three theoretical class dimensions into five operational dimensions drawing from Wright's class survey questionnaire (Survey Research Center 1980). As shown in Table 2, for the first theoretical dimension, control over money capital, I identify if the incumbent for a given occupation decides the overall size of the budget either for the organization or the subunit/department they work at.

For the second theoretical dimension, control over the production process, I distinguished this control at two levels. At the organizational level, the operational dimension identifies if the incumbent can decide policies that can significantly change the products, programs, or services offered by their organization. At the individual level, the dimension asks about the worker's autonomy, i.e. if the incumbent designs important aspects of their own work and puts their own ideas into practice.

For the third theoretical dimension – control over others' labor power, I distinguished two types of authority: (1) sanctioning authority, which is defined as the authority to promote, hire, fire, or suspend subordinates; (2) task authority, which is the ability to supervise, monitor or assign specific tasks for subordinates. It should be highlighted that sanctioning authority and task authority are qualitatively different. While sanctioning authority suggests the power to impose sanctions on other workers and therefore implies a higher position in the organizational hierarchy, task authority simply refers to one's ability to assign and supervise the tasks of subordinates. This type of authority is a further delegation from managers, and therefore having task authority usually does not imply consequential power in the workplace. Task authority often describes the work of foremen, forewomen, and first-

line supervisors, who are often more similar to the proletariat (Armstrong et al. 2022). In contrast, sanctioning authority implies consequential power over subordinates, as the person can initiate personnel actions such as promotion and dismissal of subordinates.

Different from the previous operationalization of relational class, I distinguish the five operationalized class dimensions as having varying theoretical importance. Three out of the five dimensions are theorized as key decision-making powers that distinguish *managers* from *workers*. This includes financial decision-making power, production decision-making power, and sanctioning authority. The remaining two class dimensions (autonomy and task authority) are used to distinguish class strata amongst the non-managerial employees.

For each operational dimension, a binary classifier is trained to categorize the task descriptions as either positive or negative. The training is based on 605 hand-coded occupational task descriptions. To ensure a balance of different styles of the language across years and different types of occupations, and to accommodate potential future use on earlier data, I sampled roughly 100 occupation descriptions for three years from the ONET releases in 2003, 2010 and 2020, and three years from *The Dictionary of Occupational Titles* (which is the antecedent of ONET) in 1965, 1977, and 1991. And I proportionally sampled occupations from each aggregate occupational group (managerial and professional, clerical and sales, service, farming, manual production and others).

[Table 2 About Here]

The hand-coding process involves a coder reading the occupational title and task description, then coding the description according to the five questions listed in Table 2. Consistent with Wright's class survey, the first two questions regarding decision-making power allow four different codes: 3 (decide), 2 (decide subject to approval), 1(advise), and 0 (excluded). The rest of the questions allow two different codes: 1 (Yes) and 0 (No). If any of the questions get an answer other than 0, the coder is asked to provide textual evidence to support the coding choice. This helps the coders reconcile differences and reach a shared understanding of the coding scheme. Two coders independently coded 45 occupations across 5 operationalized

class dimensions, reaching substantial agreement with Krippendorff's alpha at 0.802.

Among the five questions, some are more straightforward while others are less so. For example, Questions 1, 4, and 5 are relatively straightforward. If one has control or participates in decision-making processes, it is usually stated directly in the description. However, the wording of Questions 2 and 3 is more vague as people may have different understandings of what counts as "significant" or "important." In the hand-coding, the coders determine positive cases for Question 2 as those occupations whose descriptions explicitly state tasks that plan, direct, develop or formulate policies, programs, or procedures at the organizational or departmental level. The coders determine positive cases for Question 3 if the occupation description suggests that the incumbent needs to plan or design their work content (not at the organizational or departmental level). Compared to survey research where each respondent may have a different understanding of the question, hand-coding using a consistent standard is likely to result in more consistent coding and robust results.

While hand-coding allows the coder to assign a set of more fine-grained codes to the operationalized class characteristics, for simplicity and better performance, these codes are collapsed into binary categories to train machine learning models, as shown in the last column in Table 2.

To obtain the final classification models, I fine-tuned pre-trained large language models developed by OpenAI. The core idea behind fine-tuned models is to let a base model "learn" how to perform a specific task based on a set of high-quality examples. Pre-trained large language models like GPT-3.5 have been shown to be capable of performing complicated Natural Language Processing tasks such as translation, question-answering, and content generation (Brown et al. 2020). By fine-tuning such pre-trained large language models using a labeled dataset, well-performed classification models can be obtained leveraging the base model's language capability.

I experimented with GPT-3.5-turbo, GPT-4o, and GPT-4o-mini as base models, and fine-tuned classifiers for each class dimension using hand-coded data. After comparing the

performance of the fine-tuned models of the three different base models, I select the ones with the highest balanced accuracy for each class dimension. This resulted in five best-performed classifiers, three of them are fine-tuned on GPT-4o-mini, one on GPT-4o, and one on GPT-3.5-turbo.[6]

The performance of the classifiers is shown in Table 3. Overall, the performance of the five classifiers exceeds the performance of state-of-the-art classifiers in social science research, with an average balanced accuracy of 0.926. Four out of five classifiers have a balanced accuracy of over 0.9. Even the weakest classifier (production decision-making) still achieved a balanced accuracy of 0.87. The performance of the classifiers on work autonomy, sanctioning authority, and task authority is particularly accurate. See Appendix B for details on evaluation metrics and methods. Applying the five classifiers on the 2003 and 2020 releases of the ONET occupational task descriptions, I obtained the task-based class scores for all occupations in these two years.

[Table 3 About Here]

3.4 Identification of Individual's Class Position in Survey Data (Step 3)

With task-based class scores for all occupations in 2003 and 2020, the next step was to use this information to identify individuals' class locations in the survey data (step 3 in Figure 1). This step involves combining an individual's employment information and occupational titles (linked to their class dimension scores) to identify their class position. The identification process is guided by the decision tree shown in Figure 2.

First, individuals are distinguished by their employment status as either self-employed (including employers and owner-operators) or wage/salary workers, according to ASEC's "class of worker last year" variable (CLASSWLY). For the self-employed, individuals are

[6] I also experimented with conventional supervised machine-learning methods such as decision trees and ensemble models, but the performance was less satisfying than fine-tuned GPT models, with balance accuracies around 0.7 to 0.8.

further distinguished by the number of employees using ASEC's "number of employees last year" variable (FIRMSIZE). For the number of employees, following previous categorization (Wright et al. 1982; Marshall et al. 1988; Goldthorpe 2016; Livingstone 2023), those that have 25 or more employees are categorized as "capitalists, proper." Those that have between 10 and 24 employees are categorized as "capitalists, small scale."

While those who only employ themselves should consist of their own "owner-operators" class, ASEC does not differentiate this and grouped owner-operators with other small employers with 9 or less employees. Due to this limitation, I cannot distinguish the owner-operator class from a portion of the "capitalists, small scale" class. As a compromise, I group them together and label the class as "small employers and owner-operators."

Individuals who are wage/salary workers are coded following a different map. For employed individuals, their detailed occupations linked with their task-based class scores are used to identify their class. First, if an individual's occupation is "Chief Executive" and they work in private companies, they are assigned with the "capitalists, delegated" class category. This is an exception where the occupational title, instead of its task statements, is used to identify one's class. This is due to the particular nature of "Chief Executives": the occupational title itself conveys a class location where the incumbents have the capacity to make decisions *on their own* across all class dimensions at the *highest level* of the company. From a class perspective, the only difference between Chief Executives and traditional capitalists is the legal ownership of the company (Wright 1979; Means and Berle 1991). Therefore, it is more appropriate to categorize Chief Executives as "capitalist" rather than "manager."[7]

For the rest of the cases, I identify if they belong to the managerial class by examining their decision-making capacity. This includes financial decision-making power, production decision-making power, and sanctioning authority. Those that make three, two, or one such decisions are assigned as high-level, mid-level, and low-level managers, respectively. While

[7]For a small portion of individuals whose occupational title is "Chief Executives" but are government employees, they are grouped with "high-level managers." These are mostly cases when the individuals' detailed occupations are "government service executives" or "legislators" but are assigned with the same census occupational code as private company executives.

these decision-making powers are not interchangeable, they are accumulative in the sense that those with more power have a more advantageous class position than those that have less. Although those that are allocated to each level of manager may have different types of decision-making power, their strata within the managerial class are treated as equal.

For employees who have none of the above-mentioned decision-making power, I examine their work autonomy and task authority. Those who have work autonomy and task authority are "semi-autonomous supervisors." Those who have work autonomy but no task authority are "semi-autonomous workers". Those who have no work autonomy but have task authority are "task supervisors" and those that are excluded from any of the class-related powers are "proletarian workers."[8] Following this decision tree, each individual is assigned with a detailed class label that indicates one's class stratum within the overall class structure. These detailed class labels can be collapsed into four aggregate class categories: capitalists, small employer and owner-operators, managers, and non-managerial employees, as shown in the legend of Figure 2.

[Figure 2 About Here]

3.5 Decomposition Analysis

In addition to tabulating the population for each class at the two time points, I supplement this with a decomposition analysis to identify the sources of class structural change. As discussed earlier, an advantage of the task-based class identification model is that it can distinguish changes in the technical division of labor from changes in the occupation-level social division of labor. At two time points, the observed change in class structure involves two changes: (1) *occupational structural change*, defined as changes in each occupation's employ-

[8]The term "proletarian worker" may appear redundant, as proletariat inherently denotes "worker." However, I intentionally avoid more conventional labels such as "blue-collar workers" or "unskilled workers." First, not all individuals in this category are "blue-collar": many are employed in white-collar clerical occupations. Second, some of the workers are also "skilled" (such as bookkeepers), although what counts as "skilled" and "unskilled" is dynamically defined by the current state of the technical division of labor. In the absence of a more suitable label, I use "proletarian worker" to indicate those occupying the most disadvantaged segment of the working class.

ment size including the disappearance of old occupations and emergence of new occupations. This is the change in the technical division of labor; (2) *occupation-level class/stratum shifts*, defined as change in the class strata composition within the same occupation. This is the occupation-level change of the social division of labor, which includes changes in both ownership status (the distribution across employers, owner-operators, and employees) and, for employees, the occupation's task-based class location.

To disentangle these effects, I decompose the change in a class's share in the overall employment population into three components following the standard method proposed in Kitagawa (1955): (1) the effect of occupational structural change, (2) the effect of occupation-level class/stratum shifts, and (3) modification terms that adjust for population change and correct for double entry in the decomposition procedure. Mathematical details of the decomposition procedure are presented in Appendix C.

3.6 Statistical Modeling

To better understand the economic implications of class, I use both standard OLS and multilevel regressions to estimate the association between class and income while accounting for the effects of occupational groups. First, the standard OLS regressions (Equation 1) model income using class, occupational group dummies, and other covariates. This naive approach, however, tends to overstate the variation across groups and yields less reliable estimates when the sample size of the group is small (Gelman and Hill 2006). To avoid these issues, multilevel regressions with varying intercepts are used to model the effect of class *within occupations*, as shown in Equation set 2. The model has two levels. At the individual level, income is modeled by an occupational group-specific intercept ($\alpha_{j[i]}$), class, and other covariates. At the group level, the intercept for occupational group j is modeled to have a population mean μ_α with group-level errors η_j.

$$Y_i = \alpha_0 + \Sigma_{n=1}^{N} \beta_n Class_{in} + \Sigma_{m=1}^{M} \zeta_m Z_{im} + \Sigma_{j=1}^{J} \gamma_j Occ_{ij} + \epsilon_i \quad (1)$$

$$
\begin{aligned}
Y_i &= \alpha_{i[j]} + \Sigma_{n=1}^{N} \beta_n Class_{in} + \Sigma_{m=1}^{M} \zeta_m Z_{im} + \epsilon_i \\
\alpha_j &= \mu_\alpha + \eta_j, \eta_j \sim \mathcal{N}(0, \sigma_\alpha^2)
\end{aligned}
\tag{2}
$$

The outcome variable is *log weekly income*, calculated based on employment status and income sources. For individuals who are employees, their weekly income excludes any non-wage income, since the main focus of the modeling exercise is to examine the association of work-based decision-making power and work-based income (i.e. wages). For those who are employers or self-employed, their income includes wages as well as business and farm income, since many of the self-employed respondents have reported their income only as wage income.

The key predictor variables, *class*, are specified in two forms: one uses class categories directly and one uses numeric class dimension scores while controlling for ownership class (i.e., capitalist, small employer and owner operator, or employee). For categorical predictors, I use the eleven-level class categories as identified in Figure 2. For numeric predictors, I use class dimension scores to directly measure the effects of particular types of class-related power. However, since the three key decision-making powers that distinguish the managerial class are highly correlated (see Appendix D for correlation matrix), I performed principle component analysis (PCA) to avoid the impact of multicollinearity (James et al. 2013). Using PCA, I extracted the first two dimensions that explain 92% of the variance for the three decision-making dimensions, and used them as a "decision-making index" in the models. In addition, two other class dimension scores – the autonomy and task authority scores – are included as numeric class predictors. Lastly, since the class dimension scores do not distinguish ownership, these models also control for being in the capitalist, small employer and owner-operator, and employee aggregate class.

Occupations are measured in two forms: the eleven-category aggregate occupational groups[9] that roughly overlap with the classification used in Autor (2015) and the 82-category

[9]The eleven aggregate occupational groups are: management, professionals and technicians, health services, protective and cleaning services, personal services, sales, administrative, farming, construction and mining, production, and transportation and material moving.

institutionalized occupational groups developed by Jonsson et al. (2009) based on Weeden and Grusky's micro-class occupation schema (2005, 2012).[10] A set of covariates are included to account for demographic and contextual factors. Consistent with previous studies on class and income (Wodtke 2016), I included the following covariates: gender (binary, male or female), race (binary, black or not), Hispanic ethnicity (binary), education (less than high school, high school, some college, college graduate, above college degree), age (16-25, 26-35, 36–45, 46–55, and 56–64), geographic region (Northeast, Midwest, South, and West), urbanicity (urban, suburban, rural),[11] part-time worker (binary), and survey year fixed effects.

The above models include all individuals in the 2003 and 2021 CPS-ASEC aged 16 to 64 and worked in the preceding calendar year. Military occupations and unpaid family workers are excluded. Observations with zero or negative income are removed. The resultant sample contains 181,079 observations. All results are weighted and ASEC's COVID weights are used for the results of 2020 to account for nonrandom nonresponse of the survey year due to COVID-19.

4 Results

4.1 The American Class Structure: 2002 and 2020

The class structure viewed at an aggregate level has four "big classes": capitalists, small employer and owner-operators, managers, and non-managerial employees. From 2002 to 2020, the American class structure has remained stable with respect to these four big classes. There was a slight expansion of the managerial class, at the expense of the three other classes.

[10] The data contains only 80 "micro-class" occupations as the military "micro-class" occupation is excluded and one "micro-class" occupation (No.66 which includes "inspectors, testers, and graders" and "adjusters and calibrators") is not present in the data.

[11] Urbanicity is defined using the variable METRO. Urban residents are those who reside in the central or principal city of a given metro area. Suburban residents are those who live in a metro area but not in the central or principal city. Rural residents are those who do not live in a metro area, and also those whose METRO status is unidentified.

Panel A of Figure 3 shows the class structure of the four aggregate classes: the share of non-managerial employees has hardly changed at all, with a share of 75.9% in 2002 and 75.2% in 2020. The share of the managerial class is the second largest, with a share of 14.2% in 2002 and 15.8% in 2020. Small employers and owner-operators were 8.0% in 2002 and 7.3% in 2020. The capitalist class was 1.9% in 2002 and decreased to 1.7% in 2020.

[Figure 3 About Here]

However, the stable aggregate class structure masks important shifts between class strata. In particularly, significant changes have occurred within the non-managerial employee class, as shown in Panel B of Figure 3 (for detailed counts, see Appendix Table E1). Proletarian workers, as the largest class category in both years, witnessed a significant decrease of 8.2% (dropping from 46.7% in 2002 to 38.5% in 2020). This represents a reduction of roughly 9 million workers. In the meantime, the employment for "supervisor" doubled in its employment share, which represents a gain of 8.5 million workers from 2002 to 2020. It seems that almost all the losses in the proletarian worker strata were recouped in the "supervisor" stratum. Decomposition analysis will examine if this was mainly driven by occupational structural change or occupation-level class shifts.

While workers without work autonomy (supervisor and proletarian worker) take up about half of the workforce (52.2% in 2002 and 49.3% in 2020), semi-autonomous employees have an increased share from 23.7% in 2002 to 25.9% in 2020. In terms of change, both semi-autonomous supervisors and workers have grown faster than overall employment.

The managerial class is the only aggregate class that has expanded, increasing from 14.2% in 2002 to 15.8% in 2020. Within it, the class strata of "high-level manager" and "mid-level manager" increased from 4.5% to 5.1% and 5.1% to 6.9%, respectively. The share of "low-level manager" declined from 4.6% to 3.8%. As will be analyzed later, the expansion of the "high-level manager" stratum was driven by increased *occupational structural change*, whereas the increase of "mid-level manager" is driven by both occupational structural change and *occupation-level class/stratum shifts* from the high- and low-level manager strata.

In general, the share of capitalists and owner-operators are decreasing. Within the capitalist class, the shares of both "capitalist, proper" and "capitalist, small scale" have declined. "Capitalist, proper" decreased from 0.5% in 2002 to 0.4% in 2020, and the share of the "capitalist, small scale" decreased from 0.7% to 0.6%. "Capitalists, delegated" which represents the share of private company Chief Executives have sustained a 0.7% share in both time points. The downward trend also applies to the small employer and owner-operators class, with a decrease from 8% in 2002 to 7.3% in 2020.[12]

Overall, despite the general stability of the class structure at the aggregate level, there are important shifts within the managerial and the non-managerial employee classes. Within each of the two classes, the general trend is an expansion of higher strata at the expense of the lower strata. In other words, there seem to be a prevalent *upward* shift among employees of all strata: employees seem to be shifting towards work with more decision-making power, workplace autonomy, and supervisory authority.

The significant decline of the "proletarian worker" stratum is consistent with sociological and economic studies. For example, in Wright's (1997) estimation of the U.S. class structure from 1960 to 1990, the share of "workers" (similar to my definition of "proletarian worker") has been declining from the 1970s to 1990s.[13] In employment polarization research, Hunt and Nunn (2022) and Cheng, Levine, and Martin-Caughey (2024) have both found that the share of low-wage workers, which empirically should overlap greatly with the "proletarian worker" stratum, has been declining since the 1970s, with only a slight increase in the period from 2002 to 2012. Meanwhile, the share of high-paying, high-skill workers, which should

[12]The count of small employers and owner-operators in CPS-ASEC 2021 is potentially affected by COVID-19 and the rollout of the Paycheck Protection Program (PPP) in 2020 which might artificially boost the share of this class. To examine if COVID-19 presented a shock to this class, I examined annual share of all types of employers and owner-operators in CPS-ASEC from 2003 to 2024, and as shown in Appendix F, the share of these class and class strata show a continuous, smooth trend. In addition, even if the PPP inflated the share of small employers and owner-operators, the influence is an underestimation of the decline of this strata, rather than a reversal of the finding.

[13]Wodtke (2016) found a slight increase in the share of workers (from 53% in 1980s to 57% in 2000s), but his definition included what I define as "semi-autonomous workers." In addition, he used the GSS survey data with respondent's self-reported workplace authority, rather than task description-based identification. Therefore, the data is less comparable to results presented here.

include managers and semi-autonomous workers, has increased significantly since the 1970s (see also Zhang 2023).

4.2 Decomposing the Sources of Change in the American Class Structure

As discussed earlier, the observed change in class structure is mainly driven by two factors: the growth or decline of an occupation's size (occupational structural change) and the shift of an occupation's class composition due to changes in ownership status and occupational tasks. Decomposition analysis allows identification of the influence of each of these factors. The results of class decomposition are shown in Figure 4. The y-axis is the change in employment share in percentage points for each class stratum, as indicated by differences of the paired bars shown in Panel B, Figure 3.

[Figure 4 About Here]

First, for both the *capitalist* and the *small employer and owner operator* classes, decomposition analysis suggests that the decline is mainly driven by occupation-level class shift. This implies a gradual absorption of business owners to formal organizations, converting their class from employers and the self-employed to employees. Occupations with such changes span across professional services (lawyers, secretaries, physicians), managerial occupations (chief executives, construction managers), and supervisory occupations (first-line supervisors of construction, of retail sales, and of personal care). At the same time, occupational structural change negatively affected both the number of private-sector chief executives (the "capital, delegated" stratum) and small employers and owner-operators. This pattern suggests a declining demand for chief executives as well as for occupations characterized by a higher share of small employers or self-employed individuals. However, overall changes in these class and class strata are slight compared to the managerial and non-managerial employee classes.

The managerial class is the only aggregate class whose size expanded from 2002 to 2020. The expansion mainly occurred amongst high- and mid-level managers, as shown in Panel B, Figure 3. Decomposition shows that the expansion of the two strata is mainly driven by the increase in employment size (occupational structural change), while occupation-level class/stratum shifts also contributed to the growth of mid-level managers. The share of low-level managers decreased slightly as a result of both employment shrinkage and occupation-level class/stratum shifts.

To better understand the underlying shifts, alluvial diagrams are plotted for the managerial and non-managerial employee classes in Figure 5. The figure depicts the size and flow of occupations from their original stratum in 2002 to their final stratum in 2020. Each band, separated by white borders, represents an occupation, with its width indicating the occupation's size in 2002 and 2020. The dominant class stratum for each occupation (i.e. the stratum with the highest within-occupation share) is indicated by the starting and ending positions in the stacked bars for the respective years.

[Figure 5 About Here]

As shown in Panel A Figure 5, the size of the *high-level manager* stratum expanded primarily because of employment expansion. Specifically, the increase in the number of "Other Managers" contributed over 40% to the stratum's total observed increase. The continuous increase of this occupation and its internal heterogeneity affirm the dynamic nature of the technical division of labor, where new managerial occupations are created but not captured by the occupational classification code (Mouw and Kallenberg 2010).[14]

Similar to high-level managers, *mid-level managers* also experienced a significant increase in employment, driven by the expansion of both new and existing mid-level manager occupa-

[14]This occupation category is notorious for its internal heterogeneity. In this study, the class scores of this occupation are an average of all managerial occupational titles in ONET. This score is directly used for the CPS-ASEC "Other Managers" occupation. In 2002, the variance of the class scores across five dimensions were low (smaller than 0.5). But for 2020, the variance for financial decision-making and sanctioning authority are flagged to be high (equal to or large than 0.5). This suggests that new managerial occupations may become more diverse in their class positions.

tions. For instance, the new occupation "Project Management Specialists" contributed 23% to the stratum's increase. This stratum also benefited from occupation-level class/stratum shifts from the high and low-level manager strata, as indicated by the flows originating from these class strata in 2002 to mid-level manager in 2020 shown in Panel A, Figure 5. For example, "Human Resource Managers" shifted up from low- to mid-level managers, while "Transportation, Storage, and Distribution Managers" shifted down from high- to mid-level managers.

Low-level manager is the only shrinking managerial stratum, with both reduced employment size and shifts to other class strata. The majority of the stratum's shrinkage is caused by employment decreases, mostly in first-line supervisor occupations such as office and administration, food preparation/service, and non-retail sales.[15] Occupation-level class/stratum shift had a negative impact on this stratum as a small number of occupations either shifted upwards to mid-level managers or downwards to the non-managerial employee class (not shown in Panel A, Figure 5. See Appendix G). For example, "Credit Counselors and Loan Officers" have shifted from low-level manager to semiautonomous supervisors, because the ONET occupation "loan officers" no longer has the task of "interview[ing], hir[ing], and train[ing] new employees" which suggests a removal of sanctioning authority in 2020 as compared to 2002.

The non-managerial employee class encapsulated the most dynamic change in the American class structure. Decomposition analysis shows that each class stratum experienced a different combination of the two forces of occupational structural change and occupation-level class/stratum shift. First, as shown in Figure 4, *semi-autonomous supervisors* benefited from occupational structural change, but negatively impacted by occupation-level class

[15] An important finding related to the managerial class that distinguishes my method from the occupation-based class schema is the classification of first-line supervisors. While these occupations are often assumed to be in the supervisor class in occupation-based class schema, their tasks have substantial variation and a majority are in the managerial class rather than simply being supervisors with only task authority. A number of the first-line supervisor occupations belong to the managerial class, having at least one decision-making power above task authority or work autonomy. This demonstrates the danger of merely using occupational titles to identify one's class. It is necessary to study each occupation's task content to understand its position in the decision-making hierarchy.

shifts. Employment expansion of "Computer Software Engineers," "Registered Nurses," and "Elementary and Middle School Teachers" have contributed most to the expansion of this stratum. On the other hand, a set of occupations have shifted downwards, either to semi-autonomous workers (by losing task authority), or to supervisors (by losing work autonomy). Examples of the former include "Market Research Analysts and Marketing Specialists" and "Occupational Therapists," and examples of the latter include "Clinical Laboratory Technologists and Technicians" and "Electricians."

Semi-autonomous workers have the two driving forces (occupational structural change and occupation-level class/stratum shifts) pulling towards the same direction, resulting in positive growth. On the one hand, the employment of semi-autonomous workers is increasing, including occupations such as "Management Analyst," "Compliance Officers," and various computer-related occupations such as "Web Developers" and "Information Security Analysts." On the other hand, occupation-level class/stratum shifts have an overall positive effect, although some semi-autonomous worker occupations such as "Counselors" and "Designers" have also shifted up to semi-autonomous supervisor, gaining task authority.

The remarkable increase of *supervisors* and the significant decline of the *proletarian workers* go hand in hand because of occupation-level class/stratum shifts. For supervisors, decomposition analysis and the alluvial graph demonstrate that the stratum's increase is driven by the downward shifts from semi-autonomous supervisors (as discussed above) and, more importantly, by the upward shifts from proletarian workers. In the meantime, occupational structural change has a negative effect on the stratum. This is hardly surprising as one of the biggest supervisor occupations is "Secretaries and Administrative Assistants" – a classic example of the "mid-skill jobs" that have been in decline since the 2000s (Autor 2015).

For proletarian workers, the driving force of class shrinkage is occupation-level upward shifts, while occupational structural change also imposes significant negative impact. Among the 8.2% decline in shares of proletarian workers, over 6% is attributable to occupation-level

class/stratum shifts and over 2% is due to negative occupational structural change. The great numbers of workers shifting upward (roughly 9 million) are partially driven by one big proletarian occupation gaining task authority: "Cashier" had 3.5 million workers in 2002 and 2.8 million workers in 2020, and its shift contributed to over 33% of the increase in the supervisor stratum. While it seems counterintuitive to think of cashiers as supervisors, ONET's incumbents survey in 2018 suggests that over 65% of the respondents perform tasks that involve supervision on a weekly or daily basis.

The addition of task authority is not idiosyncratic to only a few occupations. In total, 18 occupations have witnessed the expansion of their occupational tasks that now include supervision. For example, "Cashiers" has a newly added task of "supervis[ing] others and provid[ing] on-the-job training." "Police Officers" have a new task that states "supervise law enforcement staff, such as jail staff, officers, and deputy sheriffs." "Maintenance and Repair Workers, General" have added the task of "train[ing] or manag[ing] maintenance personnel or subcontractors." And "Hotel, Motel, and Resort Desk Clerks" are now in charge of "plan[ing], schedul[ing] or supervis[ing] the work of other employees."

The increase in task authority seems to be accompanied by a decrease in occupational size. Two-thirds of the upward-shifting proletarian occupations are declining in their employment share. The shedding of employment is even more prevalent in proletarian occupations whose class or stratum did not shift (N = 182): about 72% of them have reduced in employment share, compared to 40% in managerial class and 53% in the three other non-managerial employee strata. Overall, changes in the bottom class stratum seem to suggest that they are most susceptible to being scrapped because of technological change, but the remaining workers tend to experience an upgrade in their *social* division of labor.

4.3 Class and Income

The previous two sections provide descriptive analysis of how the class structure of the American workforce has changed from 2002 to 2020. As has been shown, the most dynamic

change in class is the "elevation" of the proletarian worker to the supervisor and even higher employee class strata. However, are such upward class/stratum shifts associated with an increase in economic prospects? Table 4 displays modeling results on the effects of class on income.

Since the results of simple OLS and multi-level regressions are consistent in coefficient signs and significance levels, Table 4 only displays results of multilevel regressions to save space. Models in Table 4 are organized by the type of class predictors used, with Models 1 and 2 indicating results using the eleven class categories and Models 3 to 4 showing results using numeric class dimensions scores. Models 1 and 3 use aggregate occupations and Models 2 and 4 use the micro-class occupations as the group variable for multi-level regressions.

[Table 4 About Here]

For models that use categorical class predictors, the effects of class are generally aligned for Models 1 and 2. Both models suggest significant income advantages for other classes and class strata when compared to proletarian workers, except for the small employer and owner-operator and the supervisor class. The only difference between Models 1 and 2 is the effect of "supervisor." Within aggregate occupational groups, being a supervisor is associated with about a 6% increase in weekly income compared to proletarian workers. However, within the more disaggregate "micro-class" occupational groups, the positive effect turns negative: being a supervisor is associated with a 2% *decrease* of weekly income compared to proletarian workers within "micro-class" occupations.

Similar patterns are replicated in models using numeric class predictors. Within both aggregate and "micro-class" occupational groups, class-related dimension scores are positively correlated with income. However, results differ on the supervisor-related class dimension: task authority. Here again, Model 3 shows that task authority is associated with a significant increase in income within aggregate occupational groups. However, Model 4's examination of associations within "micro-class" occupations suggest a *nonsignificant* effect of task authority on income. Comparing models using different granularity of occupational groups,

it seems that the positive effect of supervisor in Model 1 and task authority in Model 3 is fully explained by "micro-class" occupational level income variations. Within "micro-class" occupations, however, being a supervisor/having additional supervisory responsibilities does not lead to positive wage gain as compared to proletarian workers.

The modeling results yield the following conclusions. First, class and occupation are related but nevertheless distinct sources of income variations. Class categories and class-related power present consistently significant effects on income when controlling for occupation in both aggregated and "micro-class" levels. Second, different levels of occupational grouping can lead to contrasting conclusions about the effect of supervisory responsibilities. Using more disaggregated, "micro-class" occupations is better at capturing the effects of class because it minimizes variations resulting from one's positions in the technical division of labor. Third, increases in class-related decision-making power and autonomy are both associated with income gains, while increases in task authority or supervisory responsibilities are *unlikely* to result in income gains, when examined within "micro-class" occupations.

From a dynamic perspective, the results of Models 2 and 4 (final models with best fit) both suggest that, for occupations belonging to the "proletarian worker" stratum, if the "elevation" in the social division of labor only consists of adding task authority (i.e. becoming a "supervisor"), it is unlikely to improve their economic prospects. In other words, the significant occupation-level shifts from proletarian workers to supervisors observed in the descriptive analysis are unlikely to accompany wage gains.

5 Discussions

By conceptualizing work as consisting of both a technical and a social nature, this paper proposes a *task-based class identification* strategy that measures the multi-dimensional class characteristics of detailed occupations based on time-varying task descriptions. The study demonstrates that key dimensions of the social relations of production can be extracted from

text data. By linking dynamic occupation-to-class mappings to large scale surveys, it incorporates the new measurement of class to microdata to provide a comprehensive examination of the American class structure, both descriptively and analytically.

Findings reveal that the American class structure at the aggregate level has remained stable over the past two decades. Four major classes – capitalists, small employers and owner-operators, managers, and non-managerial employees – comprised approximately 2%, 8%, 14%, and 76% of the workforce in 2002, respectively. By 2020, the managerial class expanded slightly to 16%, while the shares of other classes saw marginal declines. Beneath this stability, significant shifts occurred within the four aggregate classes. First, the absorption of professional and other service providers into formal organizations has led to a reduction in capitalists – big or small – and a decline of small employers and owner-operators. This trend partially explains the expansion of the managerial class. However, the key to the managerial class's expansion is the employment increase of the high- and mid-level managers, most notably the residual managerial occupation "Other Managers."

The most dynamic change occurred within the non-managerial employee class. The proportion of proletarian workers – those with no decision-making power, minimal autonomy, and no task authority – declined substantially from 47% in 2002 to 39% in 2020. This change is driven by both occupation-level class/stratum shifts and occupational structural change. On the one hand, occupations conventionally considered as working-class have seen an expansion and "upgrading" of their tasks, moving workers in the same occupation from the proletarian worker stratum to higher class strata through added task authority and work autonomy. The most prevalent shift is the growth in task authority, or supervisory responsibilities, in proletarian workers' occupations. On the other hand, the sizes of most proletarian occupations are declining, whether they experience upward stratum shifts or not. Consequently, the share of proletarian workers has decreased while the proportion of supervisors has grown. This "elevation" of proletarian workers to supervisors, however, is *not* associated with positive wage gains, as suggested by the best-fitting multilevel models

that examine the effect of class within "micro-class" occupational groups.

Given the heterogeneity of job content across organizations and within the same occupational title (Tomaskovic-Devey and Avent-Holt 2019; Martin-Caughey 2021), the numeric estimates of this occupation-level class/stratum shifts are likely to be an *overstatement* of the real shift. A more realistic interpretation of this finding is that only some workers are given new supervisory responsibilities. And even for them, task descriptions indicate that these supervisory responsibilities are more likely to involve training and mentoring new workers rather than asserting real authority over other workers in the conventional Marxist sense (Armstrong et al. 2022). Nonetheless, such a shift driven by expended supervisory duties is not idiosyncratic. It is observed across various occupations and robust to using OEWS data directly and to using only "core" tasks rather than all tasks (see Appendix E).

The prevalent addition of supervisory tasks to conventionally working class occupations and the lack of compensation for these new tasks raise important empirical and theoretical questions for class research. Here I offer three hypotheses that may explain this trend. First, this "upgrading" of social division of labor may suggest a real increase in workplace authority for workers in these occupations, as the research on lean production suggests that workers are increasingly taking on diversified tasks and participating in workplace decision-making processes (Thompson and McHugh 2009:216-232). Alternatively, the finding may convey a spurious change driven by the "empowerment" ideology in management theories that affects how occupational tasks are recognized and described (Attewell 1990; Lincoln et al. 2002). It could be that workers in these occupations have always performed tasks like training and mentoring new employees, but they were not conceptualized as "supervising" other workers in earlier enumerations of occupational tasks.

Yet there is a third possibility that there has been *a divorce between supervision and power* at the workplace. When surveillance technologies can effectively replace human monitors to track workers' productivity, supervisory work is reduced to mentorship and on-the-job training. In this context, managers, while maintaining their power and capacity to supervise,

are less involved in the day-to-day monitoring, training, or supervision of their subordinates. In contrast, such tasks are "sent down" to workers as an added responsibility without a real increase in their workplace power or pay. In fact, a recent study lends support to this hypothesis by finding decreasing demand for supervisory work from managers (Zhang 2023).

To find out which of the above hypotheses can best explain the observed trend would require new empirical research that examines how supervisory tasks are defined and performed in various workplaces. Findings of such research would have important theoretical implications for Marxist class theory, as supervision has always been conceptualized as a "function of capital" that involves monitoring and disciplining workers (Carchedi 1977; Wright 1979). Yet it seems that technological change alters not only the technical division of labor, but also the *social* division of labor by advancing technologies that replace humans with machinery that performs the function of capital.

The "dual nature of work" theory and the "task-based class identification" methodology proposed in this study make two contributions to class and stratification research. First, by offering a standardized, text-based method to measuring class, it overcomes previous class research's reliance on original survey data that are high in cost, influenced by respondents' subjective interpretations of survey questions, and limited sampling, particularly on minority groups. In addition, this method retains the multi-dimensional, relational conceptualization of class and identifies not only the aggregate class categories, but also detailed class strata.

Second, this framework bridges class and occupation research. While previous class research has recognized the conceptual distinction between class and occupation, it has been insufficiently attentive to their *unity* in social practices, i.e. that the performance of work tasks consists of both a social and a technical nature. Recognizing the relational aspect of occupations, this methodology enables analysis that examines changes in the social and technical division of labor simultaneously.

As shown in this study, because of the task-based, dynamic mapping of occupation-to-class, changes in the class structure can be decomposed to changes arising from the technical

division of labor (occupational structural change), and from the social division of labor *within* occupations (occupation-level class/stratum shifts). Statistical modeling further shows that it is imperative to consider *both* class and institutionalized occupations when examining the economic implications of class power. The lack of positive effect of task authority on income cannot be accurately identified unless the model controls for detailed "micro-class" occupations.

At the same time, the study has several limitations. First, the current study uses public data that only has occupation-level task descriptions, which cannot capture the between-organization and within-occupation heterogeneity of task content. This, as discussed earlier, is likely to result in an overstatement of occupation-level class/stratum shifts, as changes in an occupation's task is assumed to affect all workers in that occupation. Fortunately, this problem can be solved by applying the same methodological framework to job-level task descriptions and employment data, which is often restricted or proprietary but nonetheless still obtainable. Future research should delve into such resources to provide more accurate estimates.

Another limitation of the study is the lack of analysis of people not in the labor force. Theoretically, a society's class structure should include all working-age people whether or not they are working. Marx has pointed out the important role played by the "reserve army of labor" – the unemployed and underemployed population – in facilitating the fluctuating demand for labor and acting as a downward force on the wage rate (Marx 1976/1990; Botwinick 2018). In addition, as Wright (1997) discussed before, the underclass, or people excluded from economic activity due to various unjust social and political institutions including racism, urban poverty, and carceral state, should be included in class analysis. The lack of accurate data on these populations forms a challenge, but future research should attempt to examine how the underclass – including the incarcerated, homeless, disabled, and other such groups – have shifted in the population over time.

Last but not the least, the current study only covers the past two decades, leaving out

the important transitional period in American capitalism from the 1960s to 1990s. While ONET only goes back to 2002, its precedent, *The Dictionary of Occupational Titles*, goes back to the early 20th century with tens of thousands of job titles accompanied by job descriptions. Future studies should incorporate the early period and examine the question of class structural change and the effect of technological advancement on the changing content of occupations.

Despite these limitations, this current research has presented a promising agenda in understanding a society's class structure from a production relation-based perspective. With the availability of higher-quality job and occupation data, and with the many important questions raised above, sociologists will have many significant contributions to make to our understanding of class and inequality in capitalist societies.

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Tables

Table 1: The "Contradictory Class Locations" (CCL) Class Schema

Class Locations	**Control of Money Capital**	**Control of Production Process**	**Control of Other's Labor Power**
Capitalist Class (Big and Small)	+	+	+
Managers (High, Mid, Low)	+/-	+/-	+
Semi-autonomous Employees	-	+	-
Supervisors	-	-	+
Proletariat	-	-	-
Owner-operators	+	+	-

Table 2: Operationalization and Coding of Class Dimensions

Theoretical Class Dimensions	**Operational Class Dimensions**	**Coding Questions**	**Hand-Coding Scheme**	**Machine-Learning Classifier Scheme**
Control over Money Capital	Financial Decision-Making	Q1. Can the incumbent decide the overall size of the budget for the organization or the function unit they work at?	3 = Decide: The incumbent determines or makes the final decision on this aspect on their own authority. 2 = Decide subject to approval: The incumbent makes decisions on this aspect subject to approval from above. 1 = Provide advice: The incumbent makes recommendations and/or provides information to authorities who make decisions. 0 = Excluded: The incumbent is not involved in the decision-making process.	3 or 2 in hand-coding = 1 (Yes) 1 or 0 in hand-coding = 0 (No)
Control over the Production Process	Production Decision-Making	Q2. Can the incumbent decide policies that significantly change the products, programs, or services offered by the organization or the function unit they work at?		
	Work Autonomy	Q3. Does the incumbent require the occupants to design important aspects of their own work and to put their ideas into practice?	1 = Yes 0 = No	Same as hand-coding
Control over Others' Labor Power	Sanctioning Authority	Q4. Can the incumbent grant raises or promotions, or fire or suspend the subordinates?		
	Task Authority	Q5. Can the incumbent decide specific tasks or work assignments for subordinates?		

Table 3: Performance of Machine Learning Classifiers

Operationalized Class Dimensions	**Balanced Accuracy (Bootstrapped Mean)**
Financial Decision-Making	0.915
Production Decision-Making	0.870
Work Autonomy	0.912
Sanctioning Authority	0.975
Task Authority	0.958
Average	0.926

Table 4: Modeling Results

	Dependent variable: Log weekly income			
	Categorical Class Predictors		Numeric Class Predictors	
	1	2	3	4
Eleven-Level Class Categories [Ref: Proletarian Worker]				
Capitalist, proper	.313***	.199***		
	(.027)	(.027)		
Capitalist, small scale	.422***	.283***		
	(.023)	(.023)		
Capitalist, delegated	.655***	.558***		
	(.023)	(.023)		
Small employer and owner operator	−.167***	−.227***		
	(.008)	(.008)		
High-level manager	.196***	.098***		
	(.013)	(.013)		
Mid-level manager	.157***	.054***		
	(.010)	(.012)		
Low-level manager	.234***	.164***		
	(.009)	(.012)		
Semi-autonomous supervisor	.193***	.117***		
	(.007)	(.008)		
Semi-autonomous worker	.165***	.135***		
	(.008)	(.009)		
Supervisor	.058***	−.023**		
	(.007)	(.008)		
Class Dimension Scores				
Decision-making index component 1			.006*	.018***
			(.003)	(.003)
Decision-making index component 2			.049***	.036***
			(.003)	(.003)
Autonomy			.223***	.196***
			(.007)	(.008)
Task Authority			.060***	.009
			(.006)	(.006)
Three-Level Class Categories [Ref: Employee]				
Capitalist			.237***	.172***
			(.017)	(.017)
Small employer and owner operator			−.287***	−.297***
			(.007)	(.007)
Log Likelihood	−229,504.0	−226,126.6	−229,298.7	−226,185.9
Akaike Inf. Crit.	459,070.1	452,315.2	458,651.5	452,425.9
Bayesian Inf. Crit.	459,383.4	452,628.5	458,924.3	452,698.8
Occupational Group	Aggregate	Micro-class	Aggregate	Micro-class
Number of groups	11	80	11	80
Var: Occupation (Intercept)	0.016	0.051	0.011	0.044

NOTE: N = 181,079. Results show multilevel regressions with varying-intercept at the occupation level. Covariates (not displayed) are included in all models. Results are robust to using simple occupational fixed effects.

*P < .05

**P < .01

***P < .001

Figures

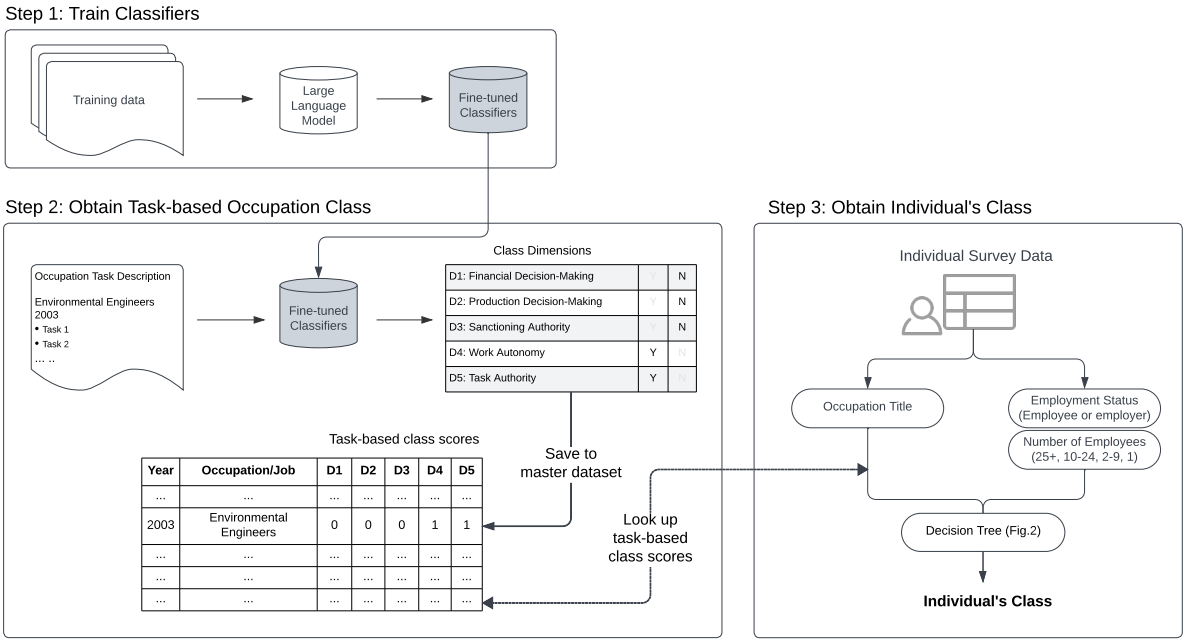
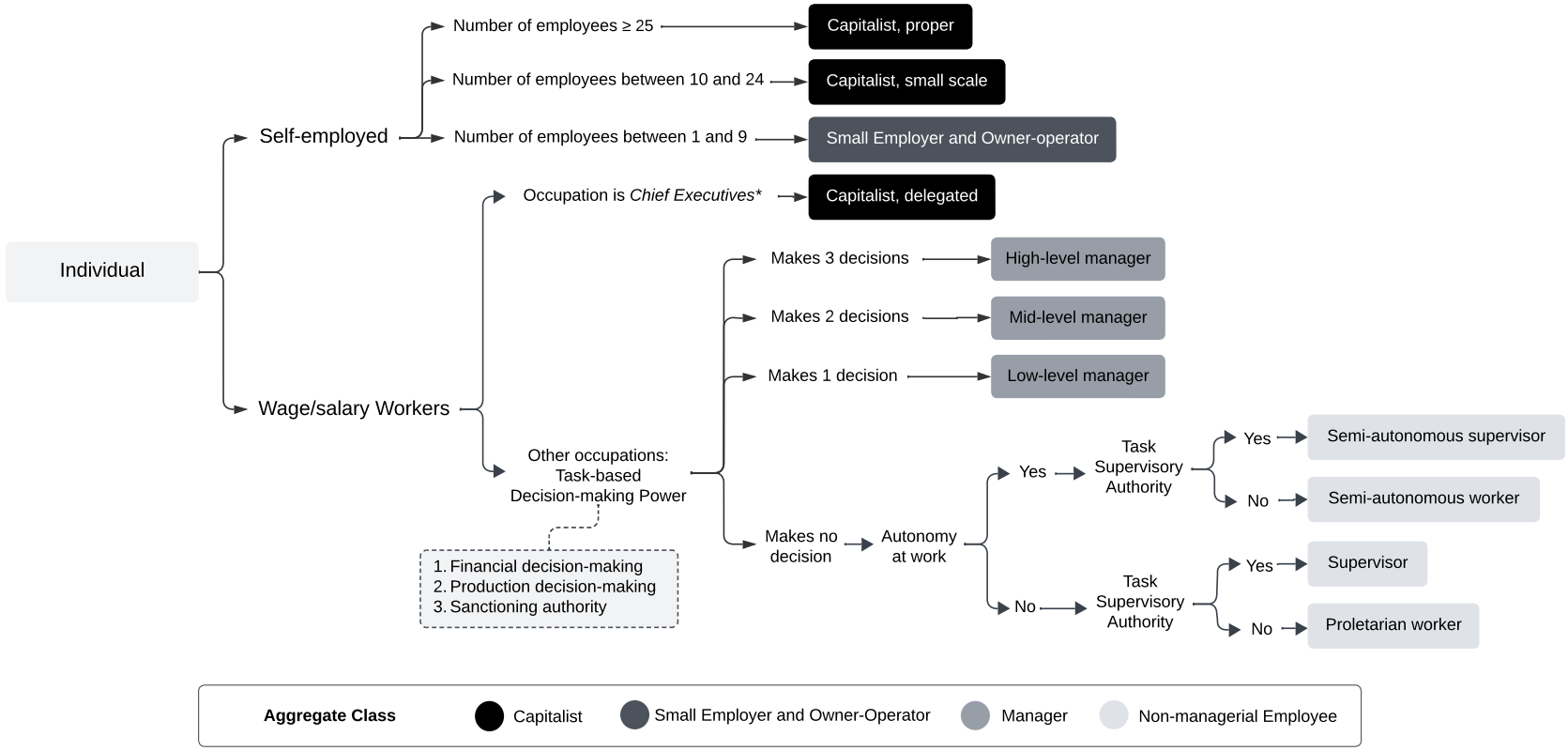


Figure 1: The Task-based Class Identification Framework



*Individual whose occupational title is Chief Executives but is also a government employee is categorized as "high-level manager" instead of "capitalist, delegated."

Figure 2: Decision Tree to Identify Individual's Class Position

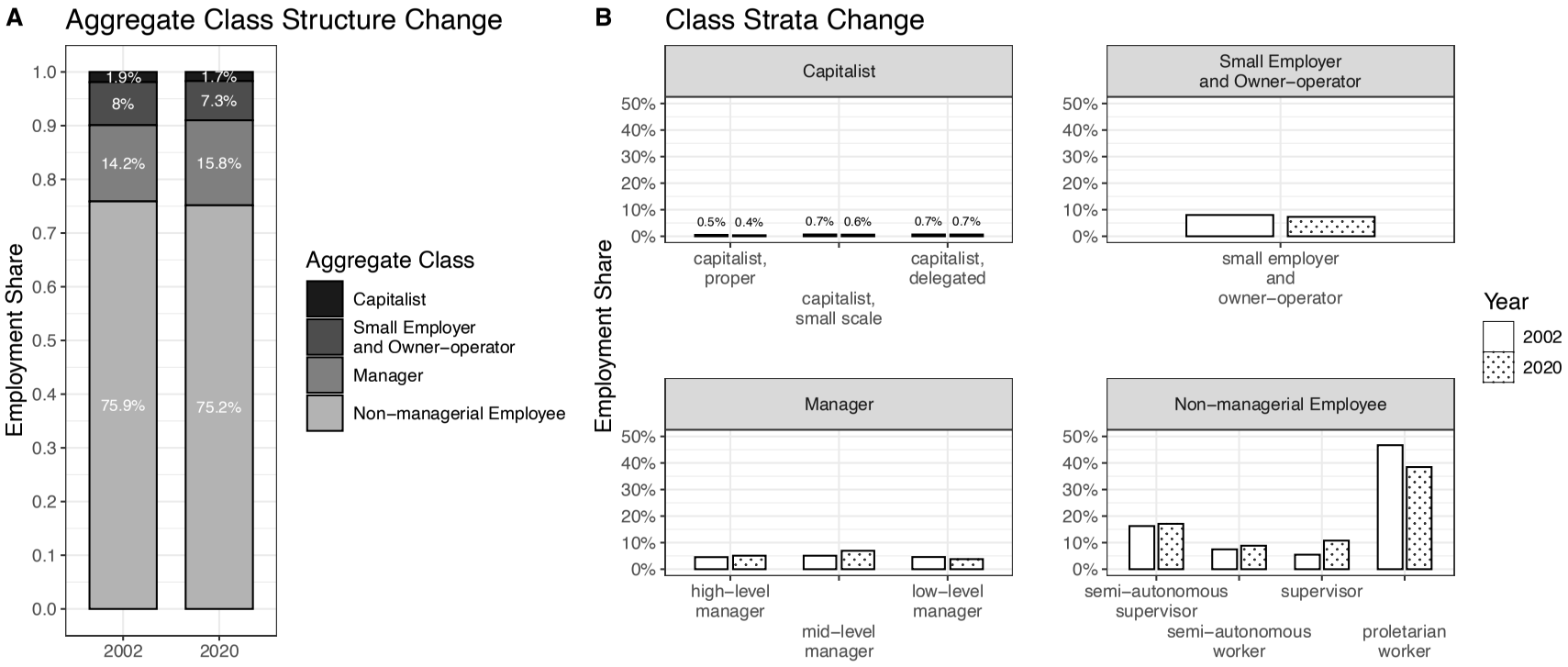


Figure 3: The American Class Structure, 2002 and 2020

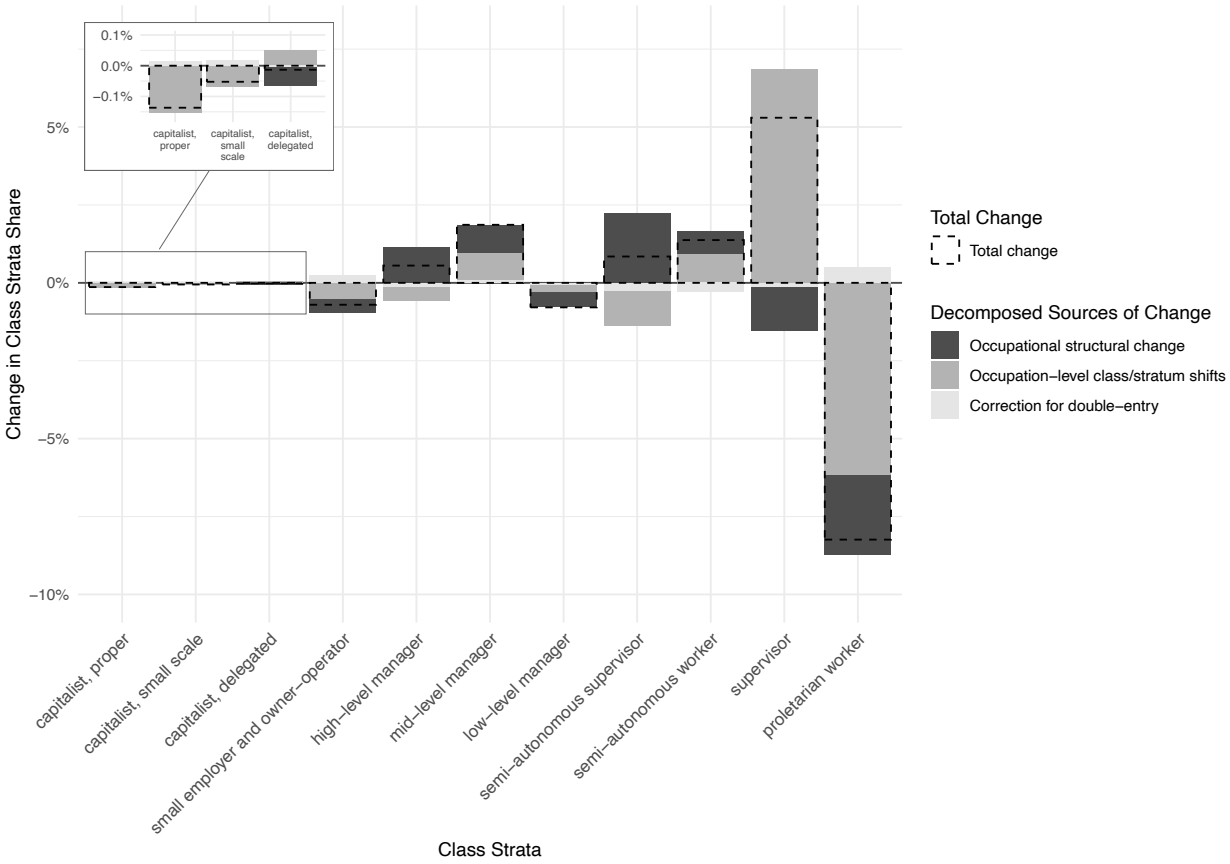


Figure 4: Decomposition of Class/Strata Share Change, 2002 to 2020

Figure 5: Occupation-level Class/Stratum Shifts for Occupations Dominated by Managerial (A) and Non-Managerial (B) Class Strata, 2002 to 2020

NOTE: Occupations whose dominant class stratum is in the capitalist or small employer and owner-operator aggregate classes are not shown. For a full visual presentation, see Appendix G.

Appendix

A. Calculating Weighted Average Class Scores for CPS-ASEC Occupations using OEWS

While both ONET and OEWS use the standardized SOC occupational classification system containing over 900 occupational titles, CPS-ASEC uses census occupational codes with only 400 to 500 distinct occupations. Consequently, the task-based occupation class identified in step 2, Figure 1 for ONET occupations cannot be directly merged with individual survey data in step 3, Figure 1 which uses the more aggregated CPS-ASEC occupations. In such cases, class categories for CSP-ASEC occupations are obtained by calculating the weighted averages of the ONET occupations' class scores, using employment population data from OEWS as weights. The process is demonstrated in Figure A1.

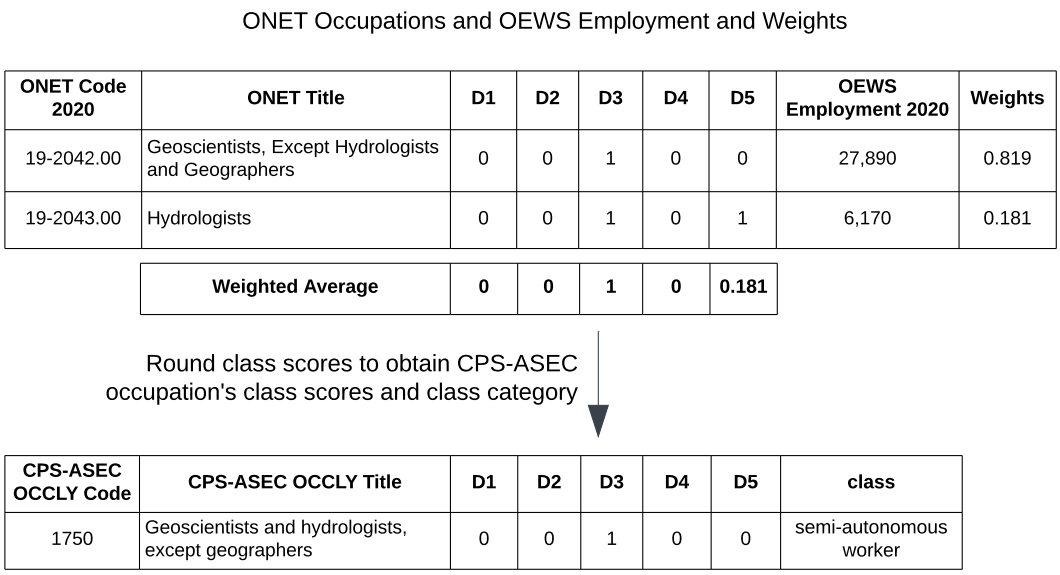


Figure A1: An Example of Calculating Weighted Average Class Scores for CPS-ASEC Occupations Using OEWS as Weights

To reconcile the differences in occupational codes, I matched the ONET occupational codes to the 2003 and 2018 census occupational codes, which are used as CPS-ASEC's OCCLY code for 2003 and 2021. This step either led to a one-to-one or a many-to-one matching from ONET to the CPS-ASEC occupational codes.

For one-to-one matches, the class scores and class categories of ONET and CPS-ASEC occupations stayed the same. For many-to-one matches, I took the average of the ONET occupations' class scores, weighted by their occupational size according to the respective year's OEWS. Then, the weighted average class scores are rounded to the nearest integer (either 0 or 1) for each class dimension to obtain the class category of the CPS-ASEC occupation. (For rounding, I used R's default "rounded to even" which means a score of 0.5 is rounded to 0 rather than 1.)

For example, as shown in Figure A1, in 2020, the CPS-ASEC occupation "Geoscientists and Hydrologists, Except Geographers" is an aggregate of two ONET occupations: "geoscientists, except hydrologists and geographers" and "hydrologists." The class scores for the two ONET occupations are listed in Figure A1, so are their employment estimates and resultant weights.

In 2020, the employment of the ONET occupation "geoscientists, except hydrologists and geographers" is significantly higher than "hydrologists," thus the weights for the former occupation is higher, at 0.819. Using these weights and class scores, I calculated the weighted average class scores for each of the class dimensions and rounded each score to the nearest integer to obtain the CPS-ASEC occupation's class scores and class category. In this case, the class category for the CPS-ASEC occupation "Geoscientists and Hydrologists, Except Geographers" is semi-autonomous worker, reflecting the class position of "geoscientists, except hydrologists and geographers" since its employment dominates this aggregate occupation.

For 2003, I used the May 2004 OEWS because this is the earliest available OEWS that matches with the 2003 ONET SOC codes. For 2021, I used the May 2020 OEWS as the OCCLY reflects the respondents' occupation in the preceding calendar year, which is 2020. While the response rate for the May 2020 OEWS is affected by COVID-19, the impact is limited because OEWS estimates are produced using six semiannual survey panels over a three-year period. The May 2020 OEWS estimates were calculated using data from November 2017 to May 2020 (Bureau of Labor Statistics 2021).

In the process, I also calculated the variance of the class scores and flag those with more than 0.5 variance. On average, about 15% of many-to-one matches have high variance, which suggests that the class rating is in general consistent before and after collapsing to ASEC occupational codes.

An alternative method is to use the weights to break down the CPS-ASEC occupations so that, for example, 81.9% of the CPS-ASEC's respondents with the "Geoscientists and Hy-

drologists, Except Geographers" occupational title are allocated to the "semi-autonomous worker" class stratum, and the rest to the "semi-autonomous supervisor" class stratum. However, this could create confusion in later analysis that treats each CPS-ASEC occupation as the analytical unit, such as the decomposition analysis. Therefore, I choose to use the weighted average class score to obtain one definite class category for each CPS-ASEC occupational title rather than this alternative method.

B. Classifier Evaluation on Imbalanced Data using Bootstrapped Method

The evaluation of the machine learning models' performance in this study faces a challenge: the distribution of class characteristics in occupational task descriptions is imbalanced due to the rarity of positive cases. As shown in previous studies of class and in my hand-coding process, occupations that have decision-making power at the organizational or departmental level are a minority. Therefore, it is important to evaluate the machine learning classifiers on testing data that mimic the realistic distribution in the overall occupational task description data.

Based on the distribution of class characteristics across aggregate occupational groups in the hand-coded data, I estimated the realistic distribution of the positive cases for each class dimension. Then, to robustly test the performance of the classifiers, I applied a bootstrapping approach and set 50 different random seeds to randomly sample testing data from the testing set using sample with replacement. This method effectively leverages all testing data while ensuring the testing set is distributed similarly with the real data.

Table B1: Machine Learning Model Performance with Bootstrap Testing Set (N = 50)

Operationalized Class Dimensions	**Total Sample Distribution**	**Training Set**	**Testing Set (Mimic Realistic Distribution)**	**Balanced Accuracy (Bootstrapped Testing Set N = 50)**
Financial Decision-Making Power	yes: 63 no: 542	yes: 50 (12.5%) no: 350 (87.5%)	yes: 8 (4%) no: 192 (96%)	Mean: 0.915 (SD: 0.071) 95%CI: (0.744, 1)
Production Decision-Making Power	yes: 51 no: 554	yes: 40 (10%) no: 350 (90%)	yes: 7 (3%) no: 204 (97%)	0.870 (0.075) CI: (0.706, 0.985)
Work Autonomy	yes: 193 no: 412	yes: 110 (34%) no: 210 (66%)	yes: 80 (40%) no: 120 (60%)	0.912 (0.017) CI: (0.881, 0.941)
Sanctioning Authority	yes: 111 no: 494	yes: 50 (14%) no: 270 (86%)	yes: 12 (5%) no: 224 (95%)	0.975 (0.023) CI: (0.909, 0.995)
Task Authority	yes: 211 no: 394	yes: 82 (39%) no: 129 (61%)	yes: 40 (20%) no: 160 (80%)	0.958 (0.022) CI: (0.914, 0.992)

For performance evaluation, I used the bootstrapped mean and the 95% confidence interval of the balanced accuracy, a metric commonly used for imbalanced data. The results are shown in Table B1.

C. Technical Detail and Numeric Results of Decomposition Analysis

To tease out the effects of occupation-level class/stratum shift versus the effect of occupational structural change on the overall class structure change, I decompose the change in class stratum proportion for a given class stratum i as the following:

1. Overall population at time 0 and 1 is written as: P_0 and P_1
2. The proportion of occupation j at time 0 and 1 is written as: τ_{j0} and τ_{j1}, and the difference between the two is written as: $\Delta\tau_j = \tau_{j1} - \tau_{j0}$
3. The occupation population for occupation j and time 0 and 1 can be expressed as: $\tau_{j0}P_0$ and $\tau_{j1}P_1$
4. The occupation-level proportion of class stratum i within occupation j at time 0 and 1 is written as: π_{ij0} and π_{ij1}, and the difference between the two is written as: $\Delta\pi_{ij} = \pi_{ij1} - \pi_{ij0}$
5. The overall population for class stratum i at time 0 and 1 can be expressed as: $\sum_{j=1}^{J} \pi_{ij0}\tau_{j0}P_0$ and $\sum_{j=1}^{J} \pi_{ij1}\tau_{j1}P_1$
6. The proportion for class stratum i at time 0 and 1 can be expressed as: $\frac{1}{P_0}\sum_{j=1}^{J} \pi_{ij0}\tau_{j0}P_0$ and $\frac{1}{P_1}\sum_{j=1}^{J} \pi_{ij1}\tau_{j1}P_1$

The difference in class stratum proportion for class stratum i can be written as:

$$
\begin{aligned}
\Delta p_{class=i,t_0\to t_1} &= \frac{1}{P_1}\sum_{j=1}^{J}\pi_{ij1}\tau_{j1}P_1 - \frac{1}{P_0}\sum_{j=1}^{J}\pi_{ij0}\tau_{j0}P_0 \\
&= \frac{1}{P_1}\sum_{j=1}^{J}(\pi_{ij0}+\Delta\pi_{ij})(\tau_{j0}+\Delta\tau_j)P_1 - \frac{1}{P_0}\sum_{j=1}^{J}\pi_{ij0}\tau_{j0}P_0 \\
&= \frac{1}{P_1}\sum_{j=1}^{J}\pi_{ij0}\tau_{j0}P_1 - \frac{1}{P_0}\sum_{j=1}^{J}\pi_{ij0}\tau_{j0}P_0 \\
&\quad + \frac{1}{P_1}\sum_{j=1}^{J}\pi_{ij0}\Delta\tau_j P_1 \\
&\quad + \frac{1}{P_1}\sum_{j=1}^{J}\Delta\pi_{ij}\tau_{j0}P_1 \\
&\quad + \frac{1}{P_1}\sum_{j=1}^{J}\Delta\pi_{ij}\Delta\tau_j P_1
\end{aligned}
$$

The above formalization assumes a fixed occupation set, J, in both time points. More realistically, there are three types of occupation sets: occupations that exist at both time points (set J), new occupations that only exist in time 1 (set A), disappeared occupations that only exist in time 0 (set D). To account for the change in types of occupations, the above decomposition can be complicated as the following:

$$
\begin{aligned}
\Delta p_{class=i,t_0\to t_1} = \frac{1}{P_1}(\sum_{j=1}^{J}\pi_{ij1}\tau_{j1}P_1 + \sum_{a=1}^{A}\pi_{ia1}\tau_{a1}P_1) - \\
\frac{1}{P_0}(\sum_{j=1}^{J}\pi_{ij0}\tau_{j0}P_0 + \sum_{d=1}^{D}\pi_{id0}\tau_{d0}P_0) \\
= \frac{1}{P_1}\sum_{j=1}^{J}(\pi_{ij0}+\Delta\pi_{ij})(\tau_{j0}+\Delta\tau_j)P_1 + \frac{1}{P_1}\sum_{a=1}^{A}\pi_{ia1}\tau_{a1}P_1 - \\
\frac{1}{P_0}\sum_{j=1}^{J}\pi_{ij0}\tau_{j0}P_0 - \frac{1}{P_0}\sum_{d=1}^{D}\pi_{id0}\tau_{d0}P_0 \\
= \frac{1}{P_1}\sum_{j=1}^{J}\pi_{ij0}\Delta\tau_j P_1 \ (1) \\
+\frac{1}{P_1}\sum_{j=1}^{J}\Delta\pi_{ij}\tau_{j0}P_1 \ (2) \\
+\frac{1}{P_1}\sum_{j=1}^{J}\Delta\pi_{ij}\Delta\tau_j P_1 \ (3) \\
+\frac{1}{P_1}\sum_{a=1}^{A}\pi_{ia1}\tau_{a1}P_1 \ (4) \\
+\frac{1}{P_0}\sum_{d=1}^{D}\pi_{id0}\tau_{d0}P_0 \ (5) \\
+\frac{1}{P_1}\sum_{j=1}^{J}\pi_{ij0}\tau_{j0}P_1 - \frac{1}{P_0}\sum_{j=1}^{J}\pi_{ij0}\tau_{j0}P_0 \ (6)
\end{aligned}
$$

The six components can be interpreted as the following:

1. Part (1) is the effect of the occupational structural change for occupations existed in both times;

2. Part (2) is the effect of occupation-level class/stratum distribution change for occupations existed in both times;

3. Part (3) is the interaction of part (1) and part (2), which is a modification term that fixes the interaction of part (1) and part (2):

(a) Part (1) + part (3) is the actual consequence from occupational structural change, with occupation-level class/stratum distribution fixed at time 1;

(b) Part (2) + part (3) is the actual consequence from occupation-level class/stratum shifts with the occupational structure fixed at time 1;

4. Part (4) is the effect of newly added occupations;

5. Part (5) is the effect of disappeared occupations;

6. Part (6) is a residual term that is related to population change. Since P_0 and P_1 are very large, the value of this part can be ignored.

In the decomposition graph presented in Figure 4, the occupational structural change includes parts (1), (4), and (5).

Table C1 shows the detailed results of decomposition analysis by different parts as shown above.

Table C1: Detailed Results of Decomposition Analysis

	Class Strata	**Part 1: Occupational Structural Change**	**Part 2: Occupation-level Class Shifts**	**Part 3: Interaction/ Correction for Double Entry**	**Part 4: New Occupation**	**Part 5: Old Occupation**	**Part 6: Population Change**	**Overall Change**
1	capitalist, proper	-0.01%	-0.15%	0.02%	0.01%	0.00%	0	-0.14%
2	capitalist, small scale	0.00%	-0.07%	0.02%	0.00%	0.00%	0	-0.05%
3	capitalist, delegated	-0.06%	0.05%	0.00%	0.00%	0.00%	0	-0.01%
4	small employer and owner operator	-0.47%	-0.49%	0.24%	0.04%	-0.02%	1.39×10^{-17}	-0.70%
5	high-level manager	1.13%	-0.46%	-0.12%	0.00%	0.00%	6.94×10^{-18}	0.55%
6	mid-level manager	0.39%	0.87%	0.08%	0.52%	0.00%	0	1.86%
7	low-level manager	-0.51%	-0.22%	-0.06%	0.00%	0.00%	0	-0.79%
8	semi-autonomous supervisor	2.31%	-1.13%	-0.24%	0.12%	-0.21%	0	0.84%
9	semi-autonomous worker	-0.03%	0.91%	-0.30%	0.79%	0.00%	-1.39×10^{-17}	1.37%
10	supervisor	-1.27%	6.85%	-0.12%	0.00%	-0.16%	-6.94×10^{-18}	5.30%
11	proletarian worker	-2.57%	-6.16%	0.49%	0.00%	0.00%	-5.55×10^{-17}	-8.24%

D. Correlation of Log Weekly Income and Numeric Class Measures

Table D1: Correlation of Log Weekly Income and Numeric Class Measures, before PCA

	Log Weekly Income	Financial Decision-Making	Production Decision-Making	Sanctioning Authority	Autonomy	Task Authority
Log Weekly Income	1.00					
Financial Decision-Making	0.22	1.00				
Production Decision-Making	0.16	0.57	1.00			
Sanctioning Authority	0.19	0.68	0.73	1.00		
Autonomy	0.35	0.39	0.42	0.52	1.00	
Task Authority	0.26	0.40	0.43	0.57	0.69	1.00

E. Detailed Distribution of the American Class Structure, 2002 and 2020, with Sensitivity Checks

1. Detailed class strata distribution using CPS ASEC, weighted by OEWS

Table E1 shows the detailed distribution of class both at the aggregate and detailed levels, using CPS ASEC data with class categories calculated by first weighting the class ratings by OEWS employment of detailed ONET occupations and then round to nearest integer. Table E2 and E3 shows the basic characteristics of each class stratum, including income, gender, race, thnicity, and government employee shares. Note that for the income in Table E2 and E3 is total income which includes wage, business, farm, and all other types of incomes, adjusted to 1999 dollars. These accountings use the employment status and detailed occupation variables in CPS ASEC data. See main text for details on data processing.

Table E1: Detailed Distribution of the American Class Structure, 2002 and 2020

	Class and Class Strata	Workforce Population 2002	Share 2002	Workforce Population 2020	Share 2020	Change in Share	% Growth
	Capitalists, overall	2,757,718	1.9%	2,593,396	1.7%	-0.2%	-6.0%
1	capitalists, proper	769,311	0.5%	600,726	0.4%	-0.1%	-21.9%
2	capitalists, small scale	992,311	0.7%	964,422	0.6%	-0.1%	-2.8%
3	capitalists, delegated	996,096	0.7%	1,028,248	0.7%	0.0%	3.2%
4	Small employers and owner operators	11,630,420	8.0%	11,166,156	7.3%	-0.7%	-4.0%
	Managers, overall	20,600,873	14.2%	24,168,055	15.8%	1.6%	17.3%
5	high-level managers	6,581,018	4.5%	7,771,544	5.1%	0.6%	18.1%
6	mid-level managers	7,370,738	5.1%	10,601,608	6.9%	1.9%	43.8%
7	low-level managers	6,649,118	4.6%	5,794,904	3.8%	-0.8%	-12.8%
	Non-managerial workers, overall	110,129,058	75.9%	114,788,905	75.2%	-0.7%	4.2%
8	semi-autonomous supervisors	23,579,563	16.2%	26,104,433	17.1%	0.8%	10.7%
9	semi-autonomous workers	10,849,245	7.5%	13,512,965	8.8%	1.4%	24.6%
10	supervisors	7,930,272	5.5%	16,436,522	10.8%	5.3%	107.3%
11	proletarian workers	67,769,977	46.7%	58,734,986	38.5%	-8.2%	-13.3%
	Total	145,118,070	100%	152,716,512	100%	0%	5.2%

Table E2: Basic Characteristics of Detailed Class Strata, 2002

	Class Stratum	N	Weighted N	Mean Total Income	SD Total Income	% Female	% Black	% White	% Asian	% Hispanic	% Government	Employment Share
1	**capitalist, proper**	579	769,311	90,755	111,274	0.32	0.06	0.89	0.04	0.05	0.00	0.01
2	**capitalist, small scale**	733	992,311	86,227	100,352	0.26	0.03	0.92	0.04	0.06	0.00	0.01
3	**capitalist, delegated**	696	996,096	124,143	105,922	0.26	0.03	0.93	0.04	0.03	0.00	0.01
4	**small employer and owner operator**	8874	11,630,420	40,227	57,748	0.35	0.06	0.88	0.04	0.08	0.00	0.08
5	**high-level manager**	4844	6,581,018	59,514	51,556	0.44	0.08	0.86	0.04	0.06	0.22	0.05
6	**mid-level manager**	5321	7,370,738	46,455	43,134	0.42	0.07	0.87	0.04	0.08	0.05	0.05
7	**low-level manager**	4871	6,649,118	43,838	45,594	0.44	0.09	0.86	0.03	0.10	0.13	0.05
8	**semi-autonomous supervisor**	17138	23,579,563	45,027	47,636	0.55	0.09	0.83	0.06	0.08	0.26	0.16
9	**semi-autonomous worker**	7766	10,849,245	45,625	45,020	0.45	0.08	0.85	0.04	0.08	0.21	0.07
10	**supervisor**	5909	7,930,272	28,134	25,624	0.76	0.12	0.82	0.04	0.09	0.24	0.05
11	**proletarian worker**	50358	67,769,977	23,180	23,835	0.46	0.14	0.80	0.03	0.18	0.11	0.47

Table E3: Basic Characteristics of Detailed Class Strata, 2020

	Class Stratum	N	Weighted N	Mean Total Income	SD Total Income	% Female	% Black	% White	% Asian	% Hispanic	% Government	Employment Share
1	**capitalist, proper**	281	600,726	92,554	197,808	0.40	0.09	0.85	0.04	0.18	0.00	0.00
2	**capitalist, small scale**	484	964,422	79,182	103,743	0.29	0.05	0.87	0.06	0.13	0.00	0.01
3	**capitalist, delegated**	520	1,028,248	149,138	152,059	0.28	0.05	0.86	0.08	0.07	0.00	0.01
4	**small employer and owner operator**	5685	11,166,156	40,702	59,675	0.38	0.09	0.83	0.06	0.18	0.00	0.07
5	**high-level manager**	3878	7,771,544	67,548	68,151	0.47	0.11	0.78	0.07	0.09	0.20	0.05
6	**mid-level manager**	5143	10,601,608	51,157	52,117	0.45	0.09	0.81	0.06	0.14	0.07	0.07
7	**low-level manager**	2843	5,794,904	45,550	50,157	0.46	0.12	0.80	0.05	0.17	0.12	0.04
8	**semi-autonomous supervisor**	12791	26,104,433	57,261	58,029	0.56	0.10	0.75	0.12	0.10	0.25	0.17
9	**semi-autonomous worker**	6565	13,512,965	50,515	53,867	0.51	0.12	0.76	0.09	0.13	0.22	0.09
10	**supervisor**	8253	16,436,522	28,667	40,957	0.51	0.14	0.77	0.05	0.23	0.17	0.11
11	**proletarian worker**	28433	58,734,986	26,092	31,180	0.45	0.16	0.75	0.05	0.25	0.10	0.38

2. Detailed class strata distribution using OEWS directly

As discussed in the main text, the aggregation of ONET to CPS occupations may amplify changes in a detailed occupation to changes in a CPS occupation that is much larger in size, resulting in an overstatement of change. Compared to CPS, OEWS has more fine-grained occupation employment data that better matches to ONET occupation classifications. However, OEWS only collects data for employed individuals, thus excluding business owners and self-employed. To check the robustness of the results with more detailed occupation-level employment data, I estimated the employment population and their class distribution using OEWS data. To make the results comparable with the main analysis, I kept the estimated population for business owners and self-employed the same as the main analysis based on CPS data, and calculated the estimated population for the "employees" population using the class shares I obtained using OEWS data. For example, in the OEWS accounting, 3% of the employees were high-level managers in 2004, and since 90.1% of the employed population were employees in 2002, the adjusted share of the high-level manager stratum using OEWS data is 3% times 90.1%, which is 2.7%. As discussed in Appendix A, 2004 OEWS is used for the estimation because previous years of OEWS use incompatible occupational codes. Table E4 shows the estimated class structure using OEWS occupations and employment counts directly.

As shown in Table E4, OEWS provided more conservative estimates across class strata. The share of delegated capitalists, all levels of managers, and semiautonomous supervisors are all smaller than the CPS data, whereas the share of semiautonomous workers, supervisors, and proletarian workers are larger. This is expected, as previous research has shown that self-reported occupational titles tend to be more inflated compared to establishment survey reported by employers (Abraham and Spletzer 2010).

Consistent with main analysis, the managerial class expanded at the expense of other

classes, except that OEWS suggests a marginal increase of the non-managerial employee class. Similar with main analysis, the share of proletarian workers decreased remarkably while the share of supervisors increased.

Table E4: Detailed Distribution of the American Class Structure, 2002 and 2020, using OEWS Occupational Employment

	Class Strata	**Share 2002**	**Share 2020**	**Change in Share**
	Capitalist, overall	1.46%	1.16%	-0.30%
1	capitalist	0.53%	0.39%	-0.14%
2	capitalist, small scale	0.68%	0.63%	-0.05%
3	capitalist, delegated	0.24%	0.13%	-0.11%
4	Small employer and owner operator	8.01%	7.31%	-0.70%
	Manager, overall	9.37%	10.35%	0.98%
5	high-level manager	2.71%	3.04%	0.33%
6	mid-level manager	2.78%	3.37%	0.59%
7	low-level manager	3.88%	3.94%	0.06%
	Non-managerial worker, overall	80.48%	80.51%	0.03%
8	semi-autonomous supervisor	14.71%	14.05%	-0.66%
9	semi-autonomous worker	7.46%	12.24%	4.77%
10	supervisor	5.91%	11.19%	5.28%
11	proletarian worker	52.39%	43.03%	-9.36%

3. Detailed class strata distribution using core tasks only

The class categorization in the main analysis included all tasks for a given occupation. However, as the ONET database developed, there are task-level meta information available that specifies whether a task is "core" or "supplementary" to the occupation. It is possible that the observed trends of upskilling and added supervisory responsibilities are mostly changes of the "supplementary" tasks rather than "core." However, a limitation of the ONET data is that only a small proportion of occupations have the "core vs. supplementary" task information in 2003, while most occupations have that information in 2020. Given the data limitation, I use task descriptions consisting of only core tasks whenever that information is available. This means that for a bulk of the 2003 occupations, their task description is the same as the main analysis due to lack of such information, resulting in an overestimation of downward class shifts as their 2003 task descriptions included all tasks while the 2020 one only included core tasks. Nevertheless, I produced the results as a robustness check for readers' reference.

The results are shown in Table E5. For 2002, the distribution is quite similar for the reasons mentioned above. There is a slight increase in the share of semi-autonomous workers and proletarian workers, indicating that some occupations' supervisory responsibilities were indeed supplementary rather than core tasks. For 2020, the estimates have a lower number

for the managerial class and a higher number for the non-managerial employee class. This is expected because with core tasks, some occupations' decision-making power was suggested by supplementary rather than core tasks. In addition, the share of semi-autonomous supervisors and supervisors are both about 3 to 4% less than what is reported in the main analysis (Table E1), indicating that a notable portion of the added supervisory responsibilities are supplementary tasks for the occupation. This aligns with my hypothesis that the added task authority is only an added burden to workers, rather than a focus of their job. Nevertheless, even when the analysis is restricted to core tasks, the share of supervisors still increased while the share of proletarian workers decreased.

Table E5: Detailed Distribution of the American Class Structure, 2002 and 2020, using Core Tasks for Classification

	Class and Class Strata	**Workforce Population 2002**	**Share 2002**	**Workforce Population 2020**	**Share 2020**	**Change in Share**	**% Growth**
	Capitalist, overall	2,757,718	1.9%	2,593,396	1.7%	-0.2%	-6.0%
1	capitalist	769,311	0.5%	600,726	0.4%	-0.1%	-21.9%
2	capitalist, small scale	992,311	0.7%	964,422	0.6%	-0.1%	-2.8%
3	c-suite and top manager	996,096	0.7%	1,028,248	0.7%	0.0%	3.2%
4	Small employer & owner operator	11,630,420	8.0%	11,166,156	7.3%	-0.7%	-4.0%
	Manager, overall	20,600,873	14.2%	23,104,545	15.1%	0.9%	12.2%
5	high-level manager	6,471,264	4.5%	7,732,211	5.1%	0.6%	19.5%
6	mid-level manager	7,255,657	5.0%	10,197,498	6.7%	1.7%	40.5%
7	low-level manager	6,873,953	4.7%	5,174,836	3.4%	-1.3%	-24.7%
	Non-managerial worker, overall	110,129,058	75.9%	115,852,415	75.9%	0.0%	5.2%
8	semi-autonomous supervisor	21,146,630	14.6%	21,501,384	14.1%	-0.5%	1.7%
9	semi-autonomous worker	12,768,479	8.8%	18,633,817	12.2%	3.4%	45.9%
10	supervisor	6,779,764	4.7%	9,399,735	6.2%	1.5%	38.6%
11	proletarian worker	69,434,186	47.8%	66,317,479	43.4%	-4.4%	-4.5%
	Total	145,118,070	100%	152,716,512	100.0%		5.2%

F. Annual share of all types of employers and owner-operators in CPS-ASEC from 2003 to 2024

Figure F1 shows the annual employment share of the capitalist and small employer and owner operator class and class strata from 2003 to 2024 CPS-ASEC. The results are weighted, and COVID weights are used for the survey year 2019 to 2021. Since the information reflects the preceding calendar year, the trend effectively represents the share change from 2002 to 2023.

From survey years 2011 to 2018, CPS ASEC used cruder categories for the number of employees who worked for the respondent in the preceding calendar year ("FIRMSIZE"). Therefore, during this period, "capitalist, small scale" is not available as those with 10 to 24 employees are collapsed together with those with 25 to 50 employees. As a result, for these years, the "capitalist, proper" class includes all employers with 10 or more employees.

The sudden jump of the "capitalist, proper" and "capitalist, small scale" in survey year 2020 is due to a data coding error in the original ASEC data that IPUMS has not corrected in their current release. This error will be fixed in future releases of the IPUMS CPS-ASEC data. See an exchange about this problem on the IPUMS forum here: `https://forum.ipums.org/t/religious-occupations-by-classwly-in-asec-2020/6229`.

The overall distribution of the four class/strata has been rather stable, with the "small employer and owner operator" class gradually declining by about 1 percent in the past two decades.

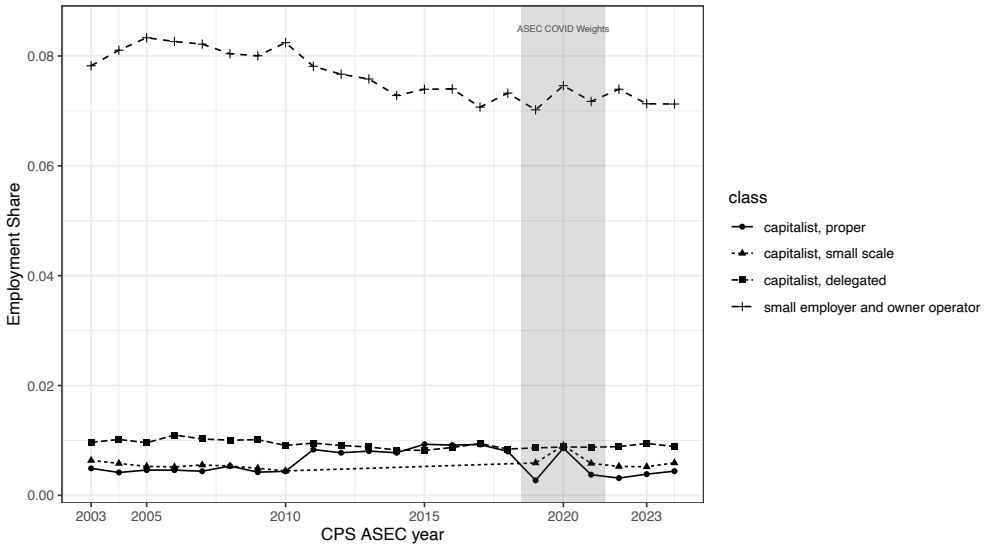


Figure F1: Employment Share of the Capitalist and Owner Operator Class and Class Strata, CPS-ASEC 2003 to 2024

G. Alluvial Graph for All Class Strata

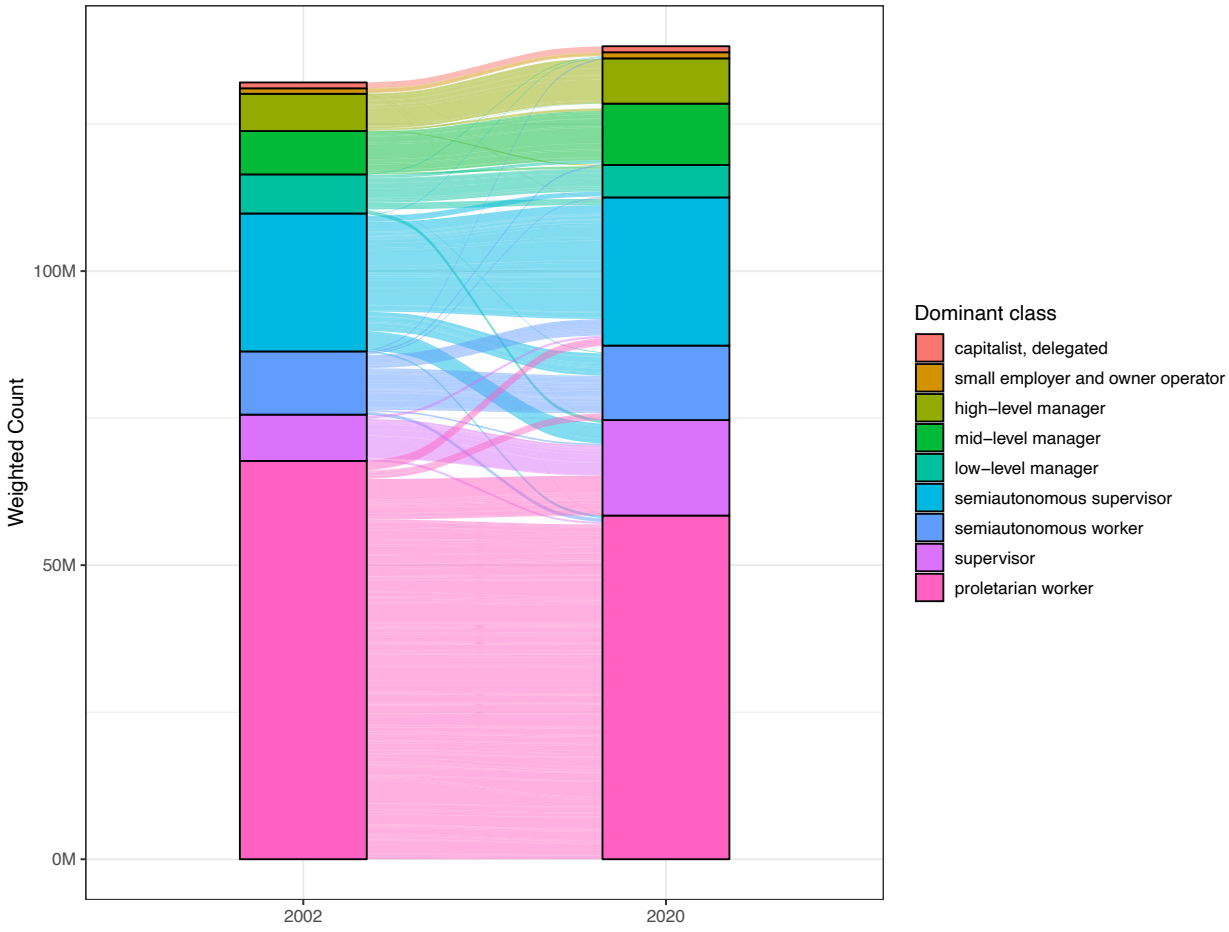


Figure G1: Alluvial Graph for All Class Strata

NOTE: Capitalist, proper and capitalist, small scale are not presented because they are not the dominant class stratum for any of the occupations in the data.

Appendix References

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