REGIONAL EMPLOYMENT CHANGE — TASK CHANGE, OCCUPATIONS AND INDUSTRIES

BY

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THESIS

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ABSTRACT

In this thesis, I study how routinization—the process of codifying and automating job tasks—influences regional employment change. I examine two questions. First, does routinization drive employment change in US metropolitan areas after controlling for occupation and industry mix? Second, does overall employment change occur more strongly through occupational change than industry change across US metropolitan areas?

My analysis finds that routinization is a major determinant of both total and relative changes across industry–occupation employment groups; changes in industry group employment have been more important influences on overall employment change than changes in occupation group employment; the difference between occupation group and industry group effects are lessening over time; and joint industry and occupation effects are decreasingly less important in understanding employment change. These findings underscore the importance of task–change in determining employment change and in understanding industries versus occupations as categories for analyzing the evolution of regional economies.

To my parents, friends, family, and colleagues for providing the support and privilege to complete this project.

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CHAPTER 1

INTRODUCTION

1.1 Overview

The "task"–model theory of employment change was developed to explain specific facts about polarizations in employment, wage changes, and more recently, aggregate employment change. This model disaggregates employment into a bundle of workplace tasks accomplished through a mix of workers and technology. Task–routinization (the process of codifying and specifying tasks to aid in automation, computerization or applications in labor cost reductions) has been examined both as an important determinant of these wage–polarizations, and for its effect on aggregate employment (David H. Autor & Dorn, 2013, p. 1076).

Separately, regional economics has attempted to examine regional systems and success through human capital and physical capital centered methods and theories. I argue that the constructs from the task model can be bridged and applied to regional economics to help examine changes in local employment structures and to explain continuous changes in the types and kinds of employments needed by local employment mixes.

The task model intersects with regional economics literature in that tasks—units of work activities, are fulfilled by worker skills—the stock of capacity for performing tasks (David H. Autor, 2013, p. 2). The interaction of occupations and industries, two related conceptual groupings of economic structures can be combined for analysis in the task model. Occupations (the types, skills, and human capital of workers) are hired to provide bundles of skills to accomplish specific tasks for industries (the existing groupings of firms, organizations, and managers who together produce goods and services). Restated, the two accounts, firm–industrial and human capital/occupational, respectively, determine the demand and supply sides of industrial location and production (Currid & Stolarick, 2009), while the task model undergirds employment change through firm decisions determined by group labor and technology costs.

This provides a path for approaching an overarching question in regional economics: Is local success driven by occupations—the type of jobs that people in places are doing, or industries—where people work (K. King, Mellander, & Stolarick, 2010), by possibly directing it through a causal path, and how much of total employment changes cities can be explained through task routinization?

Recent work in task model literature has begun to approach the effect of routinization on employment at a larger level, examining the effect of large changes in service–based employment change (David H. Autor & Dorn, 2013), or finding that during cyclical economic troughs middle–skill jobs are lost permanently, leading to successive jobless recoveries in aggregate (Jaimovich & Siu, 2012). Additionally, studies in the task literature have explored the effect of the industry mix on employment polarization, but again, not their effect on larger employment changes (Acemoglu & Autor, 2011a; David Autor & Dorn, 2009; D.H. Autor, Levy, & Murnane, 2003; David H. Autor & Handel, 2009).

I argue that a substantial portion of employment change in metropolitan cities has been driven by task changes and task routinization, measured directly through task measures and indirectly through occupations. Employment changes are decomposed into industry and occupation effects, and are comparatively tested along with the effect of routinization on occupation demand in metropolitan areas. Together these sources answer an open question in regional science: what matters more for employment change, what places make (the industrial work of a place) or what people do (the types of people, skills located in a particular space), via a clear "how"—the routinizability of employment in metropolitan areas.

I use full hierarchical regression models to test the effect of task–routinization on metropolitan employment; measures for routinization of employment are found to be significant determinants of employment change with large effect sizes after controlling for related occupation and industry group level variables: wage, education, and city–level variables. Stacked time period regressions show that the effect of routinization results was strongest from 1990 to 2000.

A second analysis uses Bayesian Hierarchical ANOVA and presents a method and baseline for comparing occupation and industry group effects over time. When routinization models are corroborated by results (with explored caveats) from these exploratory models, industry effects are stronger than occupation effects. This result was again found to be strongest between 1990 and 2000. Differences between secular occupation group and industry group effects have been lessening over time, while joint industry and occupation effects have become more important influences on employment. Discussion of these results explores, with evidence, whether task models can be correctly mapped to occupations for the purpose of using the task model to explore regional changes.

The paper proceeds with Section 2, where I introduce the task model/skill–biased technical change literature and its use in understanding occupation changes. Occupations serve as a bridge into Section 3, which focuses on regional economics and employment research. Section 4 introduces the empirical methods and approach. Sections 5 and 6 present results from Bayesian Hierarchical ANOVA, which directly compares effects of changes in occupations and a major related confounding factor—industries—allowing a preliminary test of the hypothesis that occupations (and by proxy task changes) are more important than industries in determining employment change in metropolitan regions. These are explored further with hierarchical linear models to examine the effect of routinization on employment change after controlling for city and occupation level factors.

1.2 Problem Description and Contributions

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CHAPTER 2

USING THE TASK MODEL TO EXPLAIN EMPLOYMENT CHANGE IN CITIES

The "canonical" task model was created to formally describe changes in employment through the supply and demand for skills and technology in the economy. The model was developed to explain three decades of empirical developments that did not fit the traditional "canonical production model" in labor economics; these include declines in real wages of low skill workers, non-monotonic or "polarized" changes across both the earnings and skills spectrum. The model failed to accommodate two realities of the late twentieth century: accelerating technological innovations that allowed for inter-firm capital and labor substitutions, and the facilitation in transfers of labor tasks from domestic to foreign locations. In subsuming technological changes and labor decisions into tasks, the canonical task model makes technology endogenous and updates the production model so that both types of labor and capital can interact as either complements or supplements to each other based on non-assumed costs and productivities (David H. Autor, 2013, p. 1).[1]

Relative demands for the types of labor (designated as "high-skill" and "low-skill") and capital are both "task inputs" between which firms constantly shift, given the costs and productivity of capital inputs and factors. In contrast to the canonical production model, "artificial distinctions between labor, capital, and trade (or offshoring)" (ibid, p. 3) are removed in lieu of tasks which are assigned fluidly, based on comparative advantage and the development of new technologies where labor tasks are transformed into capital tasks through routinization.

Routinization is an important factor in the current task model, introduced in (D.H. Autor et al., 2003), as a specific replacement for the previous catch-all term 'technology.' Routinization is the causal link between job polarization and declines in the cost of information technologies and related standard-

[1]Recent theoretical and empirical work on the task model include Acemoglu & Autor, 2011; D.H. Autor et al., 2003; David Autor & Dorn, 2009; David H Autor, Dorn, & Hanson, 2011, 2013; Firpo, Fortin, Lemieux, & Firpo, 2009; Goos, Manning, & Salomons, 2009, 2010; Hynninen, Ojala, & Pehkonen, 2013; Reenen, 2011

izable computations'. Standardizable computations are specific "procedural, rule-based activities to which computers are currently well-suited [to be programmed] as "routine" (or "codifiable") tasks" (Acemoglu & Autor, 2011, p. 1076).

Middle-skill occupations have tasks and procedures that are well known and have been more likely to be easily codified, computerized, off-shored, or face international cost disadvantages. They have also have lost comparative advantage to high-skill "cognitive" workers in combination with technology. The tasks previously accomplished by Administrative Assistants the largest occupational loser over the past decades is now accomplished by a higher skilled worker using a computer. Low-skill occupation groups (like health professions, nursing, janitors, cleaners, construction, and security) have manual task structures that are largely not routinizable: for example, a vacuum cleaning robot that can climb stairs to do its job is an extremely complicated machine (Autor and Dorn 2013).

Workers whose skills are complemented by routinization and computing gain productivity rewards at the expense of others (see also D.H. Autor et al., 2003; DH Autor, Levy, & Murnane, 2002; Bartel, Ichniowski, Shaw, & Correa, 2009). Routinization coincidentally bifurcates workers into routinizable and non-routinizable jobs; the latter can be further split into "high-skill" abstract and "low-skill" manual tasks. Technologies are factor-augmenting in that they complement both skilled and unskilled workers against middle-skilled workers whose tasks have been routinized. This high-low effect also creates wage polarizations across skill groups because of unequal comparative productivity gains to highly skilled workers versus medium and lower skilled workers across a range of task demands.[2]

The model is not without its criticism; secondary scholarship asserts that these effects are due to politics and policy, and not necessarily to technology change. Howell points to concurrent institutional and political preferences as

[2]Earlier sociologists of occupations in 70s, 80s and 90s, posited that technology based occupation change could have varied effects based on task content; up-skilling, down-skilling, and composition effects each could raise or lower demand for particular types of occupations and task content could combine in a multitude of ways to affect the distribution of jobs, wages. See Committee on Occupational Classification and Analysis - National Research Council, 1980; Kashefi, 1993; Kenneth I Spenner, 1979, 1983, 1990) Also see Bound & Johnson, 1989, 1995; Juhn, 1999; L. F. Katz & Autor, 1999; L. Katz & Murphy, 1991 for an earlier period of economists work on "skill-biased technological change".

confounding factors in pushing down wages (Howell, 1999). Lefter and Sand found that the employment crosswalks were marred with major coding errors affecting low-wage occupations (Lefter & Sand, 2011). A more salient criticism points out that computerization and routinization changes had peaked by 1990/2000 and could not directly explain more recent changes at the top of the skill/wage spectrum (Beaudry, Green, & Sand, 2013; Bidner & Sand, 2012; Lefter & Sand, 2011; Mishel, Schmitt, & Shierholz, 2013; Sand, 2013).

In following sections I link existing work on regional employment models to the task model through occupations and propose studying employment change using the task-centered model.

2.1 Occupation and Industry Analysis in Employment Change

Employment change has been determined by the interaction of two related factors in local economies: the types, skills, and human capital of workers (occupations), and the existing groupings of firms, organizations, and managers who together produce goods and services (industries). Clark et al. write that "places will not be known by what they produce so much as by who is employed there at certain stages of specific production processes" (Clark, Gertler, & Whiteman, 1986, p. 26, as quoted in Bagchi-Sen & Pigozzi, 1993, p. 45). Thus, the role of occupations and industries in understanding the "occupational-functional role of a place" are two crosshairs to "trace the continuing transformations of a local economy, to understand and guide that change" (Thompson & Thompson, 1985, p. 20).[3]

Regional economic development thought has bifurcated its work and policy proposals into separate human capital- and physical capital-centered methods and theories of regional success. Bridging the two types of research and their policy implications is the question of whether regional development is driven by occupations (the type of jobs that people in places are doing) or industries (where people work). Exploring this link between the kinds of regional economic structures and performance has become "one of the most important subjects of inquiry in the regional development and planning literature" (Wan, Kim, & Hewings, 2013, p. 614).

Industry sectoral mix research often looks at the absolute or comparative

[3] Also see: Thompson & Thompson, 1985, 1987; Thompson, 1986

concentrations of industries using location quotients, buyer-seller relations, institutional capacities, or other measures of assessing businesses that create agglomerative, or positive, externalities through close geographic or business relationships. The industry mix, or industry employment mix, is "defined as the number of persons employed in particular industries as percentage of total [industry] employment" (Tschetter, 1987, p. 36). Industries produce varying services and goods, employing specific occupation mixes based on individuals of different skills and abilities.

Where industrial analyses fail to capture the types of regional roles occupations play or specialize in, occupational analysis can help (Barbour & Markusen, 2007; Currid & Stolarick, 2009; A. Markusen, 2004; Mellander, 2009). Occupational mix analysis began as a supplementary method of analyzing production of places, specifically examining the growth of producer services that were coterminous with manufacturing declines.[4]

Recent scholarship has advanced theories and methods of occupational analysis to understanding the importance of human and occupational capital—that certain types of workers with human capital are necessary for regional development (A. Markusen & Schrock, 2008; A. Markusen, 2008; Mathur, 1999).[5] Analyses have been developed into both occupational cluster detection and analysis tools and tools to match industry recruitment and retention to extant labor pools or occupations mixes (Chrisinger, Fowler, & Kleit, 2012; Currid-Halkett & Stolarick, 2011). Characteristics of groups of workers in metropolitan areas can be examined through cluster analysis indicators; workers in "knowledge-intensive occupation clusters" were found to be associated with metropolitan success (Feser, 2003, p. 1948), recreated in Chile by Varas & Ubeda, 2010; see also (Chrisinger et al., 2012; Koo, 2005; Nolan, Morrison, Kumar, Galloway, & Cordes, 2010). Types of human capital have been found to systematically differ based on metropolitan class size, work, and human capital indices, as well as in "cognitive and relational" skills, self-motivation, and relational skills (A. J. Scott & Mantegna, 2008). Practical/basic skills are, on the other hand, more important in smaller areas

[4]For examinations of employment changes due to regional convergence and rust belt employment decline see S. Bagchi-Sen, 1995; Bluestone & Harrison, 1982; Bluestone, 1986; R. G. Sheets, Nord, & Phelps, 1987; R. Sheets, 1985; G. Sternlieb & Hughes, 1977; George Sternlieb & Hughes, 1975.

[5]Also see Markusen, Wassall, DeNatale, & Cohen, 2008; A. Markusen & Schrock, 2001; A. Markusen, 2004.

(albeit with lower returns in wages) among low-skilled workers, and wage returns to social skills in larger cities were found to have increased over time (Florida, Mellander, Stolarick, & Ross, 2012; Kok & Weel, 2011; Allen J Scott & Mantegna, 2010).

2.2 Hypothesis Testing

The empirical analysis undertaken is guided by the synthesis and application of several main factors from the SBTC literature, regional economics, and urban studies—occupation-based analysis (incorporating tasks and routinization), industry-based analysis—and using metropolitan regions as the basis for aggregation and understanding local employment changes. I build on several recent findings: 1) a large percentage of net employment changes in the United States and Western Europe fall under the service employment changes (Spence & Hlatshwayo, 2011); 2) a large portion of service employment change in the past decades has been attributed to routinization and task based changes (David H Autor & Dorn, 2013); and 3) Industry analysis ("what places do") as guided by decades of regional analysis should be given a primary role incorporated into the analysis of the effect of tasks on local employment change.

I propose that the same ideas and tools of task analysis can theoretically explain an effect witnessed in regional economic development: how much of total employment change in cities can be explained through task/occupation changes as opposed to industry changes. The cumulative effects of task changes may be measured and compared at regional levels using occupations and industry employment factors. My analysis conducted differs from the SBTC approaches and tests in that, instead of grouping occupations based on factors of cognitive and routinizability and testing for polarization of employment types and wage levels across skill levels, I test for the effects on total employment change and percentage change. I also include routinization measures in full models which allow variables to vary by industry and occupation groups. Prior work in the SBTC literature has largely ignored the effect of industries as a confounding variable on employment change.[6]

[6] Autor and Acemoglu (2011) incorporate industry analysis in testing routinizations effect on employment polarization. They conduct a shift-share analysis to test the alternative hypothesis that employment polarization is caused by industry mix changes that shift employment towards sectors that use fewer "routine" occupations. This addresses a different hypothesis: namely that polarization of skilled labor is driven by varied types

By incorporating the task model to regional changes, task changes appropriate the role of, and build on, occupational mix analyses of places. For example, "changes in the occupational composition of its workforce" is directly related to tasks as "workers' occupations are classified by the functions they perform, and it is possible to trace functional activities through occupation composition" (Eberts & Erickcek, 2000, p. 147). The task model is a bridge to occupational mix analysis's traditional use of human capital, education, and skills.

Industry analysis ("what places do") is given a primary analytical role as directed by decades of work in regional economics. The question of "what places do" (or "what people do") is analogous to asking what tasks are required of workers by employers, and where specific tasks are being sought. The existing industry-occupation regional framework can be updated from "what places do" versus "what they make" to: "do the task requirements of areas change faster than that place's industry-base changes"? That is, does the demand for tasks through firms and industries differ more quickly than the supply of individuals providing those tasks?

To approach these questions, two related hypotheses are tested. First, I test whether changes to employment are determined by the routinizability of particular occupations. Having shown this, I test whether employment changes in places are driven by occupation changes versus industry changes. If occupations are shown to be more important than industries when examining group effects, then there is strong evidence that, across cities, employment change has been driven by routine-task changes via city workforce requirements.

I present evidence that employment change in metropolitan cities has been driven by the increasing importance of occupations through the mechanism of task routinization. Two related sources for employment change are analyzed: the ongoing changes in the mix of the types and kinds of industries and occupations required at local areas, and the effect of routinization on occupation demand in metropolitan areas.

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of cognitive, and routinized occupations, and not the effect of routinization on employment change. Autor and Dorn (2013) use share of employment industry in 1950 as an instrumental variable for service occupation routinization change. Firpo et al. (2009) include industries as a factor composition for determining wage changes across metropolitan regions.

CHAPTER 3

EMPIRICAL METHODOLOGY

3.1 Mixed and Multilevel Modeling

"Multilevel modeling" describes regression model fitting to hierarchical data where random effects explicitly model the heterogeneity (and correlation) inherent in grouped data. This type of modeling is often "conceptually more realistic as it handles the micro-scale of people and the macro-scale of contexts simultaneously within one model. Consequently, the differences between contexts are not treated as being fixed and separate (or 'unrelated') but are seen as coming from distributions that relate to a larger population" (Duncan, Jones, & Moon, 1998, p. 99).

Hierarchical linear modeling allows multiple nested or random grouping factors to affect outcomes especially in settings where one wants to account for both individual- and group-level variations when "estimating group-level regression coefficients." The simplistic approach pools all data together, ignoring the individual differences across groups, or treats each group as completely separate. MLM provides the ability to include group level predictors and indicators (whether at the city level and/or the occupation-industry level) by assuming that each individual data set is distributed according to a group distribution.

Multilevel models allow for simultaneous modeling of individual— and group—level data. All individual data points on employment change are modeled at one level of the framework, while group levels are also modeled (industry/occupation groups together are modeled using their group-level averages). Additionally, multiple types of groups can be used simultaneously; group-level averages of industry groups and occupation groups can be used together in non-nested context.[1]

[1]For a background to multilevel modeling see (J. J. Faraway, 2002; J. Faraway, 2005; Hox, 2010; Kliegl, Masson, & Richter, 2009; Pinheiro & Bates, 2000; Snijders & Bosker, 1999).

3.1.1 Mixed-Effects Models for Occupation and Industry Groups

The crossed and grouped nature of employment data lends itself to mixed effect modeling for examining the relationships and interrelations between industry and occupation employment changes. While multilevel modeling was originally devised to deal with explicitly "nested" or hierarchical data (students within classrooms), mixed-effects modeling extends multilevel or hierarchical modeling techniques and methods for groups like occupations and industries that are not nested, but "crossed," across cities: occupations reside within cities, but not all occupations of a certain type are within particular urban areas.

In crossed and mixed modeling, individual— and group—level characteristics can be included to "different contexts to be simultaneously modeled making it possible to identify contextual settings which are having a confounding influence" (Duncan, Jones, & Moon, 1998, p. 107). Similarly, to understand employment change and employment mixes, contextually we need to understand whether city-level effects (secular changes within city economies) or industry/occupation group effects (cross-city changes in industry-level changes) matter more in understanding employment change. In complex cross-tabulated structures, "it is diffcult to model the interactions among explanatory variables in classical models, since each single cell is getting sparser and the estimates become unstable. By borrowing strength across cells, a multilevel model can produce stable estimates even for cells that have few observations and thus can be viewed as a multivariate regression or interpolation procedure" (Wang & Gelman, 2014). This is particularly important for workforce city modeling as the three-way cross-tabulation of industries, occupations, and cities becomes quite sparse for detailed occupations across the distribution of cities.

The fitting of models "involves finding the right balance between the complexity of the model and faithfulness to the data" (Baayen, Davidson, & Bates, 2008), with the aim of reducing models to the maximum random-effect structure justified by model comparisons and supported by the data (given the random effects, group levels, and the parameters considered). Statistical significance of variables is an inappropriate criterion for including model group parameters; instead, model building trades matching overall model-fits to data with parsimony over parameter constraints.

Models with the same fixed parts and differing mixed effects (varying group level slope predictors) can be compared using the likelihood ratio test to justify inclusion random effects for employment or city group level (or both employment group and city level groups). The log likelihood test (2logliklihood ratio test) involves taking the difference between the two log likelihoods for the models (multiplied by 2), and follows the chi-squared distribution using the difference in parameters of the models for the degrees of freedom.[2]

Mixed-effect modeling allows for the disaggregation of employment group, city group, and individual "city-employment" (individual-level) variances.

3.1.2 Mixed Modeling Notation

The basic OLS regression model is written as

$$Y_i = \beta_0 + \beta_1 X_i + e_i$$

where the residual e_i represents the error term not captured by the equation; coefficients β_0 and β_1 represent the intercept and slope of the equation of the predictor X.

The basic multilevel analog where group-level factors have their own error term is

$$Y_{ij} = \gamma_0 + \gamma_1 X + u_{0j} + e_{ij}$$

Subset 1 represents the lowest level unit, ij represents group level units, and 0 represents a common constant for units. u_{0j} represents the group-level deviation of the jth group's average from the overall grand mean γ_{00}. The basic mixed model is represented as

$$y_i = X_i\beta + \alpha_{j[i]} + \gamma_{k[i]} + \epsilon_i for i = 1, \ldots n$$

where y_i represents the employment change for a two-way cross-tabulation of the employment particular industry where $j[i]$ represents an occupation job

[2]While the theoretical literature suggests that final estimations for mixed models should be made using Residual (or Restricted) Maximum Likelihood (REML), which are generally "more precise for mixed effects modeling" (Bayen et al., 2008), log-likelihood model comparisons can generally only be made using the regular Maximum Likelihood estimations (which allow for group-level model fit comparisons) and refitted for final models. Methods do not differ for regression coefficients, but "they do differ with respect to estimating the variance components" (Snijders & Bosker, 1999, p. 56). Differences are most important when number of groups is small, but largely negligible when for large numbers of groups (¡30) (Quen & van den Bergh, 2008:416). R using lme4 carries out the likelihood ratio test with the "anova" command (Bates, Walker, Maechler, & Bolker, 2014; R Core Team, 2014).

category that the specific data level industry change data point is located in, and $k[i]$ represents the occupation group that the industry change is located within. The data model as formulated is represented with a row presenting employment change of a specific industry-occupation pair within at a certain metropolitan area.

In this formula, $j[i]$ and $k[i]$ are occupation groups and industry groups respectively (and can be extended to a third crossed or nested group, cities) and can be further decomposed into specific constituent crossed or nested factor levels expressed by marginal groupings:

$$
\begin{aligned}
y_i &\sim N(\mu_y + \alpha_{j[i]} + \gamma_{k[i]}, \sigma_y^2),\ for\ i = 1, \ldots, n \\
y_i &\sim N\left(\mu_y + U_j a + V_k g, \sigma_y^2\right), for\ i = 1, \ldots, n \\
\alpha_j &\sim N\left(U_j a, \sigma_\alpha^2\right), for\ j = 1, \ldots, J \\
&\quad (where\ J\ represents\ 20\ broad\ industry\ groups) \\
\gamma_k &\sim N(V_k g, \sigma_\gamma^2), for\ k = 1, \ldots, K \\
&\quad (where\ K\ represents\ 23/313\ occupation\ groups)
\end{aligned}
$$

Finally, μ_y represents data level error in the marginal decomposition; U is the matrix of any Industry by Occupation level predictors included in the model; and V is the matrix of any occupation or industry level predictors to be included in the model. a is a vector of coefficients for the Industry by occupation; g is the vector of coefficients for the city-level groups; σ_α is the standard deviation of the model errors at the industry/occupation level; σ_γ is the standard deviation of the model errors at the city level; and σ_y represents the data-level errors.

Hierarchical models are used because of the relaxed assumptions of variance homogeneity. Both groups of industries and occupations have non-constant variance, and city employment over time is auto-correlated. HLM models are fit using maximum likelihood and restricted maximum likelihood estimation (ML and REML) respectively. Model parsimony asks us to choose the model with the smallest possible parameters with acceptable fits.

Model selection in mixed models is done by testing a hypothesis model with a given fixed-effects coefficient and then comparing this to an alternative model (the null model) without the coefficient of interest. The null and alternative models are nested such that the null model is a special case of the alternative model. Effects are tested sequentially, adding tested terms to null models and comparing the effect of an added fixed effect coefficient to the alternative model. To choose between non-nested models, the likelihood ratio test, where the log-likelihood function of models, are estimated for the alternative and null hypotheses and compared under the chi-squared distribution with $p(a) = p(a-1)$ degrees of freedom.

3.2 Data

This work takes an overarching quantitative approach by splitting the data, repeating, the analysis and comparing the same models over set time periods. Model results compare the effect of industry and occupation status for each period over three time periods in the past two decades, specifically from 1990 to 2000, 2000 to 2007 (the inter-decadal period prior to the recession in 2008) and 2007 to 2011, using employment aggregations at broad two-digit industry and occupation levels, and more detailed three-digit industry and occupation aggregations.

These three time periods represent distinct economic regimes in the American economy – splitting the data, quantitative work, and analysis allows for additional exploration and inferences regarding large technical and economic changes in the economy over time and through regional employment patterns of industry and occupation types.[3]

As background, 1990-2000 represent the culmination of the decline of Fordist manufacturing; decade long transitions away from manufacturing employment, and the wide introduction of computers and other technology. The 2000-2007 represent a period of relatively anemic broad employment growth buffetted by construction and housing jobs. Charles, Hurst, & Notowidigo find that a majority of manufacturing job losses were born by the transition to construction growth in cities in this period (Charles et. al, 2014). Finally, the year 2007 represented a sharp cut-off of this pattern due to a housing–led contractionary recession, followed with a slow recovery. In splitting the data and analysis I hoped to parse how industry or occupation patterns are affected by these changes.

Detailed three-digit data for occupations (based on the IPUMS *OCC1990*

[3]Use of stacked models to present effect sizes has been championed separately by statisticians Andrew Gelman (see Gelman, 2007, 2004) and Gary King(G. King & Powell, 2008; G. King, Tomz, & Wittenberg, 2000).

variable) and industries (based on the Census Bureau's 1990 industry definition system) were harmonized for cross-time period comparisons. I update data and code from Dorn 2009, and Autor and Dorn 2013's crosswalks, accessed from Dorn (2014), which incorporate Lefter and Sand's criticism of the original Meyer and Osborne crosswalk used in early SBTC work, for the fifth iPUMS revision (Lefter & Sand, 2011; Meyer & Osborne, 2005; D. H. Autor & Dorn, 2013; Dorn 2009).

For broad two-digit aggregations, two different aggregations are used: an SIC-based definition which can be used over all time periods, and a comparison dataset built using newer SOC-based aggregations, which implement important updates of occupation definitions. Broad SIC data and detailed SIC data can be compared over all time periods, while the newer SOC definitions only exist for 2000 onward. The existing literature has yet to compare the effect of SOC, and SIC definitions are tested concurrently to calibrate the effect of definitional changes on results, but results are generally equivalent. All data are processed and compiled from IPUMS version 5 (Ruggles et al., 2010).

To measure the effect of routinization at city levels, I use David Autor's measure of routine task-intensity (RTI) for each occupation weighted by the occupation's share of a city's employment (David H. Autor, 2011). RTI is calculated as

$$RTI_k = ln(T^R_{k,1980}) - ln(T^M_{k,1980}) - ln(T^A_{k,1980})$$

Where T^R_k, T^M_k, T^A_k are routine, manual and abstract task inputs from the US Department of Labor's Dictionary of Occupational Titles (DOT) for each occupation. The RTI measure was introduced in Autor, Katz, Kearney (2006), simplifying and updating Autor et al.'s 2003 measure. The composite index has low values for manual tasks, and high values for abstract tasks. Service occupations are noted to "combine high manual task content with low routine task content" (D. H. Autor & Dorn, 2013, p. 1571). [4]

[4]Examples of highly routinizable occupation include: Butchers, Secretaries, Pharmacists, Barbers, Cashiers, Bookkeepers and Tellers. Low routinizable positions are split into high skill and low skill jobs. High skill examples include : Farmers, Athletes, Firefighters and Police, Teachers, Surveyors and Cartographers. Low skll examples include : Bus and Taxi drivers, waiters and waitresses, health and nursing aids etc. see Figures 6.3 and 6.4 for more as well as D. H. Autor & Dorn, 2013

This occupation-based measure is used to create a routine employment share measure for each metropolitan area. Weighted routinized employment share measures *RTIaOCC*, *RTIaIND*, *RTIaCITY* are created for each time period—

$$RTIaOCC = \sum_{k=1}^{K} S_{jkt} * RTI_k$$

$$RTIaIND = \sum_{k=1}^{K} I_{jkt} * RTI_k$$

—where S_{jkt} is the share of employment in occupation k in metropolitan area j at time t. I_{jkt} is the occupation's share of employment in industry k. *RTIaCITY* is a weighted product of the city's total employment multiplied by its occupations' routinization measure to provide a city population-weighted routinization measure.

3.3 Routinization and Employment Change

Multilevel modeling was used to analyze the data structure with occupations and industry groups crossed within cities. The main relationship tested was how employment change and employment percentage change (level-1 outcome variables) were related to the routinized share of employment in occupations, industry, and cities. Other covariates included are average wages for the occupation during the time period, level of occupation, and total city employment.

Models are the maximal models fit, given the possible by the data. Goodness of Fit statistics are maximized by including *Education Share*, *Total City Population*, and the occupation's national *Average Hourly Wage* for each time period, and allowing the *RTIaOCC* routinization measure to vary by its intercept slope with occupations (313 detailed) nested within 20 broad industries and by its occupation group.[5] This structure was finalized and compared against crossed (non-nested), industry within occupation group specifications. Models are run for individual difference in differences for year pairs, for detailed occupations and detailed industry as well as detailed occu-

[5]Models were run in R using LMER mixed modellings package (Bates et al., 2014; R Core Team, 2014). Similar effects were achieved after testing 212 detailed grouping industries, in sporadic modmodels could not be fit for the 212 detailed industries but due to convergence issues—an issue explored in conclusions.

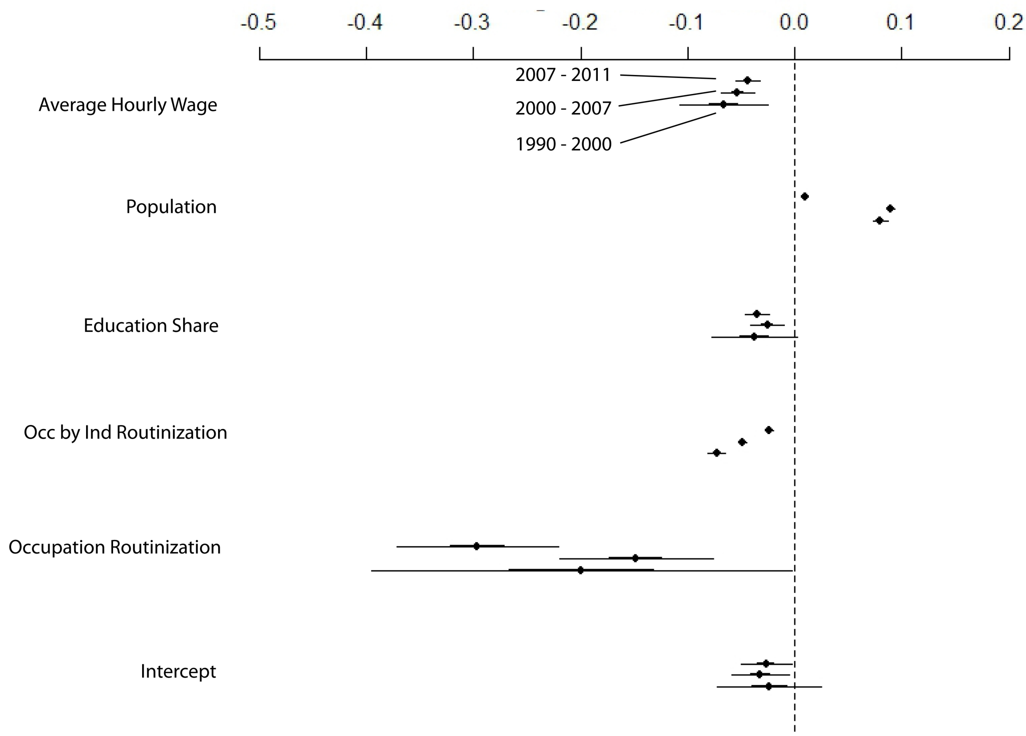

Figure 3.1: STACKED COEFFICIENT RESULTS EMPLOYMENT CHANGE (LOWER TO HIGHER: 90-00, 00-07, 07-11)

pations and aggregated industries. Model results match fully pooled regular regression models with no group effects. Diagnostic tests also show that the multilevel models are warranted, given the fixed and random effects of industries and occupations.

3.3.1 Routinization Results

Model results in Figures 3.1 and 3.2 (created from regression Tables 6.1 and 6.2) compare stacked variable effects in explaining "total employment change" (a first difference model of employment over time in the occupation-industry cell) and "percentage changes": employment change relative to the starting period employment of the occupation-industry cell over time periods tested (1990–2000, 2000–2007, 2007–2011).

The base unit of analysis is change (absolute change in thousands of jobs and percentage change points) in a specific industry and occupation within a

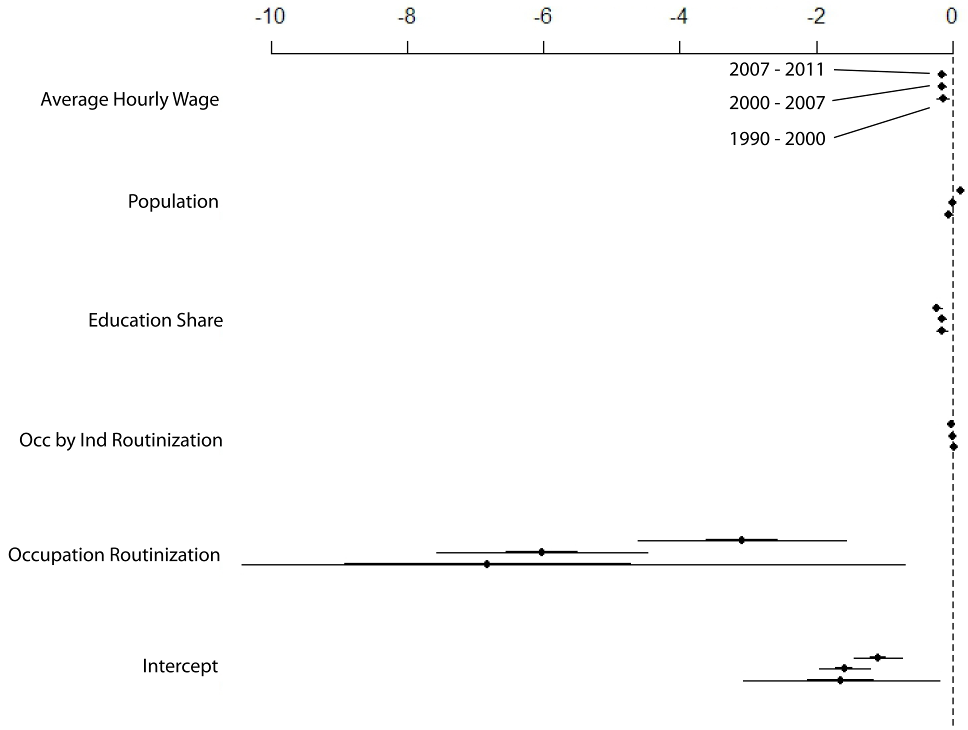

Figure 3.2: STACKED COEFFICIENT RESULTS - EMPLOYMENT PERCENT CHANGE (LOWER TO HIGHER: 90-00, 00-07, 07-11)

city. Changes measured are not a measure of aggregate employment change as commonly understood, and more closely represent total changes in the average industry-occupation pairing of a city over time. The predictor variables are grand-centered means which require closer explication.

Results confirm that routinization, broadly specified, is a major determinant of city workforce (occupation-industry employment cells) change in both absolute and relative terms after controlling for occupation and industry mix (via group level slopes) and accounting for education, wages, and city variables. Routinizable occupations are more likely to be associated with large changes in a city's industry-occupation employment cells; further routinization variable effects are orders of magnitudes larger than all other variables tested and maximize Goodness of Fit tests when included as variables that vary by group. Percentage change models similarly maximize Goodness of Fit statistics when intercepts and slopes of population variables vary by city levels, emphasizing their importance to rapid changes in a city's workforce.

Various models were tested using different iterations and interactions of industry, occupation, and city-based routinization measures. Each provided similar results, which lean general confirmation to the final model specification. *RTIaIND* was not selected for inclusion in final maximal models as specified by the overall goodness of fit testing procedure; in hierarchical models, statistical significance of variables is not used as a heuristic for their inclusion.

Even restricting the models to detailed occupation–broad industry pairings, numerical convergence of crossed–models using large numbers of group factors was an ongoing issue. Convergence was achieved by grand-mean variable transformations of all predictor variables. Grand-mean centering removes problems of high correlations between random intercept and random slopes, as well as correlations between first level and crossed group interactions (Kreft and de Leeuw; 1998).

The average unit of the predictor variable would represent a unit change in thousands of employment change and a point change in percentage change models respectively for the industry-occupation cell. Grand-mean centering of variables does not change hierarchical modeling results, grand-mean centered and non-centered variables have equivalent parameter estimates fits, residuals and predicted values, but coefficient effect meaning becomes harder to parse.

For example *RTIaOCC* showed similar negative associations with employment changes in each time period. For every unit of the routinization variable above it's mean *RTIaOCC* (.2, with a range from -2 to 6.5), an average city's industry-occupation cell will lose 200-400 jobs (depending on the time period. Similarly, a unit of routinizability will lead to a industry-occupation employment loss of 4-7 percent from its starting period. The coefficients results for *education share* (also centered to 1, sd of 1) show that an occupation with a median education (like a middle-skill job) is likely to lead to a loss of 100 jobs between 1990 and 2000 (and a 50 job loss between 2007 and 2011). The routinization variable is generally normally distributed but with a longer tail on the routinizable side. [6]

Average Hourly Wage tells a more difficult story: median wages rose across

[6]See D. H. Autor & Dorn, 2013 for further discussion of the variable's distribution.

the time period ($14, $15 $17 for 1990, 2000, and 2007 respectively) while the distribution of wages widened at the top end. An average employment mix at the average wage would still be associated with losing 75 to 50 jobs over the period, this confirms and echoes 'polarization' results that find that middle wage jobs have lost to low and high wage, but this model is not the best methodological confirmation of this finding.

City population coefficents show that if an city is of median population size, an average industry-occupation cell will grow by 100. At the same time, the average percentage change in a city's employment mix would be negative—smaller cities are more likely to have fast growing industry-occupation types, while employment change in large cities are more path-dependent. The part of this effect can be attributed construction jobs and change : smaller cities have smaller construction industries driving their growth than in larger cities. From 2007-2011, larger cities experienced more industry-occupation employment change, however.

Secondary results show that changes in city employment cells are affected (in statistically significant terms) by population size, the share of highly educated workers, wages, and city-weighted routinizability. The share of highly educated workers in an occupation and average wages are both associated with negative changes in city workforce mix. City population change is associated with positive changes in absolute workforce change, and negatively associated with relative workforce changes (although respective signs flip in the 2007–2011 period), an association that may warrant further study particularly in understanding the effect of population growth across the city spectrum on workforce changes (see Firpo, Fortin, & Lemieux, 2011 for related work). In general, effect sizes of these secondary variables are larger for total employment change than percentage change models. Relative changes in workforce employment are highly and singularly associated with occupation— and industry-based routinization measures.

The primary result from this section—that average amounts of routinization is associated with industry-occupation employment changes in U.S. metropolitan areas—confirms previous work in the SBTC literatures and extends task-change routinization analysis to analyzing employment mix changes after controlling for the occupation and industry types. Not only is routinization associated with large changes in the types of employment across the skill spectrum, but it also drives aggregate change within cities' employment mixes. This finding is statistically significant and has large effect sizes across tested time periods, while being robust to the inclusion and removal of secondary city, industry, and occupation variables

This section has focused on understanding the effect of routinization on employment change in cities after taking into account industry and occupation mix effects, and links regional employment changes to advances and theories in Skill Biased Task Change. Figures 3.1 and 3.2 delineate a second method focused on further understanding regional effects within this framework.

CHAPTER 4

OCCUPATION CHANGE VERSUS INDUSTRY CHANGE

Given that routinization and task changes are drivers of employment change, are they more important for local place-based employment changes than industries and industry mixes? The comparison of the employment effect of industry and occupation group changes (the latter as proxied bundles of task changes) incorporates task models into regional analysis and bridges the SBTC literature with regional employment change.

I present an empirical method to create a comparative baseline of changes in employment that can be accrued to industry and occupation group changes. This provides a path for comparing whether local success is driven by occupations (the type of jobs that people in places are doing) or industries (where people work). Results show that industry changes are more important than occupation changes in explaining workforce employment changes over various periods, but these differences between occupation-group and industry-group effects are decreasing over time.

Because occupations are a rough proxy for tasks, I compare results from detailed level aggregations to broad aggregations that show that results from detailed employment aggregations warrant the conflation of occupations and tasks as proposed in the general literature, but only in the case of detailed occupations.

4.1 Introduction to Bayesian Multilevel ANOVA

Comparisons of the effect of occupations and industries on employment change is tested in a Multilevel ANOVA modeling framework, a Bayesian variant of the traditional Analysis of Variance (ANOVA) model that estimates the relative effects and credible intervals (a Bayesian version of confidence intervals) of different variance components within a model. Hierarchical models have the advantage of model flexibility; there is no assumption of homogeneity of variance, and models allow leeway for both missing data and strict grouped data-model group requirements of NHST ANOVA (Gelman, 2005b; Kruschke, 2009, 2010, 2013). The standard deviations of the constrained regression coefficients are measured by each source or batch effect (Gelman & Pardoe, 2006; Gelman, 2005), or, in Kruschke's phrasing, deflections from group means, which are modeled for each set of industry and occupation coefficients (Gelman & Hill, 2007, p. 490). Models are run in JAGS through R using Krushke's implementation of the two-way ANOVA, which explicitly determines group-level interactions at the expense of computation time and complexity.[1] Final models presented include interaction effects using a 25 percent random sample of occupation-industry cells for the detailed aggregations.

Multilevel modeling allows for the analysis of residual variance at different levels of model hierarchy. Variances are calculated and reported at the individual- (unexplained variance, or the variance that is left at the lowest level of the model), and group-level variances. The change in variance components across different specifications of models, informs inferences regarding the role and importance of group-level variations to the model variables. Comparing large differences in variance due to occupation groups versus industry groups provides specific evidence of whether industry mixes or occupation mixes differ significantly enough to be of interest.[2]

4.2 Applying Hypothesis Testing to Bayesian ANOVA

For cross-time comparison, group variances and their credible intervals are recalculated across proportions of total variance per each time period tested (Variance Proportion Component [VPC], also known as Inter-Correlation Coefficient in mixed modelling uses).[3] Variances are presented visually in

[1]The empirical model can be coded to lump occupation-industry group interaction effects and model error together, to allow for faster modeling in the exploration stage of modeling. Results match faster exploratory models using full samples and the authors own code implemented in WINBUGS.

[2]Bayesian data analysis and inference yields a computed posterior distribution over parameter space, indicating "relative credibility of every possible combination of parameter values" (Kruschke, 2010, p. 295). The posterior distribution provides "credible intervals for parameter estimates" and, in this case, group-level estimates of variance errors with means and credible intervals for the effects of industry and occupation groupsour primary factors of interest (Kruschke, 2011, p. 6). Two-way ANOVA models are programmed in WINBUGS and again in JAGS, and posterior estimates of group variances are sampled for comparison inferences. Estimates take into account shrinkage, or averaging of group level effects.

[3]Intra-class correlations (ICC) or variance proportion components (VPC) are one method of variance assessments or VPCs and have two separate definitions. The first, is the "degree of resemblance between micro-units belonging to the same macro unit" (Snijders & Boskers, 1999, p. 16), or restated, "the correlation between values of two

industry-based changes, occupation-based changes, error-terms, and occupation by industry interactions. This helps in making direct comparisons across different models, but it may blur comparisons within time periods, especially if the error variance changes.

In comparing model results, Kruschke proposes a Bayesian hypothesis testing procedure as follows: the analyst establishes a *region of practical equivalence* (ROPE) around a null value which is deemed reasonable with respect to the analyst's priors. Posterior distributions are used to make decisions based on credibility of values aided with a 95% *highest density interval* (HDI, or "credible interval")—the Bayesian analog to the confidence interval. The HDI is the interval for which all values have higher credibility than values outside the interval, and the interval contains 95% of the distribution (Kruschke, 2011, p. 4). Bayesian approaches also allows for acceptance of the null value and not just failure to reject.

Given previous work presented, I use the hypothesis that occupations are more important than industries in explaining employment change, and thus the bulk of credible values for the occupation HDI should fall outside of the industry HDI.

4.3 Bayesian Two-Way ANOVA Model and Variables

Again, models were tested using "total employment change" and "percentage changes" in employment—change in employment relative to the starting period employment of the occupation-industry cell.

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randomly drawn micro-units in the same randomly drawn macro-unit" (Ibid, p. 17, and Hox, p. 15).

The second definition defines the ICC as "total variation in the data that is accounted for by between-group variation" (Gelman & Hill, 2007, p. 258), where the ICC of each level of the model explains the "population estimate of the variance explained by the grouping structure" (Hox, 1995), where the ICC "ranges from 0 if the grouping conveys no information to 1 if all members of a group are identical" (Gelman & Hill, 2007, ibid). The ICC is formally defined as

$$ICC = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_y^2}$$

where the denominator is the total variance in the data, and the numerator is the variance of a specific level of the model.

Variance components and ICCs are examined across models where group level variations change in parallel occupation and industry based model-building. Systematically assessing components of error variance is often used in fields with heavy uses of multilevel modeling (neuroimaging, educational research, organization management) as variance component analysis (P.D. Bliese, 2000; P. D. Bliese, Chan, & Ployhart, 2007; P. D. Bliese & Ployhart, 2002; Brown et al., 2011)

The effects of industries and occupations for each model are graphed and compared over time and across classification groupings to inform inferences about the underlying facets of employment and interactions of industry and occupation within cities over time.[4] A priori, the first two model types capture two different facets of change in city employment: total change and percentage change. Total change in a growth sector will be related to the starting employment levels of the place. The larger the starting employment, the larger the possible change, and, without a large shock, the smaller the chance of a large change. Percentage change may capture faster growth in industries or occupation groups and/or growth across groups of small or medium cities. Percentage-change factor effects may also be useful as leading indicators for future shifts in total employment change.

4.4 Results Summary

Results in Table 4.1 are presented from different aggregations of employment change, summarizing the results from Figures 4.1 and 4.2 for SIC broad aggregations and detailed aggregations respectively. Inferences can be made regarding changes to industry and occupation effects on total and percentage employment absolutely and relatively between effect types and across time. Inferences can also be made regarding changes over all time periods (see indicated arrows in Figures 4.2, 6.1 and 6.2)

	Aggregated Groups (SIC)		*Detailed Groups*	
Time Period	*Total Change*	*Pct. Change*	*Total Change*	*Pct. Change*
1990-2000	Ind = Occ	Ind = Occ	I > O	O > O
2000-2007	Ind = Occ	Ind = Occ	O > I	I = O
2007-2011	Ind = Occ	Ind = Occ	O = I	I > O

Table 4.1: SUMMARY OF VARIANCE EFFECTS COMPARISONS (SUMMARIZED FROM FIGURES 4.1, 4.2, 6.1 and 6.2)

Industry effects represented through HDIs for broad aggregations were

[4]This method of modeling effects can help develop understanding of more complicated models and inferences: the "ANOVA plot represents a default model and is a tool for data exploration - for learning about which factors are important in predicting the variation in the data" (Gelman &Hill 2006, p. 493). Also see Hector et al. (2011) and Yip, Ferro, Stephenson, & Hawkins (2011) for an application of Bayesian ANOVA to ecological site modeling and climate prediction uncertainty, respectively.

not large enough to meet our decision criteria for hypothesis testing. SIC based aggregations do not show distinguishable differences between industry and occupations in any time-period as 95% HDIs overlap across all models. Again, industries were not shown to be more important than occupations in broad models.Relative differences increased in the final time period but not enough to meet chosen requirments.

Detailed aggregation models present stronger HDI differences when comparing total and percentage change, and in comparison to broad aggregations. These differences are large enough to allow inferences about relative effects of industries and occupation, across time periods.

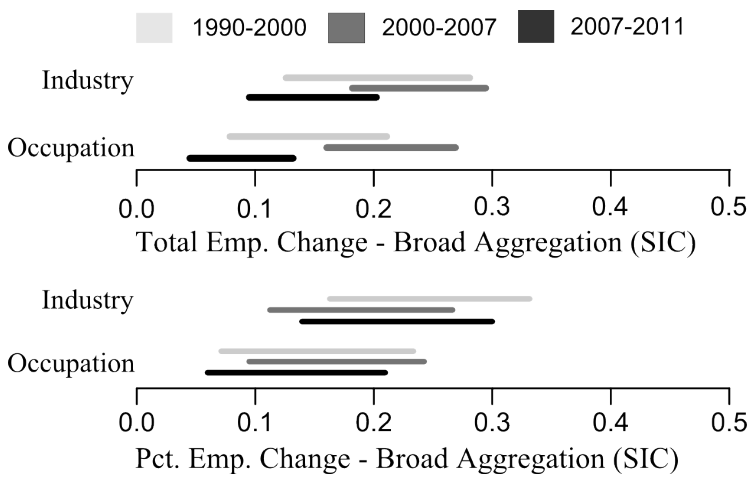


Figure 4.1: OCCUPATION AND INDUSTRY GROUP EFFECT RESULTS – BROAD EMPLOYMENT AGGREGATION

After controlling for all specific industry-occupation designations and interactions, industries explain significantly more of total employment change than occupations between 1990 to 2000. This result weakens as industries become both relatively and absolutely weaker than occupations over the subsequent periods (Figure 4.2, top graph).

In percentage change detailed models, occupations begin the study period more important and become absolutely and relatively less important over time, while industries gain strength. Industries end the study period more important than occupations. The effect of industry groups on employment change strengthens from 2000 to 2007 through 2007 to 2011 until industry effects become absolutely and relatively more important.

Industry factor HDIs were marginally (and not significantly) larger in comparison to occupation factors (Figure 4.1) in total and percentage change

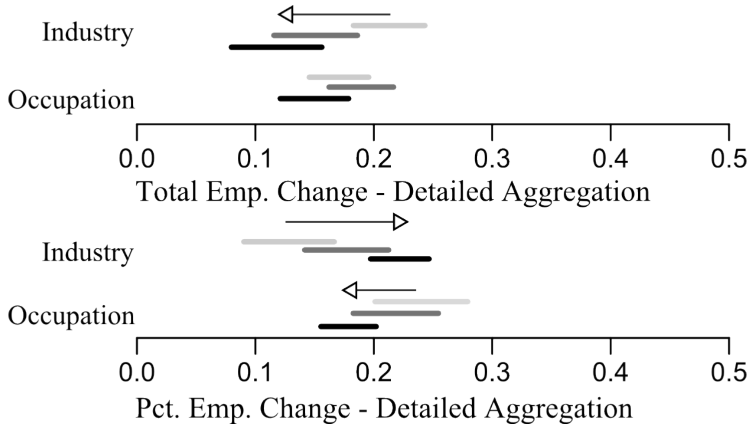


Figure 4.2: OCCUPATION AND INDUSTRY GROUP EFFECT RESULTS – DETAILED EMPLOYMENT AGGREGATION

broad aggregation models from 1990 to 2000. While there was movement in factor effects, they failed to satisfy our decision criteria for making comparisons. From 2000 to 2007, in detailed percentage employment change, occupations failed to be more important than industries in explaining percentage change variance, an effect that flipped back from 2007 to 2011 (Figure 4.2, top graph; Table 4.1 second column).

Percent occupation employment changes were most important in detailed models between 1990 and 2000, and have lessened in importance since. These findings echo results from routinization employment models from this paper and further echo evidence in the labor economics literature. Beaudry et al. found that occupation changes due to technological innovations, like computerization, reached a peak in 2000 and have lessened in importance since then (Beaudry, Green, & Sand, 2013).

Interaction and Model Changes

Until now, models have compared absolute and relative secular changes to city employment due to occupation and industries, once interaction effects have been controlled. Interactions effects are pairings of specific occupation-industry types that frequently move together: for example, management occupations in construction industries, or medical occupations (doctors, nurses) in medical industries.

In this way, occupation-industry interactions and contain information about the city employment mix and relate information about the types of employment changes within and across cities. Are changes in employment com-

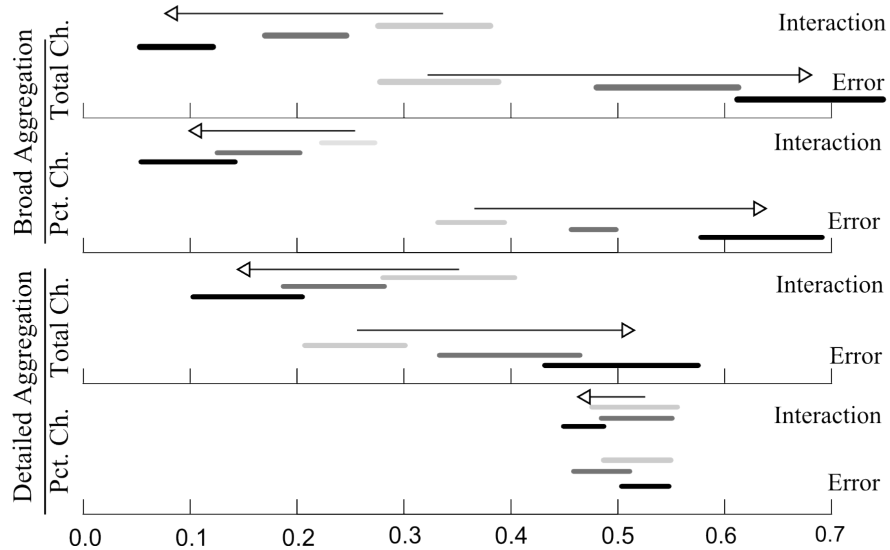


Figure 4.3: INTERACTION AND MODEL ERROR GROUP EFFECT RESULTS BROAD AND DETAILED EMPLOYMENT AGGREGATIONS

mensurate or similar to the previous period's employment mix? Are changes occurring in similar occupation-industry pairings over time?

Interaction effects begin the study period as the largest drivers of employment change, an unsurprising result given the path dependent nature of employment in regions. Over time interaction effects are a large decreasing portion of total variance in all models and time periods, with the exception of detailed aggregation percentage change models.

At the same time, model error increased across total and relative change models. Occupation and industry groups and their interactions account for less of total employment changes in cities over time; interaction effects decrease from 37 percent of total variance to 12 percent in total change models (similar to percentage change). Total model error increases from 32 percent to 65 percent (25 to 50 percent for percentage change) from 1990 to 2011. Broad industry and occupation groupings no longer account for a majority of changes in the employment structure of cities.

Several inferences can be drawn from city industry-occupation mix effect on employment change. The occupation-industry matrix of employment is for each city a large part of the heterogeneity and path dependence of its industries, firms and human capital. This employment mix has over time become weaker and weaker, confirms that major changes within the employment structures of cities were experienced in the past decades. The increase in unexplained variation of employment change in cities points to city employment bases as less dependent on larger secular changes (within occupation and occupation groups) and less dependent on the general employment mix structures of their economies.

4.4.1 Remarks about Employment Data and Results

The largest concrete result is the huge change in the direction and magnitude of industry-by-occupation interaction effects over all models and time periods. This has credible consequences for understanding the use of employment groups in economic. Occupation-industry pairings have become decoupled—new work needs to be conducted on understanding the patterns of employment change within particular industry groups that were previously clustered.

The variance component model results presented through ICCs show that occupation and industry groups capture large amounts of employment variance.in social science contexts the levels of the ICCs are quite large and indicate positively towards the use of grouped modeling methods. Local employment changes are reliably determined through their broad and detailed grouping levels, a non-controversial claim. Table 4.1 shows that changes over time in broad industry and occupation effects are non-existent in aggregate models, and small, if significant in detailed models. Even if routinization were a major driver of employment changes, a modeling framework that even controls for group level changes may still not capture broad drivers of employment change.

The limitations of this employment data for making inferences on economic change is clear: the static nature of employment data may not help deliniate the changing nature of employment itself. Over short periods, specific employment types can be born and die along with their abetting technologies; yet throughout employment categories themselves remain fixed. Task changes would tellus little. Indeed, data harmonization itself reduces the ability to see intensive changes in employment: the routinization measure used in this paper RTI was formulated using 1980 tasks–from the Dictionary of Occupations and itself locks analysts into using dated and replaced employment categories. In the next section I explore the theories of occupation change and its relation to tasks.

Again, many routinization changes are likely occurring within very particular fast moving industries. Some occupations are spread across industries, yet many are specialized and clustered in particular types of industries. The most routinizable occupations are highly visible, employing many individuals across a range of industries (Figure 6.3). In contrast, the least routinizable occupations employ fewer aggregate individuals but in larger clumps and only in specific industries (Figure 6.4). Future work in the skill-biased technical change literature should explore this avenue: low-routinization may be linked to job protection in clusters of high skill industries, while high-routinizability is linked to employment losses in broad ranges of industries.

Industry and Occupation Changes in Detailed Models

As noted by differences between detailed and broad employment results secular effects differ for industries and occupations employment change over time. I propose that this discrepancy provides empirical evidence that detailed occupation groupings are a more suitable proxy for job tasks and routinization changes, and that researchers should avoid using broad groupings for similar purposes. The following section explores the relationship between occupation definitions and task-change, and argues that detailed occupations make sense as a proxy for task-changes. [5]

4.5 Evidence for Tasks in Explaining Employment Change

ANOVA model results describe a partially conflicting story on employment change. Broad models present no difference between occupations effects and industry effects on employment change, while detailed models show a strong difference. This divergence can be explained through routinization theory, and is warranted through external evidence as well as routinization models. The argument proceeds thus: a) routinization, as shown through empirical results above, is strongly associated with local level employment changes, and b) occupations (and specifically detailed occupations) are a better proxy

[5] The differences between detailed and broad aggregations are generally not explored in the SBTC literature. Broad occupations are often used to describe or proxy for the types of individuals in a place, the types of human capital, or the aggregate distributions across separate employment sectors. They can indicate non-substitutability of jobs in general (legal occupations cannot be used or substituted in medical occupations or vice-versa, whereas other types of occupations may have overlaps across certain skillsets).

for task changes that broad aggregations fail to capture. [6]

Occupation definition changes (from the older SIC definition scheme to the post 2000 SOC scheme) also corroborate this story: the occupation update was partially driven to divorce occupations from industry roots and to make sure that occupations matched worker tasks as opposed to industry production ends (Markusen, Wassall, DeNatale, & Cohen, 2008). If differences in measurements of task requirements across occupation and industry groups were less distinct, then effects of task changes would be hidden (as compared to SOC aggregations).

Detailed aggregations are a better map of job and production tasks; occupations stand in for tasks within firms, whereas broad occupations (what people do within firms) describes more of the employment structure and employment change for a good part of the past two decades.

I explored and applied a mix of theories within and to regional development in order to help understand employment patterns of local urban areas as defined within a large national system. This work connects the higher-level national picture of employment change trends with an understanding of local processes that are captured in city-level employment data. Part of the novelty of this paper is its grounding of the theoretical task model for employment change in empirical work in employment change settings. By introducing the role of industries and occupations as comparable factors which can be measured and compared at local levels, inferences can be made that are useful both in answering older questions in regional science and in illuminating how larger shifts in the structure of the economy via employment patterns have changed and shifted.

Theories and work in regional science on employment and place have centered on the constructed compositional mix regime of the day to theorize success. Separate theories of industry mix and occupation mix have filtered into popular accounts of regional success and were operationalized into vague

[6] Autor (2013) provides a strong introduction to the task model for researchers, including a discussion of merits and problems with the use of occupations as a proxy for tasks. Census researchers testing the suitability of occupation measures to specific firm-task requirements found that detailed occupations are a close proxy to tasks within firms, a rough proxy to tasks across firms and are much better than broad occupation categories (Gibbs, Levenson, & Zoghi, 2010; Gibbs, 2009). An example: data is transformed from thousands of specific job tasks into some 800 detailed occupations, which are further reduced to 220 harmonized occupations that can be compared across time. D. H. Autor & Handel (2009) also provide a discussion of the difficulties of matching tasks to occupations.

policies for local area. To a certain extent, a task-based understanding of employment change shows that the varying emphases on mixes (industry employment versus occupational employment) in regional science can be thought of as a misunderstanding of the role that employment within firms plays at broad aggregated employment categories. Re-grounding local employment measurement to firm and regional success within the task-approach model shows that occupations and industry effects can be reasonably compared at both individual sectoral levels and industry-occupation comparisons.

The task approach to understanding employment change assumes that occupation analyses contain distinct information about economic production (Autor, 2013). Less clear is what information is transmitted about regional areas through broad and detailed occupation aggregations, and how employment counts effectively capture the explicit task-skill model (where skills are assigned to tasks via occupation employment numbers), and what measurement factors could affect understanding of the economy using this method.[7]

Occupations are, at a theoretical level, under constant flux, coming into being and being made obsolete by other occupations through new technology or industry changes. Over time, detailed occupations as measures of tasks may be unreliable through the heterogeneous mixing of tasks, technology, skills, and occupations. (Spenner, 1990; National Research Council, 1999). Broad aggregation measures can thus further under-represent economic changes if detailed occupation levels undervalue task change, creating problems in comparability of broad and detailed occupation sectors. (National Research Council, 1999, p. 86). Methodologically, incorporating the "task framework" of labor economics into micro-economic production function of firms depends that the relationships between occupations and their assigned tasks (the base unit of this micro-economic analysis) remain static: changes to tasks assigned to occupations would undercut true comparisons.

[7]Large differences in the basic measurement of economic changes in detailed and broad occupations are illustrated by the difficulty found in comparing the true job of occupations within industries in driving employment change over large periods of time. The measurement of changes to employment through occupations as driven by changes in tasks may or may not be reflected in aggregate employment data : "the reasonable assumption [is] that task changes within occupations (the intensive margin) tend to move in the same direction as task changes made visible by changes in the relative sizes of occupations (the extensive margin) then measuring job tasks using static measures of occupational content will systematically understate the extent of the task reallocations taking place" (Autor, 2013).

Still, results are in line with expectations of the task model, and show that detailed occupations are absolutely more important than detailed industries in explaining absolute total employment change, as well as in models that control for previous period employment in all time-periods. Models using broad aggregations of occupations do not accord with expectations of the tasks model; industries are more important than occupations.

The broad categories defined by services provided, used in SOC occupations systems (and the predecessor the SIC[8]), are mono-hierarchical systems in which each detailed occupation is located in one broad sector that are "exclusive, exhaustive, and the higher levels are completely described by the lower levels in the aggregation" (Emmel & Cosca, 2010, p. 2). It is expected that detailed occupations are a better, or more proper, proxy for job tasks; less expected is the finding that the broad occupation sectors commonly used are an improper substitute, given aggregations common use by researchers.[9]

The discrete groups upon which millions of individual jobs are aggregated into based on classification similarities and principles may not correctly capture the importance of the occupation to employers. Individual workers in an establishment perform a specific set of tasks that are largely dependent on factors such as the employment size and industry classification of that establishment, and the tasks performed by other workers in that same establishment.[10]

[8]The SOC classification system improved the previous SIC system by introducing professional, technical, and service occupations while removing production and administrative support occupations. "Although the designation professional does not exist in the 1998 SOC, the new classification system reflects expanded coverage of occupations classified as professional and technical in earlier classification systems" although they are dispersed across major occupational groups (Levine, Salmon, & Weinberg, 1998, p. 40). SOC changes "incorporate[d] structural features that free occupational classification from its previously industry-rooted structure (Hecker et al., 2001), although BLS statisticians acknowledge that the results were a compromise" (Markusen, Wassall, DeNatale, & Cohen, 2008). Researchers like Autor and Hurst use their own classifications of white-collar workers and professional workers for research.

[9]Mono-hierarchical systems, rather skill-based classification systems, are used in the OECD in which workers are grouped by skill and specialization systems "duration of training and/or work experience recognized" (Office for National Statistics, 2000). This is not true in the United States, where tasks take primacy and employees of different skill levels, education, experience, and credentials are classified together as long as they are performing the same tasks for that SOC level (Emmel & Cosca, 2010b).

[10]Additional considerations are raised about whether occupation data can actually track individual job tasks at the detailed occupation level (Levenson & Zoghi, 2010). Research shows that "characteristics of firms and industries ... can explain observed patterns and trends in job design" (Gibbs et al., 2010, p. 2). Job designs are most "coherent" in descending order: the same job within specific firms; for similar jobs across firms in multi-

Detailed occupations are a better, or more proper, proxy for job tasks, and job change while broad occupation sectors may capture different specificities of economic or human activity. The process of aggregating and rolling detailed occupations based on hierarchical broad categories, defined by services provided, may "obscur[e] any similarities in task content that cross broad occupational boundaries" (Autor 2013) by pushing specific occupations with similar task content into separate broad categories. So while detailed occupations may be proper for applying the task model to the economy, broad aggregations may mask or provide entirely separate information. A mismatch in the theoretical formation of jobs and tasks, and how they are empirically used based on employment data available, can thus describe some results.

establishment firms; and then for the economy overall. Finally, within industries, products and processes are more similar than in the economy as a whole (Gibbs, Levenson, Zoghi, & Levenson, 2010).

CHAPTER 5

CONCLUSION

The task model of employment change is extended to test whether occupation effects are more important effects of industry, and occupation factors in employment change are modeled using a Bayesian hierarchical ANOVA, which measures and allows for a group-level comparison of industry and occupation factors on employment change. Using multilevel models, I also show that routinization is a major determinant of workforce patterns in cities. Together, these models show that task changes have played a large role in determining what types of employment and tasks occur in cities.

Results differ based on the level of detail in employment aggregations used. Using broad sectoral aggregations, industries are found to be robustly more important than occupations in determining effects on employment change. Contrary to the previous finding, at detailed three-digit level aggregations, the opposite result is found: occupations are more important than industries—an effect found to be strongest between 1990 and 2000, and one that has been decreasing over time. Despite the absolute divergence in these findings, relative changes across broad and detailed aggregations show a common trend: industries are more important over time in explaining employment change. This trend and general group differences between industries and occupations are found to have weakened or disappeared after the 2007-2008 recession, with relative effects between industries and occupations reaching parity. Finally, the general industry and occupation factors and their interactions—a proxy for city employment mixes—are significantly less important today than 20 years ago.

This divergent result can be explained through an emerging empirical and theoretical scholarship in labor economics on the task model of employment change. The task model proposes that tasks are assigned by firms to employee occupations of differing skill levels whose work forms an input for firm output when augmented with technology. The task model suggests that as tasks are the base unit of input for a firm's production function, detailed occupations may be the most important factor for employment demand and employment change.

This paper provides confirmation and empirical evidence for the task model by taking into account a potentially confounding factor: industries. Detailed models comprehensively show that occupations are more important than industries for employment change, while also indicating that broad aggregations may not be suitable for certain theoretically based explorations in the task model.

The most salient findings are as follows: 1) I empirically show that occupation change through routinization accords best with theoretical understanding of occupations and their role in firms; 2) in detailed aggregations, occupations have become slightly more important than industries in influencing total employment change; and yet 3) occupations, industries and occupation-industry interactions together no longer explain as much as they did regarding city-level employment changes. Regular increases in model error variance proportions over time signal that other factors like task-routinization are now more relevant for understanding city-level employment changes. Both empirical results in this paper and preexisting work on industries and occupations point to this change.

These findings are replicated robustly using a variety of model specifications that examine total employment change, percentage employment change, and are replicated using several modelling approaches.

CHAPTER 6

TABLES AND FIGURES

Employment Change	1990-2000	2000-2007	2007-2011
(Intercept)	-0.02	-0.03 *	-0.03 *
	[-0.07 ; 0.02]	[-0.06 ; -0.01]	[-0.05 ; 0.00]
RTI_Occ	-0.20 *	-0.15 *	-0.30 *
	[-0.39 ; 0.00]	[-0.22 ; -0.08]	[-0.37 ; -0.22]
RTI_City	-0.07 *	-0.05 *	-0.02 *
	[-0.08 ; -0.07]	[-0.05 ; -0.04]	[-0.03 ; -0.02]
Share Educated	-0.04	-0.03 *	-0.04 *
	[-0.08 ; 0.00]	[-0.04 ; -0.01]	[-0.05 ; -0.02]
Population	0.08*	0.09*	0.01*
	[0.07 ; 0.09]	[0.09 ; 0.09]	[0.01 ; 0.01]
Avg. Hourly wage	-0.07 *	-0.05 *	-0.04 *
	[-0.11 ; -0.03]	[-0.07 ; -0.04]	[-0.05 ; -0.03]
Variance: OCC in IND (Intercept)	0.60	0.06	0.04
Variance: OCC in IND - RTI_Occ	7.03	0.20	0.29
Variance: IND (Intercept)	0.00	0.00	0.00
Variance: IND RTI_Occ	0.00	0.01	0.01
Variance: Residual	0.92	0.25	0.15
AIC	386 376.3	205 138.8	135 004.6
BIC	386 504.1	205 266.6	135 132.4
Log Likelihood	$-193\,175.1$	$-102\,556.4$	$-67\,489.3$
Deviance	386 350.3	205 112.8	134 978.6
Num. obs.	137 233	137 233	137 233
Num. groups: OCC:IND	2611	2611	2611
Num. groups: IND	20	20	20

0 outside the confidence interval

Table 6.1: MULTILEVEL MODELS EMPLOYMENT CHANGE

Percentage Employment Change	1990-2000	2000-2007	2007-2011
(Intercept)	-1.64 *	-1.70 *	-1.16 *
	[-3.08 ; -0.19]	[-2.25 ; -1.16]	[-1.52 ; -0.80]
RTI_Occ	-6.82 *	-6.54 *	-3.22 *
	[-12.94 ; -0.70]	[-8.80 ; -4.29]	[-4.75 ; -1.69]
RTI_City	0.02*	0.01	-0.01
	[0.00 ; 0.04]	[-0.01 ; 0.02]	[-0.02 ; 0.01]
Share Educated	-0.15 *	-0.12 *	-0.18 *
	[-0.23 ; -0.07]	[-0.17 ; -0.07]	[-0.25 ; -0.12]
Population	-0.05	0.00	0.14*
	[-0.11 ; 0.01]	[-0.02 ; 0.01]	[0.10 ; 0.17]
Avg. Hourly wage	-0.14 *	-0.12 *	-0.13 *
	[-0.22 ; -0.06]	[-0.17 ; -0.07]	[-0.20 ; -0.06]
Variance: OCC in IND (Intercept)	192.85	48.00	0.40
Variance: OCC in IND - RTI_Occ	3570.82	830.57	2.60
Variance: OCC (Intercept)	103.63	0.38	9.03
Variance: OCC RTI_Occ	1869.59	4.87	173.91
Variance: METRO.(Intercept)	0.03	0.01	0.00
Variance: METRO. Population	0.09	0.00	0.02
Variance: IND (Intercept)	0.11	0.64	0.06
Variance: IND RTI_Occ	0.17	10.67	0.67
Variance: Residual	3.90	2.75	4.65
AIC	588 231.65	537 963.52	605 486.44
BIC	588 418.41	538 150.27	605 673.20
Log Likelihood	$-294\,096.83$	$-268\,962.76$	$-302\,724.22$
Deviance	588 193.65	537 925.52	605 448.44
Num. obs.	137 228	137 228	137 228
Num. groups: OCC:IND	2611	2611	2611
Num. groups: OCC	327	327	327
Num. groups: PWMETRO	242	242	242
Num. groups: IND	20	20	20

* 0 outside the confidence interval

Table 6.2: MULTILEVEL MODELS PERCENTAGE CHANGE

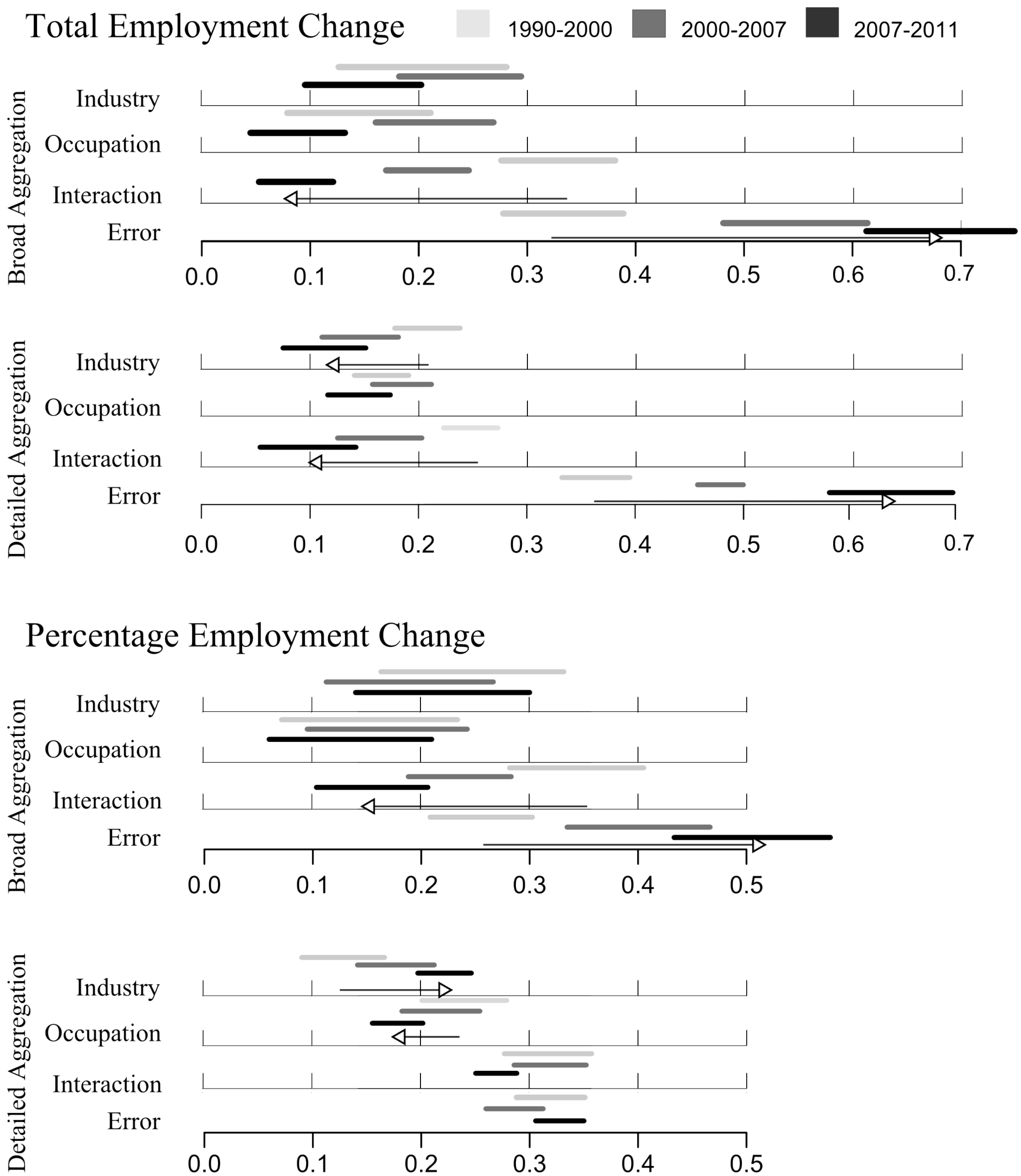


Figure 6.1: STACKED ICC/VPC. ESCALATING TIME PERIODS PRESENTED FOR SIC AND DETAILED EMPLOYMENT AGGREGATIONS (1990–2000, 2000–2007, 2007–2011)

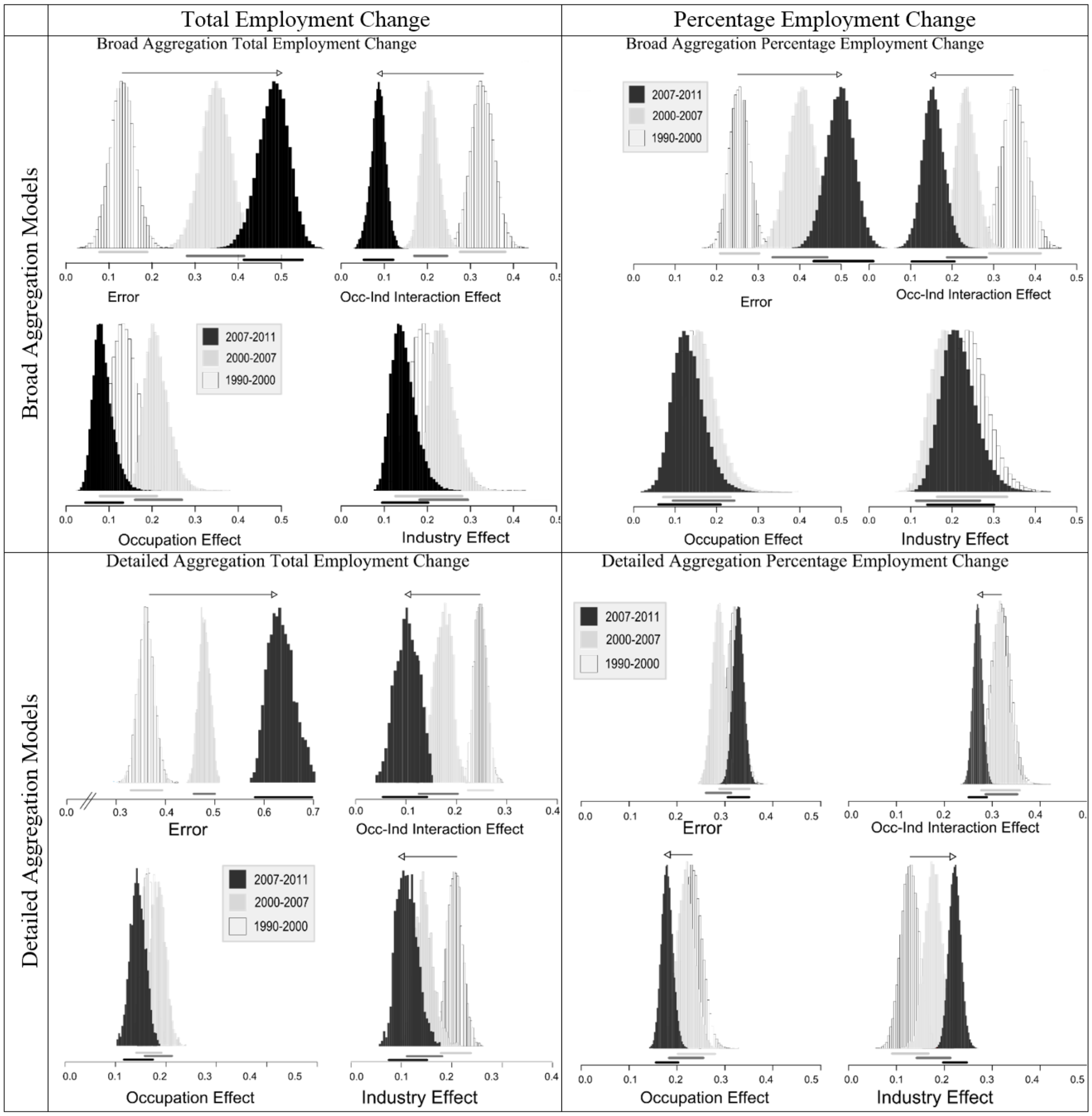
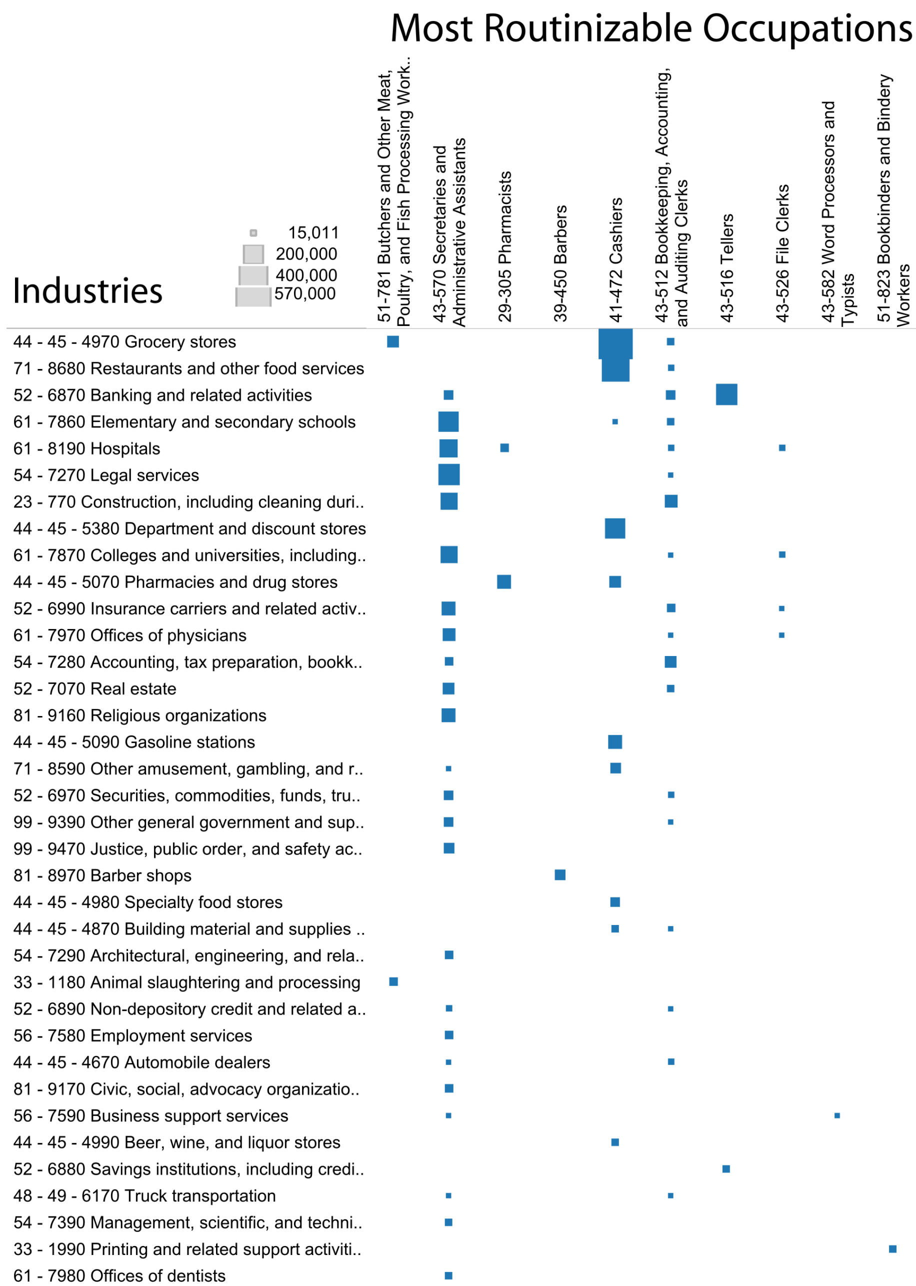


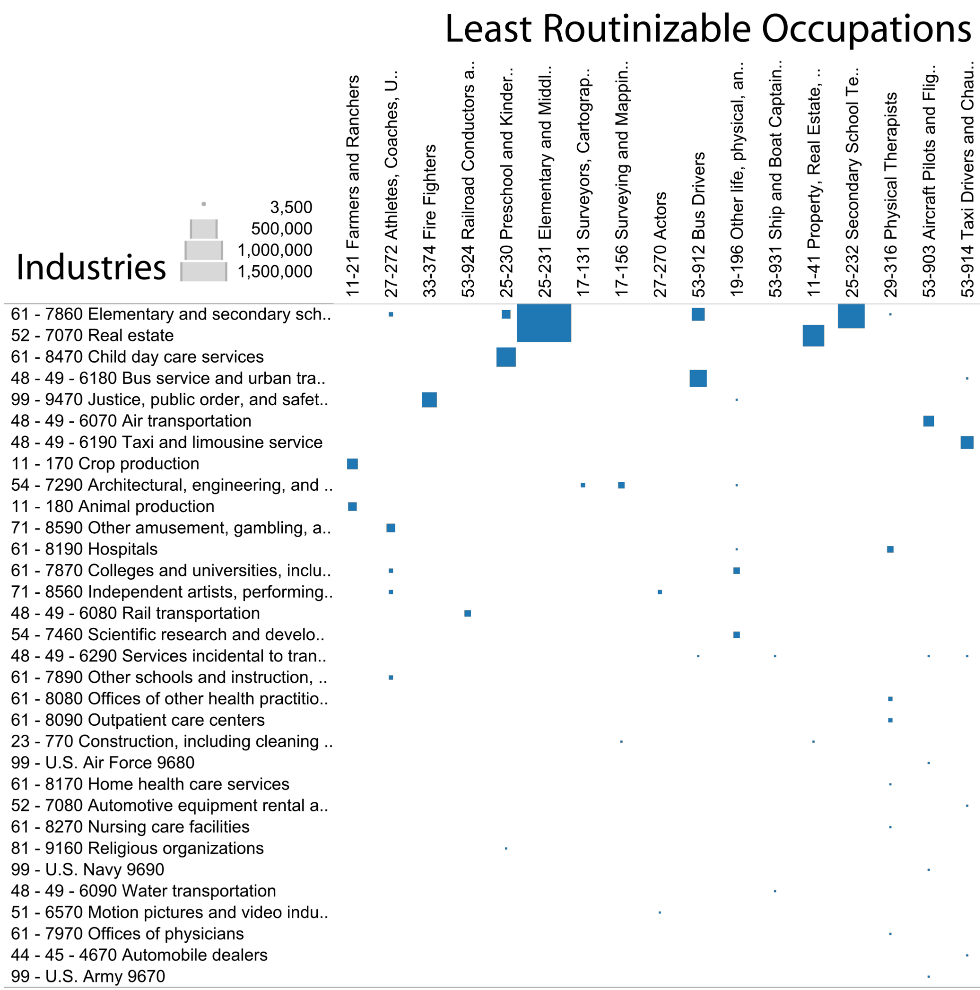
Figure 6.2: ICC/ VPC DENSITY HISTOGRAMS OF INTERACTION EFFECTS, MODEL ERRORS, OCC, IND 1990–2000, 2000–2007, 2007–2011 FOR SIC AND DETAILED EMPLOYMENT AGGREGATIONS



Most routinizable occupations (sorted descending by RTI, left to right) are presented against their largest constitutent industries (by employment size descending, top - down).
More routinizable occupations are present across more industry types, but employ fewer in each ind-occ cell than least routinizable occupations

PUMS Data from 2000.
Occupation - Industry cells with less than 15000* persons are filtered.

Figure 6.3: HEATMAP OF SELECTED MOST ROUTINIZABLE OCCUPATIONS AND CONSTITUTENT INDUSTRIES



Least routinizable occupations (sorted ascending by RTI, left to right) are presented against their largest constitutent industries (by employment size descending, top - down).
These occupations are more concentrated in fewer industries, and employ many more people than more routinizable occupations.

PUMS Data from 2000.
Occupation - Industry cells with less than 3500 persons are filtered.

Figure 6.4: HEATMAP OF SELECTED LEAST ROUTINIZABLE OCCUPATIONS AND CONSTITUTENT INDUSTRIES

CHAPTER 7

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