Job Polarization : Market Responses to Interindustry Wage Differentials *

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Abstract

In spite of the rapid growth in job polarization literature, different aspects of job polarization across industries have not yet been studied extensively. In this paper, we show that (1) the degree of job polarization is not the same across different industries and that (2) this observation is related to interindustry wage differentials. In particular, we find that job polarization is more pronounced in industries which paid relatively higher wages than other industries since the early 1980s. We argue that this phenomenon can be explained as the dynamic responses of firms to interindustry wage differentials as shown by Borjas and Ramey (2000) : firms in industries with relatively higher industry wage premia respond by replacing workers with other production factors such as capital. As it is easiest for firms to replace 'middle occupation jobs' with certain types (Information, Communication, and Technology) of capital, labor demand declines disproportionately for firms with higher relative wages, which results in different aspects of job polarization across industries.

*Preliminary and Incomplete. This version does not include model, which will be added later. We would like to thank Valerie Ramey for her insightful and helpful comments.

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1 Introduction

During the past thirty years, the U.S. economy has experienced the emergence of job polarization[1]. In order to be consistent with the literature regarding job polarization, we consider three occupational groups (we use jobs and groups interchangeably) : high occupation jobs which require cognitive skills, middle occupation jobs which require routine skills, and low occupation jobs which require manual skills. With this classification, Acemoglu and Autor (2011), Autor, Katz, and Kearney (2006), and Goos, Manning, and Salomons (2009) document that employment has become increasingly concentrated at the tails of the skill distribution since the 1980s and this hollowing out of the middle has been linked to the disappearance of jobs focused on "routine" tasks[2]. Figure 1.1a shows this phenomenon graphically. In order to draw the figure, we applied the 'conversion factor' method to the March Current Population Study (henceforth, CPS) data between 1971 and 2010 to obtain consistent aggregate employment series[3]. One can easily observe that while the growth rates of high and low occupation jobs have been stable overtime, that of middle occupation jobs has been decreased since the 1980s.

In order to explain the occurrence of job polarization, previous studies including Acemoglu and Autor (2011), Cortes (2011), Michaels, Natraj, and Reenen (2011), and Jaimovich and Siu (2012), have used the notion of 'Routine-Biased Technological Changes' (Henceforth, RBTC). Borrowing the language of Jaimovich and Siu (2012), RBTC refers to the situation where 'trend in the productivity of non-routine occupations relative to routine occupations increases overtime'. According to them, the 'exogenous' force that lowers the relative productivity of routine occupations decreases relative labor demand for middle occupation jobs, hence job polarization occurs. Notice that RBTC is not industry-specific. Thus, most literature has considered job polarization as an aggregate phenomenon (at least the differences across industries are considered to be negligible) while only a few literature has considered the possibility that job polarization may differ across industries. However, as we document below, our analysis is more extensive and fruitful in the sense that we unveil the factor that has contributed to the heterogeneous aspects of job polarization across industries, which have not yet been studied.

In this paper, we analyze to what extent the aspects of job polarization differ across industries and empirically identify which factor can be attributed to heterogenous job polarization across industries. In order to see how the aspects of job polarization are different across industries, we plot Figure A.1, which shows changes in employment share between 1980 and 2009. The decennial Census data is used for drawing the figure. The horizontal axis denotes three occupation groups (each occupation group includes 16 industries and 1 aggregate variable) and the vertical axis denotes the change in employment share of a specific occupation - industry group between 1980 and 2009. If the bar shows positive value for group A, it means that employment share has increased

[1] As emphasized by Autor (2010) and Michaels, Natraj, and Reenen (2011), job polarization is not restricted to the U.S; Several European countries experience job polarization as well.

[2] In 1981, middle occupation jobs accounted for around 60% of total employment. However in 2010, this share has fallen to 44% in the U.S. Numbers are calculated from the March CPS.

[3] See Shim and Yang (2012a) for the detailed discussion on conversion factor method and the relevant consistency issues in aggregate occupation data.

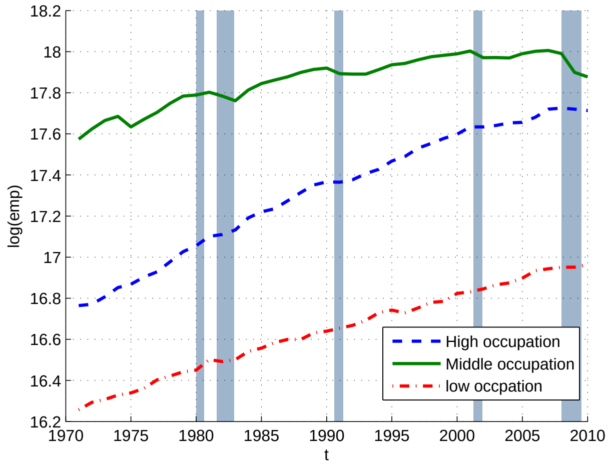

Figure 1.1a : Job Polarization - Occupation

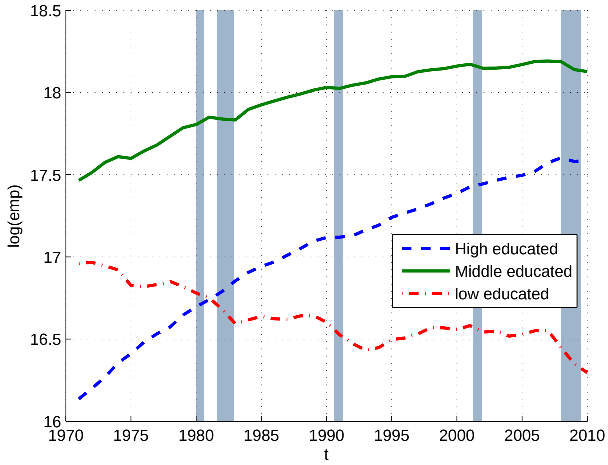

Figure 1.1b : Job Polarization - Education

Figure 1.1: Job Polarization

overtime for group A. Recall that job polarization is the reallocation of middle occupation jobs to high and low occupation jobs. In this sense, Figure A.1 shows that job polarization is more severe in some industries than other industries, which implies that the degree of job polarization is heterogenous across industries. For instance, the decrease in the employment share of middle occupation jobs is large in manufacturing, transportation, and business related services, while it is very small or even positive in wholesale trade and personal services industries. In particular, entertainment and recreation service industries exhibits very different pattern from other industries : high occupation jobs experience big losses in employment while low occupation jobs experience large increases. Notice further that the number of industries whose decline in employment share of middle occupation jobs exceeds or is similar to that of aggregate economy is only 6 among 16 industries[4]. This fact implies that relatively small numbers of industries determine the extent of job polarization at the aggregate level and this feature is one of the new findings we present in this paper that previous studies have ignored.

Then the question is why do we observe this asymmetric job polarization across industries. We argue that interindustry wage differentials is the source of heterogenous job polarization across industries : job polarization is more evident in industries which paid higher wages than others. In particular, OLS estimate of annualized employment growth rate between 1980 and 2009 on the initial wage premium in 1980 is $-.0412$ for middle occupation jobs, $-.0250$ for high occupation jobs, and .0120 for low occupation jobs where the last estimate is not significantly different from zero while the first two are economically (and statistically) significant. Note that interindustry wage differentials, which we discuss in more detail in Section 3, mean that a worker with the same socioeconomic characteristics earns differently if employed in different industries. Since there is a 'rigidity' in the relative wage structure across industries as Borjas and Ramey (2000) have shown, firms which pay

[4]'Manufacturing nondurable goods', 'Manufacturing durable goods', 'Communication', 'Finance, Insurance, and Real Estate', 'Business and Repair Services', and 'Public Administration' industries.

relatively higher wages to workers of the same characteristics will not respond to interindustry wage differentials by changing wages : rather, they replace labor with other production factors such as capital. Borjas and Ramey (2000) demonstrate that industries which paid higher than average wages in 1959 experienced significantly lower subsequent employment growth in the following 30 years, while simultaneously experienced higher than average growth in the capital-labor ratio and in labor productivity. The link between job polarization and interindustry wage differentials takes place at this point. When a firm decreases its labor demand, its effect is not even across different occupations : occupations that require routine tasks are more easily codifiable, hence they are more affected by a firm's dynamic decision to replace labor demand with capital[5]. As a result, subsequent employment growth of middle occupation jobs is lower than that of high (or low) occupation jobs for high wage industries, which results in different speeds of job polarization across industries. Our findings on the heterogenous effects of firms' dynamic responses to interindustry wage differentials makes our paper distinct from Borjas and Ramey (2000). While they focus on the 'aggregate' effect of interindustry wage differentials, our findings emphasize the importance of considering heterogenity across different workers (jobs) in studies of the labor market.

As mentioned above, only a few papers have studied the possibility of heterogenous job polarization across industries. For instance, Acemoglu and Autor (2011) argue that changes in industrial composition does not play an important role in job polarization. Jaimovich and Siu (2012) and Foote and Ryan (2012) note that job polarization may be more pronounced in construction and manufacturing industries which means that they implicitly consider other industries to share similar characteristics in terms of job polarization. One paper, Michaels, Natraj, and Reenen (2011), is closer to our study since it shows that different industries have different degrees of job polarization : they show that industries with high Information, Communication, and Technology (henceforth ICT) capital growth exhibit much faster job polarization in terms of shifting wage bills from middle educated workers to high educated workers. Our paper is different from theirs in two ways. First, they consider different education groups while we instead consider occupation groups. This makes a difference in the subsequent analysis since we are more interested in 'employment'. In Figure 1.1b, we plot the employment series by each education group following Michaels, Natraj, and Reenen (2011)[6] [7]. One can easily observe that contrary to Figure 1.1a, there is no job polarization in terms of employment when education is used to classify workers. Instead, as is well-known, there is a decreasing trend in employment for low educated workers while the opposite trend is observed for middle and high educated workers. Thus, in the studies of job polarization in terms of employment, we think classification of workers by occupation may be more appropriate. Second, as will be discussed in Section 4, the source of job polarization is different. While Michaels, Natraj, and Reenen (2011) consider an exogenous RBTC as a source of heterogenous job polarization across industries, we show that the heterogenous growth of ICT capital across industries is actually the optimal response of the firms. In this sense, we provide an answer to

[5]Offshoring is another possibility as Goos, Manning, and Salomons (2012) and Oldenski (2012) have shown.

[6]We use the March CPS between 1971-2010.

[7]Low educated workers are high school dropouts, middle educated workers are ones with high school diploma or with some colleges and high educated workers possess at least college degree.

the question on why the growth of ICT capital is different across industries, which Michaels, Natraj, and Reenen (2011) treat as exogenous changes.

The paper is organized as follows. Section 2 introduces data we use in the analysis and Section 3 explains the link between job polarization and interindustry wage differentials. We then present our empirical findings in Section 4. Then we conclude.

2 Data

There are two main sources of data for this paper : (1) decennial Census data (and 2009 American Community Survey (henceforth, ACS)) and (2) EUKLEMS data. The Census data is drawn from Integrated Public Use Microdata Series (henceforth, IPUMS). Following Borjas and Ramey (2000) and Acemoglu and Autor (2011), we exploit the 1960, 1970, 1980, 1990 and 2000 Census of Populations and the 2009 ACS. As Acemoglu and Autor (2011) have noted, relatively large samples of Census data makes fine-grained analysis within detailed demographic groups possible[8]. We drop farmers (and related industries) and armed forces. Age is restricted to 16 - 64 and we consider persons employed in wage-and-salary sector. Table A.2 in Appendix A describes the industry classification used in the analysis.

The second data set, EUKLEMS includes data on value added, labor, and capital for various industries in many developed countries. EUKLEMS is useful since it provides detailed information on capital : capital is divided into two parts of ICT capital and Non-ICT capital, hence we can analyze the different role of different types of capital in firm's behavior. In particular, we use U.S. data between 1977 and 2007 where industries are defined according to the North American Industry Classification System of the United States (Henceforth, NAICS). Since the industry classification is different from the Census data, we reclassify the industries to be consistent with EUKLEMS and Table A.3 in Appendix A describes the industry classification for EUKLEMS data used in the analysis.

In order to overcome the inconsistency problem of occupation codes due to the frequent changes in occupation codes in the CPS[9], we use 'occ1990dd' method to construct consistent occupation code following Dorn (2009).

3 Link between Job Polarization and Interindustry Wage Differentials

In this section, we explain interindustry wage differentials in detail and their link to job polarization. The empirical evidence to support our theory is reported in the next section.

[8] In determining the size of the sample, we follow Acemoglu and Autor (2011) : 1 percent of the U.S. population in 1960 and 1970 and 5 percent of the population in 1980, 1990, and 2000.

[9] For detailed discussion on the inconsistency issue, see Dorn (2009) and Shim and Yang (2012a).

As Borjas and Ramey (2000) have noted, persistent dispersion in wages across industries which is referred to as 'interindustry wage differentials' or 'industry wage premia' interchangeably, has been one of the most challenging subjects in (competitive) labor economics. In order to understand why it is puzzling from the perspective of competitive equilibrium theory, consider two workers with the exactly same socioeconomic characteristics including education, age, race, occupation, and sex, but who work in different industries. Then wage should be (at least in the long run) the same between the two in equilibrium since the workers are identical. If not, a worker in a low wage industry will try to find a job in a high wage industry; in equilibrium, this increases (resp. decreases) labor supply to high (resp. low) wage industries, hence wages will be equalized if the competitive theory works. Unfortunately, this competitive equilibrium is not supported by data; for instance, a worker employed in petroleum refining industry earned about 40% more than a worker employed in leather tanning and finishing industry in 1984 (Krueger and Summers (1988)). On top of that, it is not a transitory perturbation from the competitive equilibrium : Borjas and Ramey (2000) find that the rate of convergence in wages is estimated to be about .5% between 1959 and 1989, which implies that the adjustment process of wages is extremely sluggish.

Since we focus more on the 'consequences' of interindustry wage differentials in this paper, we briefly review literature that suggests possible theories to explain 'causes' of it. One theory that justifies the existence of interindustry wage differentials is 'unobserved ability of workers' (Murphy and Topel (1987)). This theory is consistent with competitive equilibrium theory; estimated persistent interindustry wage differentials is the reflection of the unobservable variables hence the phenomenon is not surprising. However, Krueger and Summers (1988), Borjas and Ramey (2000), and Blackburn and Neumark (1992) find evidence against this theory; for instance, Blackburn and Neumark (1992) show that their measure of unobserved ability (test scores) can account for only about one tenth of the variation in interindustry wage differentials. Given that the competitive model cannot explain the industry wage premia well, remaining theories should be non-competitive ones. The rent-sharing model, discussed by Nickell and Wadhwani (1990), Borjas and Ramey (2000) and Montgomery (1991)[10], is one possible non-competitive model : if a firm can share its profit with a worker (insider) by negotiation and if it can sustain a worker's productivity level with the wage level relatively higher than the competitive one, firms are willing to pay higher wages than competitive ones. Another possibility is to use efficiency wage model (Walsh (1999) and Alexopoulos (2006)). Suppose that workers can choose either work or shirk and firms in different industries have different detection rates of shirking workers. Then wage compensations for not shirking are different across industries, which generates wage dispersions across industries.

Notice that predictions of the theories and other empirical researches such as Murphy and Topel (1987), Alexopoulos (2006), and Krueger and Summers (1988) are basically static in the sense that their model cannot predict the dynamic behaviors of firms facing interindustry wage differentials. Suppose that the dispersion in

[10] Montgomery (1991) uses a version of search and matching model, but we include it in the rent-sharing model since it also incorporates the rent-sharing feature.

wage across industries exists for any reason. While previous studies could explain the occurrence of interindustry wage differentials and the associated 'static' equilibrium properties, these studies do not explain how firms react to this phenomenon. For instance, if one believes the unobserved ability hypothesis following Murphy and Topel (1987), there should be no changes in equilibrium unless any structural transformation occurs since it is already in a competitive equilibrium where workers are sorted by their abilities. In contrast, Borjas and Ramey (2000) find that there are 'dynamic' responses of firms to the persistent interindustry wage differentials. To get an idea, consider a firm in an industry which pays relatively higher wages to a worker than firms in other industries at year t_0, the initial period (of data we have). Notice that labor cost is the product of wage and employment and it is hard for firms to adjust wages (relative to that of other industries) as supported by data (see Borjas and Ramey (2000)). Then the only way to respond to the high labor cost is to adjust employment overtime. i.e. subsequent employment growth of the industries with high initial industry wage premia will be lower than those of the industries with low initial wage premia. And this prediction is a sharp contradiction to the competitive equilibrium theory; employment of an industry with high (resp. low) initial wage premium should increase (resp. decrease) overtime since t_0 in a competitive equilibrium environment in which labor mobility is not restricted as workers will migrate from the low wage industries to the high wage industries.

In order for testing the validity of competitive equilibrium theory in explaining interindustry wage differentials, Borjas and Ramey (2000) first estimate industry wage premia from the usual wage regression at the initial period (1959) and then regress the subsequent employment growth (between 1959 and 1989) of the industries on the estimated initial industry wage premia. Detailed equations are introduced in Section 4. (Not) Surprisingly, their benchmark estimates do not support the competitive equilibrium theory; subsequent average employment growth was significantly negatively related to initial industry wage premia. This implies that when restricted by rigid wage structures, firms tend to adjust employment as an alternative way to accommodate high labor costs. Figure 3.1 shows this graphically. Using Census and ACS data, we compute industry wage premia at 1980 and plot them with average employment growth between 1980 and 2009 of each industry. The size of the circle corresponds to the 1980 industry employment level and the red line is the collection of the fitted values without weights. As is clear from the figure, there is a negative relationship between the two variables. In particular, we do estimate the coefficient as Borjas and Ramey (2000) did and find that the OLS estimate is still consistent with their conclusion. Borjas and Ramey (2000) also find that both of capital to labor ratio and (average) labor productivity are positively related to initial wage premia, which supports their hypothesis that firms adjust employment and instead utilize other production factors more actively. Firms with higher initial wage premia have tendencies to replace workers with capital, hence capital to labor ratio increases in initial wage premia.

Then the question is whether interindustry wage differentials affect workers uniformly or not and we answer to this question. In particular, we demonstrate how job polarization is connected to interindustry wage differentials. Recall that job polarization occurs because skill contents of different occupations are different. To be consistent

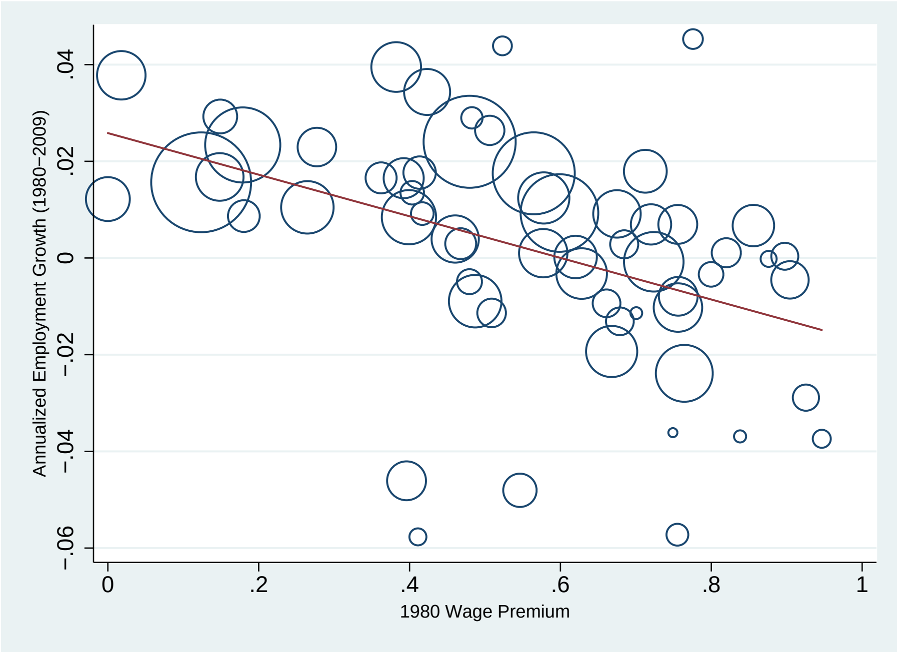

Figure 3.1: Dynamic Responses of Firms to Interindustry Wage Differentials

with job polarization literature, including Autor (2010), Acemoglu and Autor (2011), and Cortes (2011), we classify workers (jobs) into three groups as follows.

- High skill occupation jobs (require non-routine cognitive skills): Managers, Professionals, and Technicians
- Middle skill occupation jobs (require routine skills) : Sales, 'Office and Administration', 'Production, crafts, and repair' and 'Operators, fabricators, and laborers'
- Low skill occupation jobs (require non-routine manual skills) : Protective services, 'Food prep, building and grounds cleaning' and 'Personal care and personal services'

Among three groups, middle skill occupation jobs are the easiest to be replaced by ICT capital as demonstrated by Autor, Katz, and Kearney (2006); the tasks that workers who are employed in these occupations perform are easier to codify because the tasks are routine. Meanwhile, high and low skill occupation jobs are not easily replaced by capital. For instance, management decisions of managers (high occupation jobs) cannot be replaced by technology; introduction of technology such as advanced softwares does not substitute these managers, rather it is a complement to their tasks. In addition, cooking or cleaning buildings (low occupation jobs) cannot be directly replaced by machines; these jobs require humans to do non-routine manual tasks required by the jobs. Instead, a bank clerk which is included in middle skill occupation jobs is easy to be replaced by an ATM machine; their jobs are routine and machines can do the tasks more efficiently than humans. Hence these jobs disappear overtime as the economy experiences rapid technological progress in ICT type capital[11].

As a result, firms' dynamic responses to the interindustry wage differentials will affect workers (jobs) disproportionately. A decrease in labor demand for middle occupation jobs will be more evident than those for high or low occupation jobs and this is how job polarization is connected to interindustry wage differentials : the decrease in subsequent employment growth of middle occupation jobs over initial wage premia will be higher than those of high and low occupation jobs. Hence, 'Are the different aspects of job polarization across industries correlated with interindustry wage differentials?' is the first question we want to answer in this paper. The answer is, not surprisingly, yes. We find that job polarization is more pronounced in industries with high initial wage premia.

We then test if our finding is supported by the theory based on RBTC which is predominant in job polarization literature. Recall that among many types of capital, ICT type capital substitutes middle occupation jobs. To get an idea, suppose that there are two types of capital; one is ICT capital (k_i) and the other is Non-ICT capital (k_{ni}). If our theory extends arguments of Borjas and Ramey (2000), we would observe that the extent of the positive effect of initial wage premia on the subsequent ICT capital - labor ratio (k_i/N) exceeds that on the subsequent Non-ICT capital - labor ratio (k_{ni}/N) growth. As will be shown later, we find this to be true.

In summary, our hypothesis on the different speeds of job polarization across industries is as follows. Since firms cannot adjust wage[12] as they want, they dynamically substitute labor with capital. In particular, middle occupation jobs will decrease more intensively because they can be easily replaced by ICT capital, which results in disproportionate job polarization across industries.

4 Empirical Analysis

In order to test our hypothesis on the link between interindustry wage differentials and job polarization, first we estimate industry wage premia following Borjas and Ramey (2000).

$$\log w_{hit} = X_{hit}\beta_t + \omega_{it} + \varepsilon_{hit} \tag{4.1}$$

where w_{hit} is the wage rate of worker h in industry i in Census year t; X_{hit}, a vector of socioeconomic characteristics, includes the worker's age (age group is 18-24, 25-34, 35-44, 45-54, or 55-64), educational attainment (five education groups : worker with less than 9 years of schooling, 9 to 11 years, 12 years, 13 to 15 years, or at least 16 years), race (indicating if the worker is African American[13]), sex, region of residence (indicating in which of the 9 Census regions the worker lives). We also control for three occupations (high, middle, and low

[11] As we denoted earlier, 'offshorability' is also higher for middle occupation jobs than high and low occupation jobs. Most of the service jobs (low skill occupation jobs) are not tradable and occupations that require non-routine cognitive tasks are not easily offshored while factories can be relatively easily reallocated to foreign countries.

[12] While the level of wage itself can change, its relative level to other industries' wages is hard to change hence these firms still pay high wages to workers.

[13] Further classification according to race is not possible in our data.

occupation groups) instead. ω_{it}, an industry fixed effect, measures the industry wage premia.

We estimate the wage equation separately in each Census year. Result of regression (4.1) in 1980 is reported in Appendix A.1 and coefficients are estimated to be consistent with the usual intuitions : 1. African - Americans earn less, 2. wage is strictly increasing in education, 3. wage also increases in ages until workers reach prime age and then slightly decreases. After we obtain the fitted value of industry wage premia from equation (4.1), $\hat{\omega}_{it}$, we do the second-stage regression whose form is as follows.

$$\Delta y_{ijt} = \theta_j \hat{\omega}_{it} + \eta_{ijt} \tag{4.2}$$

where y_{ijt} is the variable of interest such as employment of occupation group j in industry i or capital - labor ratio of industry i[14]. Δy_{ijt} is the annualized growth rate of the variable y_{ijt} between period t and $t+k$, and $j \in \{High, Middle, Low\}$.

Note that we use the estimated value, $\hat{\omega}_{it}$, as a regressor in the second stage regression which raises concern about the generated regressor problem. In particular, it is possible that the error term in equation (4.2) is heteroscedastic. In order to address this issue, we weigh the regression by the initial employment of each industry. The high R-squared of the wage regression, which is about 99%, also relieves the generated regressor problem (see Table A.1). In addition, the large sample size of the Census data also weakens the generated regressor problem - there are at least around $1,000$ samples in each cell of the occupation j in industry i in Census year t[15]. Furthermore, in order to control the possible endogeneity of wage premium with error term η_{ijt}, we also use Instrumental Variable (IV) which is the previous decade's estimated industry wage premium.

4.1 Job Polarization : Link to initial wage premium?

We test the first question in this section : Have firms' dynamic responses to interindustry wage differentials caused different aspects of job polarization across industries? Suppose that contrary to our argument, that there is no link between interindustry wage differentials and job polarization. Then the coefficients estimated by equation (4.2) would be almost zero, i.e. subsequent employment growth of each occupation group is not related to interindustry wage differentials. However, if our hypothesis is right, we should observe $|\theta_M| > |\theta_H|, |\theta_L|$ and $\theta_M < 0$.

Figures from 4.1 to 4.3 show graphically how initial industry wage premia are related to the subsequent employment growth of each occupation group. First, industry wage premium is estimated by equation (4.1) and is put in horizontal axis. We then compute the average employment growth of each industry by occupation group between 1980 and 2009 and vertical axis denotes this. Notice that the slope of the fitted line[16] is the steepest in figure 4.2, which supports our hypothesis that firms that paid higher wages dynamically decrease their labor demand and this effect is the most evident for middle occupation jobs. Interestingly, Figure 4.3 shows that there

[14] In this case, $y_{ijt} = k_{it}/N_{it}$ since capital is not occupation - specific.
[15] For more detailed discussion on generated regressor problem, see Wooldridge (2001).
[16] This line is not weighted by initial employment.

is no relationship between initial industry wage premia and subsequent employment growth in low occupation groups. We will come back to this issue later.

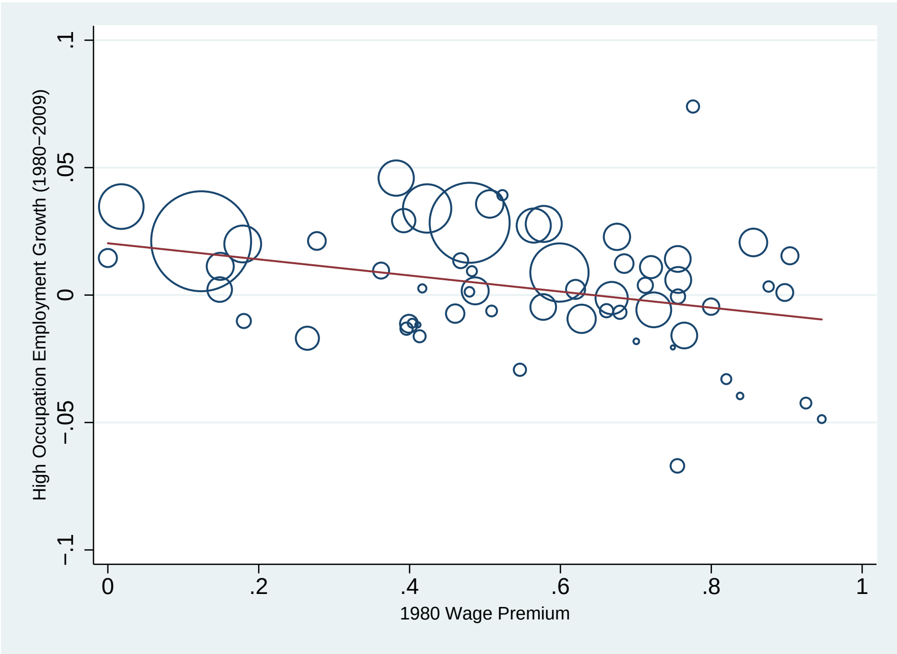

Figure 4.1: Dynamic Responses of Firms to Interindustry Wage Differentials - High Occupation group

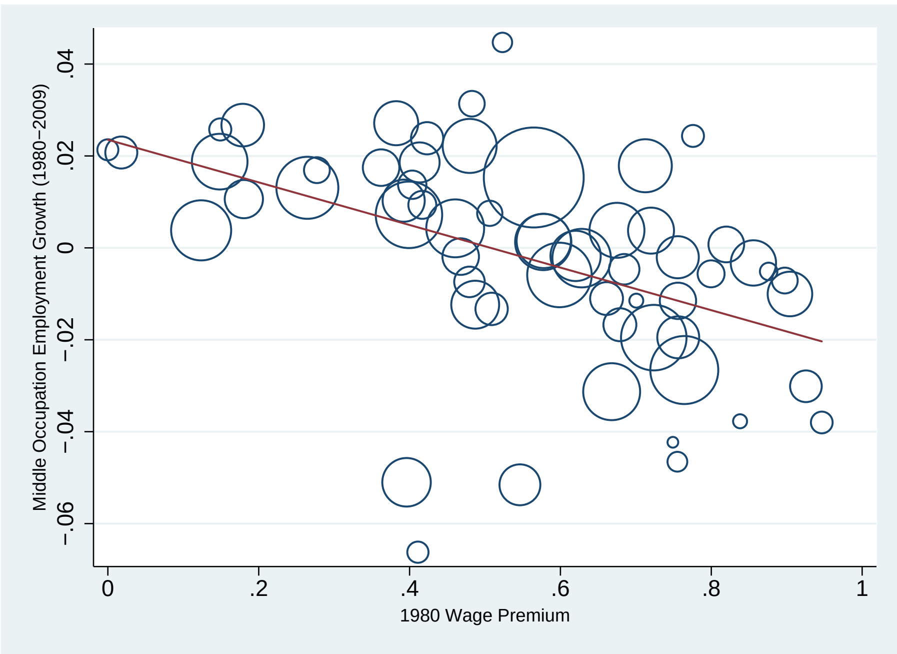

Figure 4.2: Dynamic Responses of Firms to Interindustry Wage Differentials - Middle Occupation group

We now report the first main empirical finding in Table 4.1, which is the result of the estimation of equation

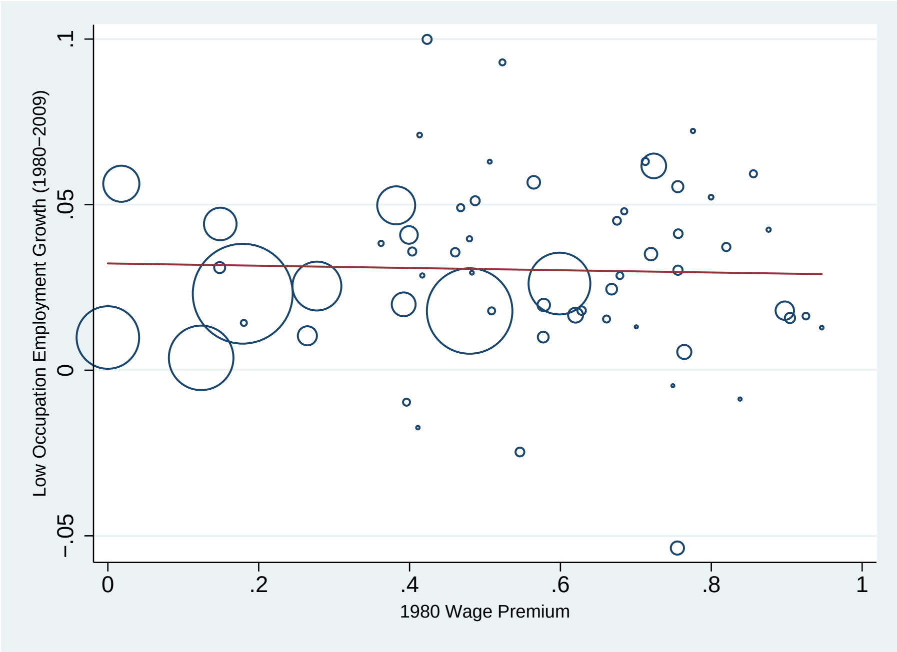

Figure 4.3: Dynamic Responses of Firms to Interindustry Wage Differentials - Low Occupation group

(4.2). For the estimation, the Census and ACS data are used. First row is the replication of Borjas and Ramey (2000) with a different period, 1980-2009, hence $y_{ijt} = N_{it}$ in this case where N_{it} is the aggregate employment of industry i at Census year t. For the remaining second to fourth row, we report the estimation of equation (4.2) with $y_{ijt} = N_{ijt}$. The dependent variable is hence the average (annualized) rate of employment growth of occupation j in industry i between 1980 and 2009. The growth rate, g_{ij}, is computed by the following equation.

$$N_{i,j,t+k} = (1 + g_{ij})^k N_{i,j,t} \tag{4.3}$$

Notice that in any regression, we use the same industry wage premium, $\hat{\omega}_{it}$ where $t = 1980$. In this sense, the regression results reported in Table 4.1 reveal how 'average' industry wage premia affect different occupation groups in a disproportionate manner.

First notice that both of OLS and IV regression yield almost the same coefficients, which implies that the endogeneity of the estimated $\hat{\omega}_{it}$ is not severe. As noted above, the estimates reported in the first row confirm the robustness of Borjas and Ramey (2000)'s main finding in the sense that their finding is also observed in a different period[17] : firms with high initial industry wage premia have more tendencies to reduce their demand for labor overtime, which is a sharp contradiction to the prediction of the competitive equilibrium theory. For competitive equilibrium theory to be supported by data, the coefficients should be estimated to be positive. However, the opposite is observed from our analysis, which suggests that non-competitive equilibrium theory may be better in

[17] Borjas and Ramey (2000) use the Census data between 1960 and 1990.

Table 4.1: Estimates of Employment Growth by Occupation Groups (1980-2009)

OLS			IV		
Occupation Groups	Coefficient	R-squared	Occupation Groups	Coefficient	R-squared
Total	$-0.0376(0.0072)$	0.24	Total	$-0.0327(0.0069)$	0.24
High Occupation	$-0.0250(0.0071)$	0.14	High Occupation	$-0.0192(0.0067)$	0.13
Middle Occupation	$-0.0412(0.0091)$	0.20	Middle Occupation	$-0.0411(0.0087)$	0.20
Low Occupation	0.0120(0.0137)	0.03	Low Occupation	0.0213(0.0113)	0.13

Note : 1. Robust standard errors are reported in parenthesis and all regressions include a constant term.
2. The regressions are weighted by each industry's initial employment and instrument is the previous decade's wage premium.
3. Sample size is 60.

explaining the interindustry wage differentials[18].

Estimated coefficients reported in the second to fourth row in Table 4.1 are consistent with Figures 4.1 to 4.3 : the coefficient for the middle occupation group is negative and the highest as an absolute value; the coefficient for the high occupation group is also negative and is still statistically significant while the size of the coefficient is almost a half of that of the middle occupation group. Furthermore, the OLS estimate confirms that initial industry wage premium does not have any (either positive or negative) impact on the subsequent employment growth rate of the low occupation group as we observe from Figure 4.3.

Table 4.2: Differences between Coefficients (1980-2009)

	p-value (OLS)	p-value (IV)
Null : $\theta_H = \theta_M$	0.056	0.007
Null : $\theta_L = \theta_H$ or $\theta_L = \theta_M$	0.007	0.000

Note : To see the significant difference between coefficients, we pool high, middle and low occupation data and estimate the coefficients of middle and low occupation industry wage premium (omitting high occupation industry premium) in one regression (where standard error was clustered by industry) instead of running a regression separately for high, middle and low occupations.

We test more formally if those coefficients are really different and Table 4.2 shows the result. The test statistics reported in the first row confirms our hypothesis; At the 10% significance level, $\theta_H \neq \theta_M$ hence the firm's response to the initial industry wage premium is not uniform between high and low occupation jobs. The second row also indicate that the low occupation group is treated differently with other occupation groups, which will be discussed in detail below. In summary, we can safely argue that middle occupation jobs are more affected by the firm's decreasing labor demand than other groups. In other words, our findings re-emphasize the importance of recognizing the heterogeneity of workers (jobs) and the asymmetric effect of changes in the economy on them in the studies of labor market[19].

[18] For more detailed discussion, see Borjas and Ramey (2000).
[19] In the other paper, Shim and Yang (2012b), we discuss the importance of considering appropriate degrees of heterogeneity across workers in the business cycles context.

Then the question that may arise is why the effect of the initial industry wage premium on low occupation jobs is not significant while that on other jobs are significantly negative. In addition, one might argue that coefficients reported in Table 4.1 may not be appropriately estimated since we use the same industry wage premium on different occupation groups. In order to address the second question, let industry - occupation wage premium, denoted as ω_{ijt}, be the wage premium of occupation j in the industry i. Suppose that there is a high wage industry and that middle occupation jobs are paid higher than high and low occupation jobs within this industry. In this case, it is natural for firms in this industry to decrease their demand for middle occupation jobs simply because they are paid more than other occupation jobs; We call this story 'relative price' explanation. Task-based explanation may not be appropriate if this is true (while the property of the task required by middle occupation jobs may enhance the firm's dynamic reactions to the interindustry wage differentials, it may not be at the first order). In order to address these issues, we estimate the following alternative wage equation :

$$\log w_{hit} = X_{hit}\beta_t + \underbrace{\omega_{it} \times \omega_{jt}}_{=\omega_{ijt}} + \varepsilon_{hit} \tag{4.4}$$

where ω_{it} is the industry fixed effect and ω_{jt} is the occupation fixed effect. Thus, $\omega_{it} \times \omega_{jt}$ is the interaction of the two fixed effects and we call this 'industry - occupation wage premium'. In this alternative wage equation, we do not include the own fixed effect terms - ω_{it} and ω_{jt}. By regressing the above equation, we obtain information on to what extent an occupation group in a specific industry earns more than the same occupation group employed in other industries and this also allows within industry comparison of wage premium.

Figure 4.4 provides our answers to the two questions that are cast above. The vertical axis denotes the estimated industry - occupation wage premium and the horizontal axis denotes the industry in order of size in average industry wage premium. In order to see how the average industry wage premium (ω_{it}) and industry - occupation wage premium (ω_{ijt}) are related, we sort the industries by the initial industry wage premium in an ascending order. All values are estimated in year 1980, which is the reference year of our study. The solid blue line denotes the industry - high occupation wage premium, the green dotted line denotes the industry - middle occupation wage premium, and the red dotted line denotes the industry - low occupation wage premium. Notice first that industry - occupation wage premium is almost monotonically increasing in average industry wage premium for high and middle occupation groups while there are many spikes for low occupation groups. This indicates that there is much variation in industry - low occupation wage premium compared to average industry wage premium while we can observe an increasing trend from it. This is the one reason why the effect of average industry wage premium on the low occupation jobs is almost negligible; even when firms face relatively higher industry wage premia, firms may not pay high wages for the workers who performs manual tasks. i.e. even in the high wage industries, low occupation jobs are not paid much relative to those employed in low wage industries. For example, 'Security, commodity brokerage, and investment companies' industry (industry 46 which is right of industry 19 in the figure) paid low occupation jobs lower than most of the other industries while it was a high wage industry. As a result, wage pressure from the low occupation group is not large to firms when compared to that from other occupation groups. Therefore, firms have less incentives to decrease their labor demand for low occupation jobs when facing high wages, which is represented by the insignificant coefficient reported in Table 4.1.

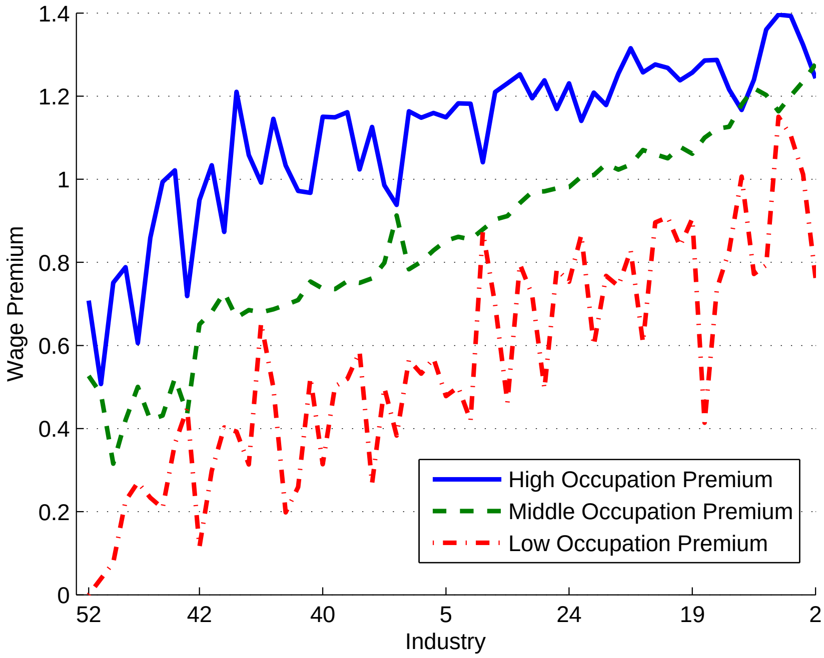

Figure 4.4: Industry - Occupation Wage Premium

Note : We order industry by the industry wage premium obtained by equation (4.1).Corresponding industry names to the numbers reported in horizontal axis can be found in Table A.2.

Figure 4.4 also provides an answer to the second question. Notice that the findings in Table 4.1 can be explained in two ways. First is the 'task content' based explanation, which is already demonstrated above : demand for middle occupation jobs declines more sensitively to initial industry wage premium than that for other occupation jobs does because these are jobs which can be easily replaced by other production factors. Second explanation is 'relative price' based explanation; If the middle occupation jobs earn more than other groups after we control for industry, it means that regardless of the skill content feature, firms would more actively decrease their demand for the middle occupation group since this group is actually the most expensive factor for production. In this sense, this explanation weakens our preferred story that explains the link between job polarization and interindustry wage differentials. However, Figure 4.4 shows that this is not supported by data : in any industry, we can observe that $\omega_{iHt} > \omega_{iMt} > \omega_{iLt}$, which means that it is the high occupation jobs that are paid the most. Hence, we can exclude the possibility that the subsequent employment growth of middle occupation jobs are lower than other occupation groups because they were paid relatively higher than other groups, which supports the usual explanations on job polarization based on 'task content' property of occupations.[20]

As a robustness check, we do the same second-stage regression with a different dependent variable, the changes in employment share of occupation groups. Notice that employment growth of the middle occupation jobs has been lower than that of high and low occupation jobs for last thirty years. This is equivalent to saying that the employment share of middle occupation jobs has declined while at least one of that of high or low occupation jobs has increased. Thus, we should observe that (1) subsequent change in employment share of middle occupation jobs is negatively related to initial industry wage premium and (2) that of high or low occupation job is (weakly) positively related to initial industry wage premium. In estimating equation (4.2), we set $\Delta y_{ijt} = es_{i,j,t+k} - es_{i,j,t}$ where $es_{i,j,t}$ is employment share of occupation j in industry i at t where number of industries is 60 and $t = 1980$. Table 4.3 summarizes the result of the alternative estimation.

Table 4.3: Estimates of changes in employment share by Occupation Groups (1980-2009)

OLS			IV		
Occupation Groups	Coefficient	R-squared	Occupation Groups	Coefficient	R-squared
High Occupation	0.0077(0.0801)	0.0007	High Occupation	0.0135(0.0814)	0.0003
Middle Occupation	−0.1833(0.0572)	0.19	Middle Occupation	−0.250(0.0617)	0.16
Low Occupation	0.1312(0.0957)	0.13	Low Occupation	0.1826(0.079)	0.11

Note : 1. Robust standard errors are reported in parenthesis and all regressions include a constant term.
2. The regressions are weighted by each industry's initial employment and instrument is the previous decade's wage premium.
3. Sample size is 60.

The result is, not surprisingly, consistent with the estimation result reported in Table 4.1. First, the fact that subsequent employment growth of the middle occupation group decreases in initial industry wage premium during 1980 - 2009 is translated into the observation that the employment share of middle occupation jobs decreases for the industry with high initial wage premium. Second, the coefficient for low occupation jobs is now much greater than 0 in both of the OLS and IV regressions while the coefficient for high occupation jobs is estimated to be almost zero. This is because (1) the negative responsiveness of employment growth of high occupation jobs to initial industry wage premium was not large compared to that of middle occupation jobs and (2) there was basically no correlation between the subsequent employment growth of low occupation jobs and initial industry wage premium. Hence the estimate for high occupation jobs is almost zero but that for low occupation jobs is positive. Similarly to Table 4.2, we find that the coefficient for middle occupation jobs is statistically different from that for high occupation jobs, which confirms our findings demonstrated above.

[20] One interesting finding is that the slope of the line in Figure 4.4 is steeper for middle occupation jobs than that for high occupation jobs. In the end, the gap between industry - high occupation wage premium and industry - middle occupation one becomes almost zero. This fact implies that while high occupation jobs are paid more than middle occupation jobs, there is a tendency that high wage industries actually pay relatively more for the middle occupation jobs than low wage industries do. This feature may have a 'price' effect on our estimates, but given that level of industry - high occupation wage premium is highest for any industries, we do not analyze further since its effect may be limited.

4.2 Has ICT capital substituted workers? Then is the observation discussed in the previous section consistent with the usual explanation (which we prefer) that tasks required by middle occupation jobs are the easiest to be replaced by ICT capital hence job polarization occurs? We address this issue in this section.

We first divide capital into two types : ICT capital and Non-ICT capital. Under this distinction, Non-ICT capital can be considered as general-purpose capital; it is complementary to any types of labor. Meanwhile, ICT capital such as ATM machine in banks does substitute the routine tasks. Likewise, the advance of computer technology has spurred the automation of production process which substitutes jobs that were originally occupied by human.

Thus, we should be able to observe the followings : a growth rate of ICT-capital per worker increases in initial industry wage premium and the responsiveness of it is higher than that of (Non-ICT) capital per worker. Recall that firms which paid relatively higher wages have higher incentives to substitute workers with capital. And this task can be done by increasing ICT-capital rather than Non-ICT capital since Non-ICT capital is complementary to workers while ICT capital is substitutable to some workers that have done routine tasks, which fits more for the firm's purpose to decrease labor demand. Notice that the growth rate of capital level may not be negatively related to initial industry wage premium. If the size of an industry shrinks as labor demand decreases, capital demand itself can also decrease. However, the rate at which capital demand decreases will be lower than that at which labor demand decreases hence resulting capital to labor ratio increases in interindustry wage differentials.

For the analysis done in this section, we use EUKLEMS data with period between 1980 and 2007. Since it provides the information of 29 industries, we recompute the initial industry wage premium in 1980 by reclassifying Census 60 industries into 29[21]. Details on the classification can be found in Table A.3. Each capital series (capital, ICT capital, and Non-ICT capital) is real fixed capital stock, which is based on 1995 prices. In order to obtain capital per worker series, we divide capital by employment of each industry which is also provided by EUKLEMS. Before we formally test our hypothesis, we draw figures to get an idea: see Figure 4.5 and 4.6.

Figures confirm our hypothesis. First, Figure 4.5 clearly shows the positive relationship between initial industry wage premium in 1980 and subsequent annualized growth rate of ICT capital per worker between 1980 and 2007, which supports our theory that firms increase demand for ICT capital in order to substitute (certain types of) workers because of the wage burden. Figure 4.6, similarly, shows that the responsiveness of the growth rate of Non-ICT capital per worker to initial wage premium is positive. While we can draw a trend line (red line) which is increasing in initial wage premium, however, many of large industries in terms of employment size are off the trend line, which suggests the possibility that changes in Non-ICT capital per worker between 1980 and 2007 may not be correctly related to interindustry wage differentials.

For the complete analysis, we estimate the equation (4.2) again and coefficients are reported in Table 4.4.

[21] EUKLEMS also provides data with more detailed industry classification with more than 50 industries (SIC Industry classification is used.) between 1977 and 2005. However, we do not use this data since we need to classify industries at discretion. We will extend our analysis this data if we find it possible.

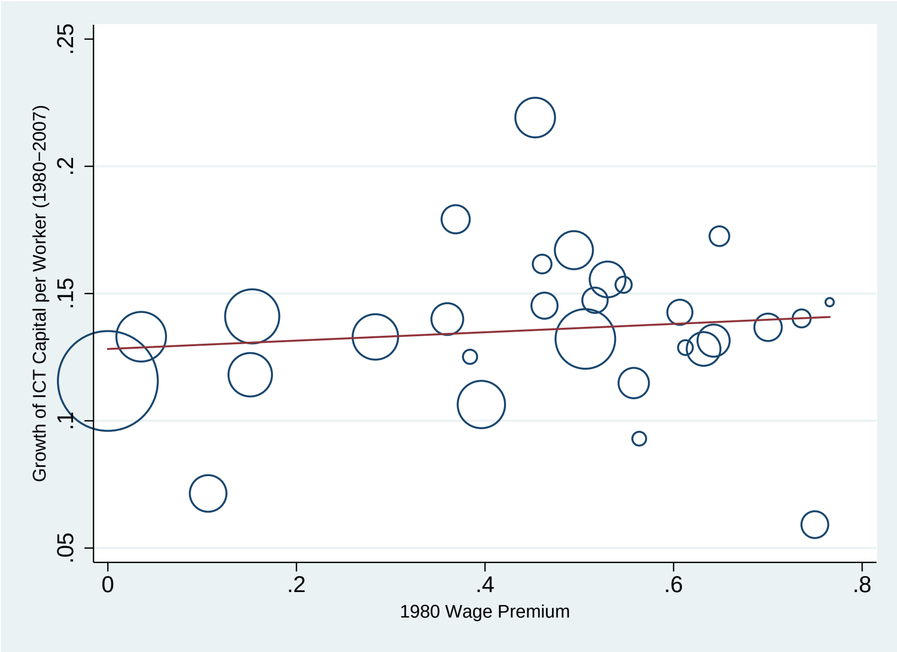

Figure 4.5: ICT Capital per Worker to Initial Industry Wage Premium (1980-2007)

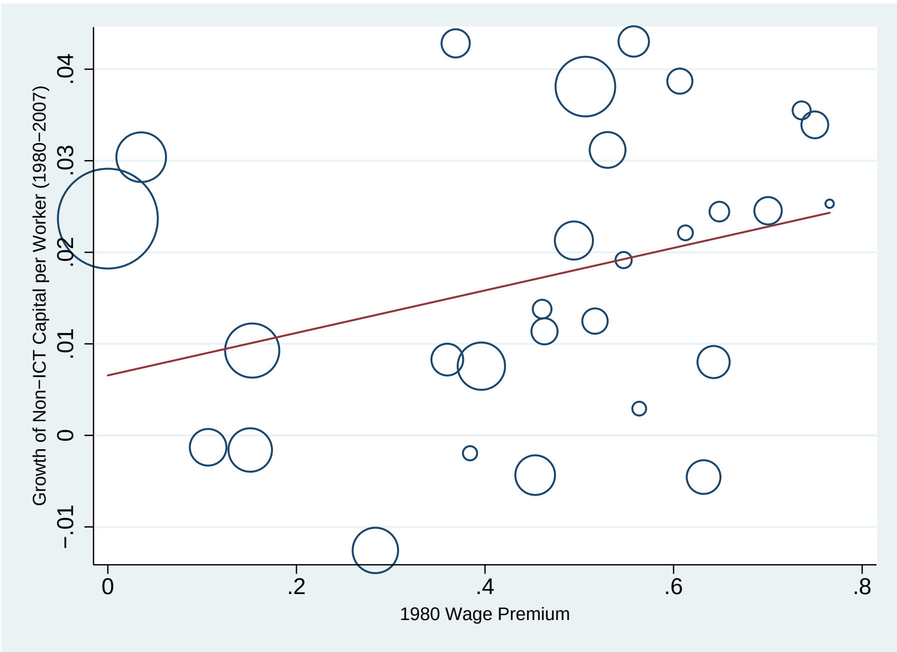

Figure 4.6: Non-ICT Capital per Worker to Initial Industry Wage Premium (1980-2007)

Relevant estimation results for different types of capital are presented in the first three rows. Before we discuss the main result, we first focus on the last row, which is the result of the regression where the dependent variable is employment growth rate. Notice that it is consistent with the coefficient obtained from the Census data

(See Table 4.1); the estimates obtained from the Census and EUKLEMS data are almost identical, which is further evidence for the robustness of our findings. The first three rows are the main results of this section. As expected, ignoring the statistical significance, we confirm the relationship among the coefficients as follows : $\theta_{ICT} > \theta_{Aggregate} > \theta_{non-ICT}$. Furthermore, if we also consider the significance level, only θ_{ICT} is significant. Hence, we can conclude that firms dynamically respond to wage pressure by increasing demand for ICT capital, not all types of capital, because only ICT capital is helpful in replacing workers. Notice that this finding is consistent with Michaels, Natraj, and Reenen (2011). They show that job polarization is more evident in industries which experience higher ICT capital growth; in so doing, they treat ICT capital growth as an exogenous change given to each industry; they do not provide an answer to why some industries have experienced faster ICT capital growth while other have not. Hence our finding has a unique contribution to this literature by showing that the asymmetric increases in ICT capital (per workers) across industries over the last thirty years may be the result of the endogenous responses of firms to interindustry wage differentials. Suppose that an economy experiences a RBTC type progress, which makes the price of ICT capital lower. Then job polarization at the aggregate level occurs because firms find it cheaper to replace middle occupation jobs with ICT capital. However, given that this technology is not exclusive to specific industries, this does not explain the different speed of job polarization across industries. Our finding fills this gap; some industries exhibit faster job polarization since firms in these industries have higher incentives to hire more ICT capital in production than firms in other industries, and the incentive increases in initial industry wage premium that the industry encountered. Hence, different speed of job polarization across industries is an endogenous consequence of the interindustry wage differentials.

Table 4.4: Estimates of Capital per Worker (1980-2007)

OLS			IV		
Dependent	Coefficient	R-squared	Occupation Groups	Coefficient	R-squared
Capital/Worker	0.0149(0.0135)	0.05	Capital/Worker	0.0138(0.0139)	0.05
ICT Capital/Worker	0.0347(0.0191)	0.09	ICT Capital/Worker	0.0400(0.0171)	0.09
non-ICT Capital/Worker	0.0041(0.0137)	0.004	non-ICT Capital/Worker	0.0030(0.0144)	0.004
Capital	−0.0201(0.0110)	0.10	Capital	−0.0181(0.0114)	0.10
ICT Capital	0.0004(0.0217)	0.000	ICT Capital	0.0081(0.0204)	0.000
non-ICT Capital	−0.0308(0.0011)	0.25	non-ICT Capital	−0.0289(0.0115)	0.25
Output	−0.0055(0.0089)	0.01	Output	−0.0044(0.0087)	0.01
Labor Productivity	0.0290(0.0091)	0.22	Labor Productivity	0.0275(0.0091)	0.22
Employment	−0.0341(0.0076)	0.26	Employment	−0.0319(0.0072)	0.27

Note : 1. Robust standard errors are reported in parenthesis and all regressions include a constant term.
2. Both of EUKLEMS and the decennial census data are used for the estimation. Regressions are weighted by each industry's initial employment and instrument is the previous decade's wage premium. Number of sample used is 29, which is the number of industries.
3. Labor Productivity is obtained by dividing industry output by employed workers. Employment and output data are from EUKLEMS.
4. Capital and output variables are real variables.

In this sense, our finding is supporting evidence to 'directed technology changes' suggested by Acemoglu (2002) : some firms have increased demand for ICT capital because the business environment pushes these firms to use ICT capital more extensively. This feature is the underlying idea of directed technology changes : observed technology progress occurs because the firms have endogenously chosen to develop better technology which makes them to fully exploit the environment they face. In job polarization literature, Acemoglu and Autor (2011) also pointed out the possibility that directed technology changes may have contributed to job polarization during the last thirty years. Our findings suggest that interindustry wage differentials is the economic environment that has generated the different speed of job polarization across industries.

Fourth to sixth rows confirm our earlier discussions and they are also consistent with other estimation results. First, both of capital and Non-ICT capital decrease in initial industry wage premium; firms with relatively high initial wage premium demand less capital because they want to reduce the size of the firms. Together with the fact that these industries also decrease demand for labor, these findings imply that capital per worker and Non-ICT capital per worker are not related to interindustry wage differentials as we can see from Table 4.4. However, ICT capital is not affected by initial industry wage premium because it plays an important role in firm's subsequent behavioral changes; as a result, ICT capital per worker increases more in industries with high initial industry wage premium.

Furthermore, we find that the growth rate of labor productivity increases in initial wage premium, which is consistent with Borjas and Ramey (2000). This is further supporting evidence for the fact that firms have dynamically substituted workers with relatively efficient technologies when they faced relatively high wages.

4.3 Job Polarization and Interindustry Wage Differentials before 1980 Notice that interindustry wage differential has been persistently observed even before 1980; for instance, the benchmark estimation of Borjas and Ramey (2000) is based on the industry wage premium in 1960. Then the natural question is if the job polarization is also observed for the period before 1980; our theory to explain the heterogenous aspects of job polarization across industries is based on firms' dynamic responses to interindustry wage differentials hence we would observe the subsequent occurrence of heterogenous job polarization whenever industry wage premium exists. We address this issue in this section. Figure A.2 shows to what extent changes in employment share of each occupation group differ across industries between 1960 and 1980. We can still observe that employment share of the middle occupation jobs decreases in most of the industries, which suggests the possibility of the existence of job polarization (or equivalent phenomenon) during 1960-1980, though its extent is lower : overall, the employment share of the middle occupation group decreases by about 5% between 1960 and 1980 while it decreases by more than 10% between 1980 and 2009.

Again, we estimate equation (4.2) but the data period is changed to between 1960 and 1980. In so doing, we first estimate the wage equation (4.1) with Census data in 1960 in order to obtain the industry wage premium in

1960. In Table 4.5, we compare the OLS estimates for the two different periods[22]. Estimated coefficients for the first period (1960-1980) are reported in the first three columns and those for the second period (1980-2009) are reported in the last three columns.

Table 4.5: OLS Estimates of Employment Growth by Occupation Groups (1960-1980 and 1980-2009)

1960-1980			1980-2009		
Occupation Groups	Coefficient	R-squared	Occupation Groups	Coefficient	R-squared
Total	−0.0165(0.0275)	0.03	Total	−0.0376(0.0072)	0.24
High Occupation	0.0063(0.0149)	0.003	High Occupation	−0.0250(0.0071)	0.14
Middle Occupation	−0.0281(0.0115)	0.09	Middle Occupation	−0.0412(0.0091)	0.20
Low Occupation	0.0592(0.0197)	0.03	Low Occupation	0.0120(0.0137)	0.03

Note : 1. Robust standard errors are reported in parenthesis and all regressions include a constant term.
2. Regression are weighted by each industry's initial employment and instrument is the previous decade's wage premium. Number of sample used is 60, which is the number of industries.

Notice that while the coefficient for the total employment growth rate is not significantly different from zero, the coefficient for the middle occupation group, which is negative, is still significantly different from zero. With the observation that θ_H and θ_L are all positive (while only θ_L is significant), we can conclude that firms with high initial industry wage premium in 1960 responded to this situation by decreasing the demand for the middle occupation jobs relative to other occupation jobs. However, the magnitude of the responsiveness (θ_M) is much lower than that of the second period; the dynamic responses of firms with high initial industry wage premium in 1980 in terms of declining their demand for the middle occupation jobs are much stronger than those in 1960. This suggests that the heterogenous aspect of job polarization across industries became more pronounced after 1980.

Why have the industrial differences in job polarization become larger after 1980? There are two possibilities : (1) routine-biased technological changes and (2) increased offshoring opportunity since 1980s. Consider an extreme case where none of the two options are available to firms. Notice that among the three occupation categories, only the middle occupation jobs are easily replaced either by (ICT) capital or by offshoring. High and low occupation jobs are not easily replaced by other production factors, as we have demonstrated before. Thus, for firms to dynamically adjust their labor demand, they need to change their demand for middle occupation jobs. However, since firms cannot access technologies that can perform the tasks done by workers who are employed in middle occupation jobs, it is not possible for them to change demand for labor. Hence, changes in labor demand will not differ across different industries if firms cannot replace workers. Suppose now instead that firms can either buy ICT capital because its price has become lower, or because they can offshore some tasks to foreign countries. Then firms with different initial wage premia will behave differently : the labor demand for middle occupation jobs will decline faster (or the growth rate of it is lower) for firms with high industry wage premia than firms

[22] IV regressions show the same result hence we omit here

with low industry wage premia. Hence, both of these changes, which are usually argued to become available or accessible to firms since 1980s (Acemoglu and Autor (2011) and Jaimovich and Siu (2012)), make it easier for firms to decrease their demand for middle occupation jobs. For instance, as it becomes easier to transfer processes offshore (due to increased trade or technology advances) firms can adjust onshore labor more actively overtime. As a result, the heterogenous aspect of job polarization across industries becomes more evident in the second period. Our finding is also consistent with the typical RBTC type story; replacing middle occupation jobs with ICT capital was difficult before 1980s, because RBTC type technology (ICT capital) was not easily accessible, hence the different levels of job polarization across industries were low. However, as the price of ICT capital has decreased due to the occurrence of RBTC since the 1980s, it has accelerated the speed of firms' dynamic responses to interindustry wage premium. Cheaper price of ICT capital makes firms with high industry wage premium behave more actively than before in replacing middle occupation jobs with ICT capital while firms with low industry wage premium still have less incentives to do so, hence a huge difference in job polarization across industries has developed since the 1980s.

Putting the above arguments drawn from the comparison between the two periods - 1960 to 1980 and 1980 to 2009 - in a different way raises an interesting issue; while the degree is smaller, we could still observe job polarization between 1960 and 1980. This is also confirmed by Figure A.2 which shows that the employment share of middle occupation jobs decreased while that of high or low occupation jobs increased between 1960 and 1980. This finding suggests that job polarization may occur endogenously even when (1) the price of ICT capital is high and (2) offshoring of tasks is not easy. And this 'nuanced' job polarization in the first period can still be attributed to the endogenous responses of firms to the existence of interindustry wage differentials. Contrary to most of the previous studies that assume exogenous shocks such as RBTC (for instance, see Cortes (2011) and Jaimovich and Siu (2012)), our findings in Table 4.5 indicate that job polarization can endogenously occur without exogenous changes. Acemoglu and Autor (2011), also points out that directed technical changes may explain job polarization. The difference between our findings and their suggested theory, however, is that their model considers 'endogenous responses of technologies to changes in (relative skill) supplies' while we find that job polarization occurs because of 'rigid' wage structure.

5 Conclusion

In this paper, we show that the degree of job polarization is not the same across industries and identify the factor that causes this phenomenon. In particular, we demonstrate that job polarization is more evident in industries which paid relatively higher wages than other industries since the 1980s. We show that this observation can be explained as the dynamic responses of firms to interindustry wage differentials; firms that paid higher industry wage premia responded to wage pressure by replacing workers with ICT capital. As a result, the heterogenous aspect of job polarization across industries is the result of optimal responses of industries to existing interindustry wage differentials.

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A Appendix - Additional Figures and Tables

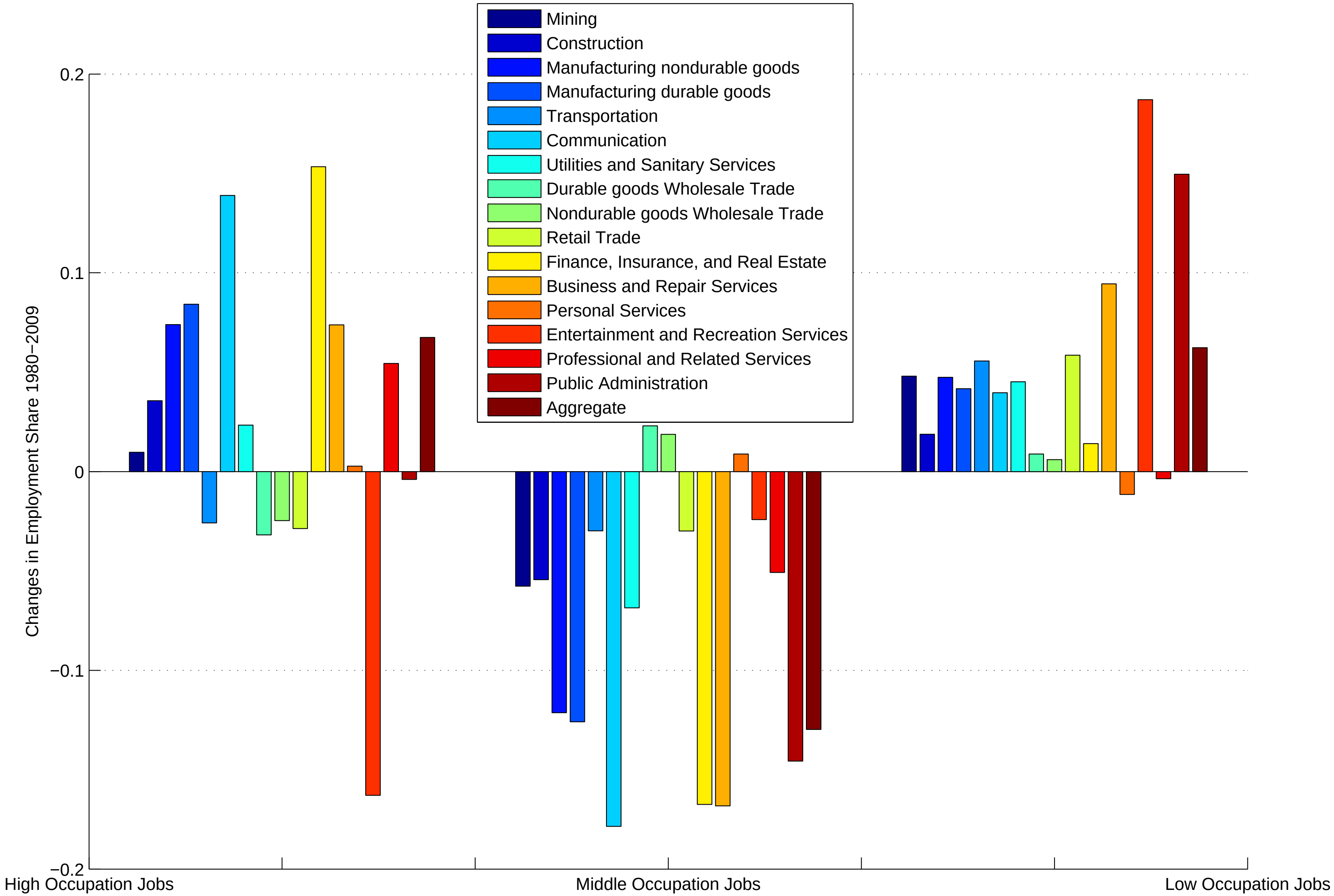

Figure A.1: Changes in Employment Shares by Occupation Groups between 1980 and 2009

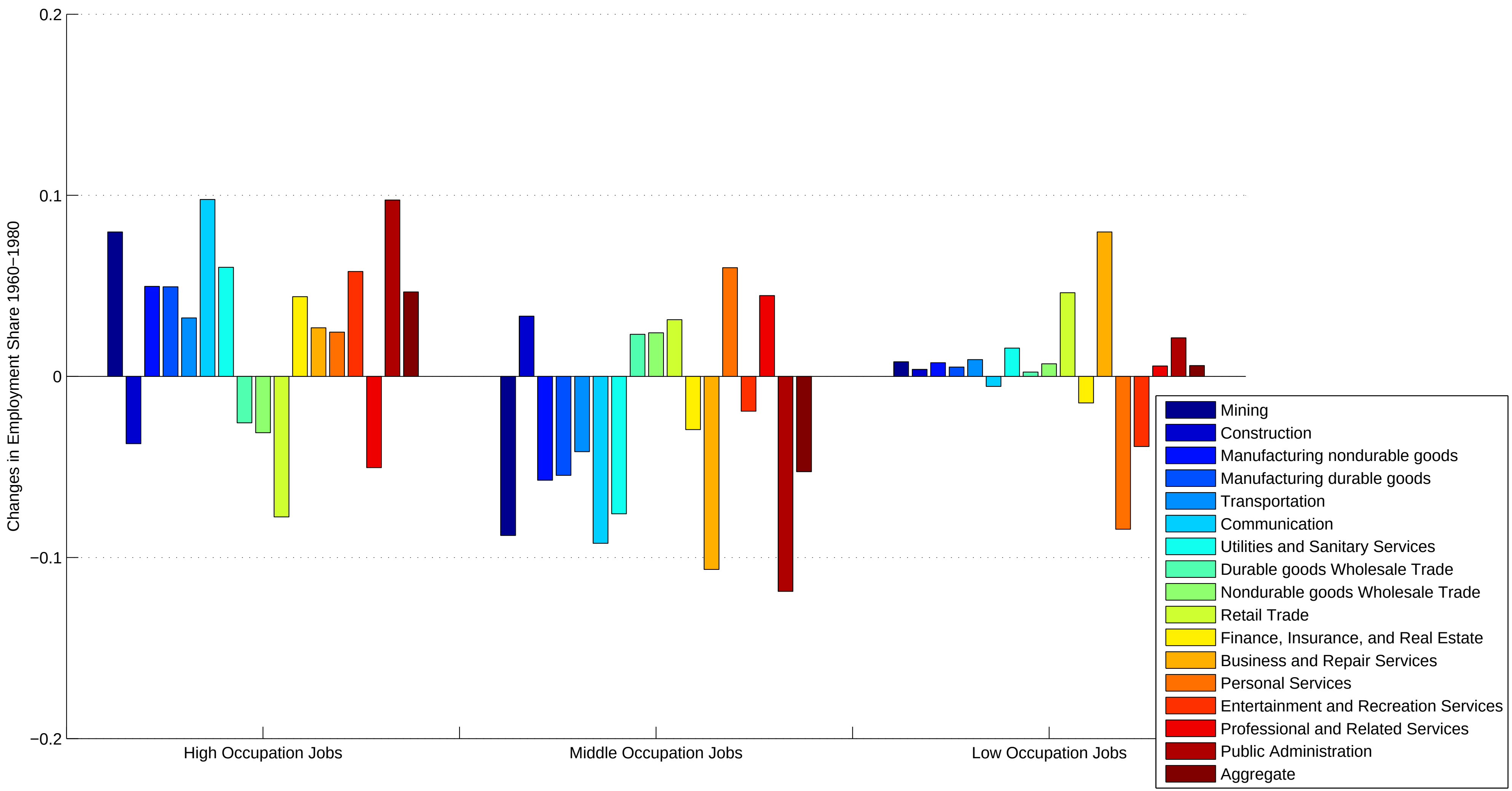

Figure A.2: Changes in Employment Shares by Occupation Groups between 1960 and 1980

Table A.1: OLS Estimates of the Wage Regression in 1980

Variable	Coefficient	Variable	Coefficient
Female	−0.5413(0.0009)	High Occupation	0.4892(0.0030)
Age1	1.0227(0.0035)	Middle Occupation	0.2267(0.0029)
Age2	1.5225(0.0035)	Low Occupation	0.0081(0.0031)
Age3	1.7141(0.0035)	Region1	−0.0355(0.0024)
Age4	1.7916(0.0035)	Region2	0.0329(0.0020)
Age5	1.7775(0.0036)	Region3	0.0684(0.0020)
Edu1	6.7711(0.0064)	Region4	−0.0188(0.0023)
Edu2	6.8486(0.0061)	Region5	−0.0045(0.0020)
Edu3	7.0597(0.0063)	Region6	−0.0612(0.0024)
Edu4	7.0868(0.0063)	Region7	−0.0011(0.0022)
Edu5	7.3286(0.0064)	Region8	0(Omitted)
African American	−0.0842(0.0014)	Region9	0.0665(0.0021)
R Squared	.9924	Observations	4, 307, 598

Notes :
1. Robust standard errors are reported in parenthesis.
2. the decennial census data is used for the estimation. Number of sample used is 60, which is the number of industries.
3. Region1 to Region9 correspond to New England Division, Middle Atlantic Division, East North Central Division, West North Central Division, South Atlantic Division, East South Central Division, West South Central Division, Mountain Division, and Pacific Division, respectively.
4. Age1 to Age5 correspond to age group is 18-24, 25-34, 35-44, 45-54, and 55-64, respectively.
5. Edu1 to Edu5 correspond to worker has less than 9 years of schooling, 9 to 11 years, 12 years, 13 to 15 years, and at least 16 years, respectively.

Table A.2: Census Industry Classification

Number	Industry	IND 1990 code
1	Metal Mining	40
2	Coal Mining	41
3	Oil and Gas Extraction	42
4	Nonmetallic mining and Quarrying, except Fuels	50
5	Construction	60
6	Food and Kindred Products	100 – 122
7	Tobacco Manufactures	130
8	Textile Mill Products	132 – 150
9	Apparel and Other Finished Textile Products	151 – 152
10	Paper and Allied Products	160 – 162
11	Printing, Publishing, and Allied industries	171 – 172
12	Chemicals and Allied Products	180 – 192

13	Petroleum and Coal Products	200 – 201
14	Rubber and Miscellaneous Plastics Products	210 – 212
15	Leather and Leather Products	220 – 222
16	Lumber and Woods Products, except Furniture	230 – 241
17	Furniture and Fixtures	242
18	Stone, Clay, Glass and Concrete Products	250 – 262
19	Metal Industries	270 – 301
20	Machinery and Computing Equipments	310 – 332
21	Electrical Machinery, Equipment, and Supplies	340 – 350
22	Motor Vehicles and Motor Vehicle Equipment	351
23	Other Transportation Equipment	352 – 370
24	Professional and Photographic Equipment and Watches	371 – 381
25	Miscellaneous Manufacturing Industries / Toys, Amusement, and Sporting Goods	390 – 392
26	Railroads	400
27	Bus Service and Urban Transit / Taxicab Service	401 – 402
28	Trucking Service / Warehousing and Storage	410 – 411
29	U.S. Postal Service	412
30	Water Transportation	420
31	Air Transportation	421
32	Pipe Lines, except Natural Gas / Services Incidental to Transportation	422 – 432
33	Communications	440 – 442
34	Utilities and Sanitary Services	450 – 472
35	Durable Goods	500 – 532
36	Nondurable Goods	540 – 571
37	Lumber and Building Material Retailing	580
38	General Merchandiser (Note 2)	581 – 600
39	Food Retail	601 – 611
40	Motor Vehicle and Gas Retail	612 – 622
41	Apparel and Shoe	623 – 630
42	Furniture and Appliance	631 – 640
43	Eating and Drinking	641 – 650
44	Miscellaneous Retail	651 – 691
45	Banking and Credit	700 – 702
46	Security, Commodity Brokerage, and Investment Companies	710

47	Insurance	711
48	Real Estate, Including Real Estate-Insurance Offices	712
49	Business Services	721 – 741
50	Automotive Services	742 – 751
51	Miscellaneous Repair Services	752 – 760
52	Hotels and Lodging Places	761 – 770
53	Personal Services	771 – 791
54	Entertainment and Recreation Services	800 – 810
55	Health Care	812 – 840
56	Legal Services	841
57	Education Services	842 – 861
58	Miscellaneous Services (Note 3)	862 – 881
59	Professional Services	882 – 893
60	Public Administration	900 – 932

Note : 1. Number 6-15 are 'Nondurable Manufacturing Goods', 16-25 are 'Durable Manufacturing Goods', 26-32 are 'Transportation', 35-36 are 'Wholesale Trade', 37-44 are 'Retail Trade', 45-49 are 'Finance, Insurance, and Real Estate', 49-51 are 'Business and Repair Services', and 55-59 are 'Professional and Related Services' industries.

2. General Merchandiser includes Hardware Stores, Retail Nurseries and Garden Stores, Mobile Home Dealers and Department Stores.

3. Miscellaneous Services include Child Care, Social Services, Labor Unions and Religious Organizations.

Table A.3: EUKLEMS Industry Classification

Number	Industry	IND 1990 code
1	Mining and Quarrying	40 − 50
2	Total Manufacturing	
2 − 1	Food, Beverages and Tobacco	100 − 130
2 − 2	Textiles, Textile, Leather and Footwear	132 − 152, 220 − 222
2 − 3	Wood and of Wood and Cork	230 − 242
2 − 4	Pulp, Paper, Printing and Publishing	160 − 172
2 − 5	Chemical, Rubber, Plastics and Fuel	
2 − 5 − 1	Coke, Refined Petroleum and Nuclear Fuel	200 − 201
2 − 5 − 2	Chemicals and Chemical Products	180 − 192
2 − 5 − 3	Rubber and Plastics	210 − 212
2 − 6	Other Non-Metallic Mineral	262
2 − 7	Basic Metals and Fabricated Metal	270 − 301
2 − 8	Machinery, NEC	310 − 332
2 − 9	Electrical and Optical Equipment	340 − 350
2 − 10	Transport Equipment	351 − 370
2 − 11	Manufacturing NEC; Recycling	371 − 392
3	Electricity, Gas and Water Supply	450 − 472
4	Construction	60
5	Wholesale and Retail Trade	
5 − 1	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	500, 612 − 622, 672, 751
5 − 2	Wholesale Trade and Commission Trade, except of Motor Vehicles and Motorcycles	501 − 571
5 − 3	Retail Trade, except of Motor Vehicles and Motorcycles; Repair of Household Goods	580 − 611, 623 − 671, 681 − 691
6	Hotels and Restaurants	762 − 770
7	Transport and Storages and Communication	
7 − 1	Transport and Storage	400 − 432
7 − 2	Post and Telecommunications	440 − 442
8	Finance, Insurance, Real Estate and Business Services	
8 − 1	Financial Intermediation	700 − 711
8 − 2	Real Estate, Renting and Business Activities	712 − 760
9	Community Social and Personal Services	761 − 810
10	Public Administration and Defence; Compulsory Social Security	900 − 932
11	Education	842 − 861
12	Health and Social Work	812 − 840, 841
13	Other Community, Social and Personal Services	862 − 893

Table A.4: Industry - Occupation Wage Premium

Industry	Average	High	Middle	Low	Industry	Average	High	Middle	Low
1	0.8382(.0097)	1.1669(.0181)	1.1801(.0110)	1.0062(.0661)	31	0.8975(.0060)	1.3960(.0104)	1.1634(.0071)	1.1503(.0131)
2	0.9465(.0073)	1.2431(.0173)	1.2766(.0079)	0.7623(.0837)	32	0.5231(.0090)	1.1482(.0159)	0.8013(.0105)	0.5324(.0478)
3	0.7997(.0063)	1.2873(.0093)	1.1212(.0075)	0.7364(.0539)	33	0.8558(.0049)	1.2392(.0069)	1.2189(.0056)	0.7720(.0342)
4	0.7006(.0102)	1.1405(.0250)	1.0065(.0112)	0.8666(.0602)	34	0.7201(.0049)	1.1788(.0069)	1.0368(.0056)	0.7673(.0170)
5	0.5646(.0045)	1.1491(.0065)	0.8521(.0052)	0.4780(.0194)	35	0.6281(.0048)	1.2307(.0068)	0.9116(.0055)	0.4629(.0303)
6	0.6201(.0050)	1.2100(.0080)	0.9034(.0057)	0.6984(.0155)	36	0.5772(.0049)	1.1828(.0073)	0.8615(.0056)	0.4997(.0238)
7	0.8382(.0121)	1.3154(.0231)	1.0356(.0137)	0.8287(.0675)	37	0.4826(.0071)	1.1260(.0153)	0.7616(.0080)	0.2679(.0811)
8	0.7491(.0053)	1.1593(.0108)	0.8290(.0059)	0.5687(.0231)	38	0.2645(.0048)	1.0214(.0077)	0.5211(.0056)	0.3637(.0129)
9	0.3960(.0052)	1.2102(.0127)	0.6670(.0057)	0.3928(.0304)	39	0.3992(.0050)	1.0583(.0098)	0.6850(.0056)	0.3135(.0156)
10	0.7558(.0055)	1.2682(.0098)	1.0506(.0063)	0.9087(.0269)	40	0.4605(.0050)	1.1502(.0093)	0.7372(.0057)	0.3142(.0291)
11	0.4870(.0053)	0.9854(.0079)	0.7989(.0061)	0.4980(.0312)	41	0.1803(.0062)	0.9936(.0122)	0.4313(.0070)	0.2081(.0420)
12	0.7556(.0049)	1.2762(.0065)	1.0600(.0058)	0.8958(.0180)	42	0.3623(.0063)	0.9500(.0120)	0.6509(.0071)	0.1153(.0521)
13	0.8760(.0074)	1.3602(.0116)	1.2026(.0088)	0.7934(.0526)	43	0.1788(.0045)	0.8593(.0068)	0.4207(.0067)	0.2336(.0054)
14	0.6611(.0057)	1.2524(.0097)	0.9429(.0065)	0.7958(.0288)	44	0.1483(.0055)	0.7884(.0092)	0.4204(.0063)	0.2258(.0246)
15	0.4110(.0079)	1.1454(.0255)	0.6868(.0085)	0.4985(.0524)	45	0.5779(.0046)	1.1815(.0058)	0.8551(.0055)	0.4191(.0189)
16	0.5088(.0062)	1.1637(.0144)	0.7835(.0070)	0.5652(.0338)	46	0.7757(.0079)	1.2856(.0138)	1.1002(.0092)	0.4139(.0576)
17	0.4794(.0063)	1.1611(.0143)	0.7548(.0070)	0.5194(.0458)	47	0.6750(.0048)	1.2381(.0066)	0.9709(.0055)	0.4960(.0295)
18	0.6788(.0057)	1.1691(.0109)	0.9782(.0064)	0.7839(.0346)	48	0.3922(.0058)	1.8732(.0095)	0.7274(.0072)	0.4029(.0108)
19	0.7642(.0046)	1.2568(.0065)	1.0615(.0052)	0.9055(.0151)	49	0.3823(.0051)	1.0335(.0068)	0.6806(.0066)	0.2981(.0086)
20	0.7238(.0045)	1.2546(.0059)	1.0233(.0053)	0.7428(.0185)	50	0.4133(.0063)	1.0331(.0142)	0.6975(.0069)	0.1983(.0572)
21	0.6679(.0046)	1.1951(.0060)	0.9696(.0054)	0.7211(.0199)	51	0.4169(.0083)	0.9720(.0219)	0.7093(.0090)	0.2590(.0821)
22	0.9043(.0050)	1.3927(.0079)	1.2010(.0057)	1.1049(.0180)	52	0.00(Omitted)	0.7079(.0119)	0.5265(.0102)	0.00(Omitted)
23	0.7562(.0048)	1.2381(.0061)	1.0781(.0057)	0.8386(.0241)	53	0.2771(.0061)	0.1790(.0132)	0.4358(.0093)	0.4479(.0078)
24	0.6846(.0056)	1.2308(.0075)	0.9811(.0067)	0.7531(.0330)	54	0.1490(.0063)	0.6056(.0098)	0.5005(.0104)	0.2706(.0091)
25	0.4678(.0061)	1.1491(.0110)	0.7355(.0069)	0.5016(.0339)	55	0.4796(.0043)	1.0236(.0052)	0.7508(.0056)	0.5848(.0054)
26	0.9255(.0055)	1.3233(.0100)	1.2355(.0061)	1.0120(.0281)	56	0.5063(.0069)	0.9381(.0106)	0.9127(.0080)	0.3834(.0700)
27	0.4035(.0072)	0.9920(.0161)	0.6796(.0080)	0.6542(.0297)	57	0.1237(.0044)	0.7510(.0052)	0.3154(.0058)	0.0773(.0062)
28	0.7126(.0051)	1.2086(.0107)	1.0098(.0057)	0.5998(.0350)	58	0.0178(.0053)	0.5074(.0066)	0.4834(.0079)	0.0390(.0092)
29	0.8199(.0054)	1.2159(.0120)	1.1264(.0060)	0.8285(.0257)	59	0.4233(.0052)	0.9674(.0062)	0.7540(.0076)	0.5233(.0276)
30	0.7551(.0094)	1.2569(.0170)	1.0706(.0108)	0.6067(.0542)	60	0.5987(.0043)	1.0410(.0054)	0.8793(.0054)	0.8738(.0057)

Note : 1. Industry numbers follow A.2. Standard errors are in the parenthesis.
2. Industry wage premium and industry - low occupation wage premium of Industry 52 are omitted.
3. Average is the industry wage premium estimated from equation (4.1) and High, Middle, Low are the industry - occupation wage premium estimated from equation (4.4). We normalize the industry wage premium.