Interindustry Wage Differentials, Technology Adoption, and Job Polarization[*‡]

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Abstract

This paper explores the relationship between job polarization and interindustry wage differentials. Using the U.S. Census and EU KLEMS data, we find that the progress of job polarization between 1980 and 2009 was more evident in industries that initially paid a high wage premium to workers than in industries that did not. With a two-sector neoclassical growth model to highlight the key mechanism, we argue that this phenomenon can be explained as a dynamic response of firms to interindustry wage differentials: firms with a high wage premium seek alternative ways to cut production costs by replacing workers who perform routine tasks with Information, Communication, and Technology (ICT) capital. The replacement of routine workers with ICT capital has become more pronounced as the price of ICT capital has fallen over the past 30 years. As a result, firms that are constrained to pay a relatively high wage premium have experienced slower growth of employment

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of routine workers than firms in low-wage industries, which led to heterogeneity in job polarization across industries.

JEL classification: E24, J24, J31, O33, O41

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1 Introduction

The structure of the labor market in the U.S. has changed dramatically over the past 30 years. One of the most prevalent aspects of the change is job polarization: employment has become increasingly concentrated at the tails of the skill distribution, while there has been a decrease in employment in the middle of the distribution. This hollowing out of the middle has been linked to the disappearance of jobs that are focused on routine tasks that can be easily replaced by machines.[1] In the U.S., routine occupations accounted for around 60 percent of total employment in 1981, while this share fell to 44 percent in 2010.[2]

While many previous studies have examined job polarization at the 'aggregate' level (see Goos, Manning, and Salomons (2009), Acemoglu and Autor (2011), Cortes (2014), and Jaimovich and Siu (2013)), the extent of job polarization differs across industries (see Autor, Levy, and Murnane (2003), Goos, Manning, and Salomons (2013), and Michaels, Natraj, and Reenen (2013)). Figure 1.1 shows changes in employment share by industry between 1980 and 2009. This figure demonstrates that job polarization is more pronounced in some industries than others. For instance, the decrease in the employment share of routine occupations is large in manufacturing, communication, and business related services, while the decrease is much smaller in transportation and retail trade.

This paper, contrary to other studies that focus on heterogeneity in production functions across industries (Autor, Levy, and Murnane (2003), for instance), provides a new perspective to understand heterogeneity in job polarization. We argue that 'interindustry wage differentials', the phenomenon that observationally equivalent workers earn differently when employed in different industries, are a key source of heterogenous job polarization across industries. Figure 1.2 shows the close relationship between job polarization and industry wage premium; industries with a higher wage premium in 1980 experienced large declines in the share of routine workers between 1980 and 2009. i.e. job polarization was more evident in the high-wage industries.

[1] As emphasized by Autor (2010), Goos, Manning, and Salomons (2009), and Michaels, Natraj, and Reenen (2013), job polarization is not restricted to the U.S.; several European countries have experienced job polarization as well.

[2] Numbers are calculated from the March Current Population Survey.

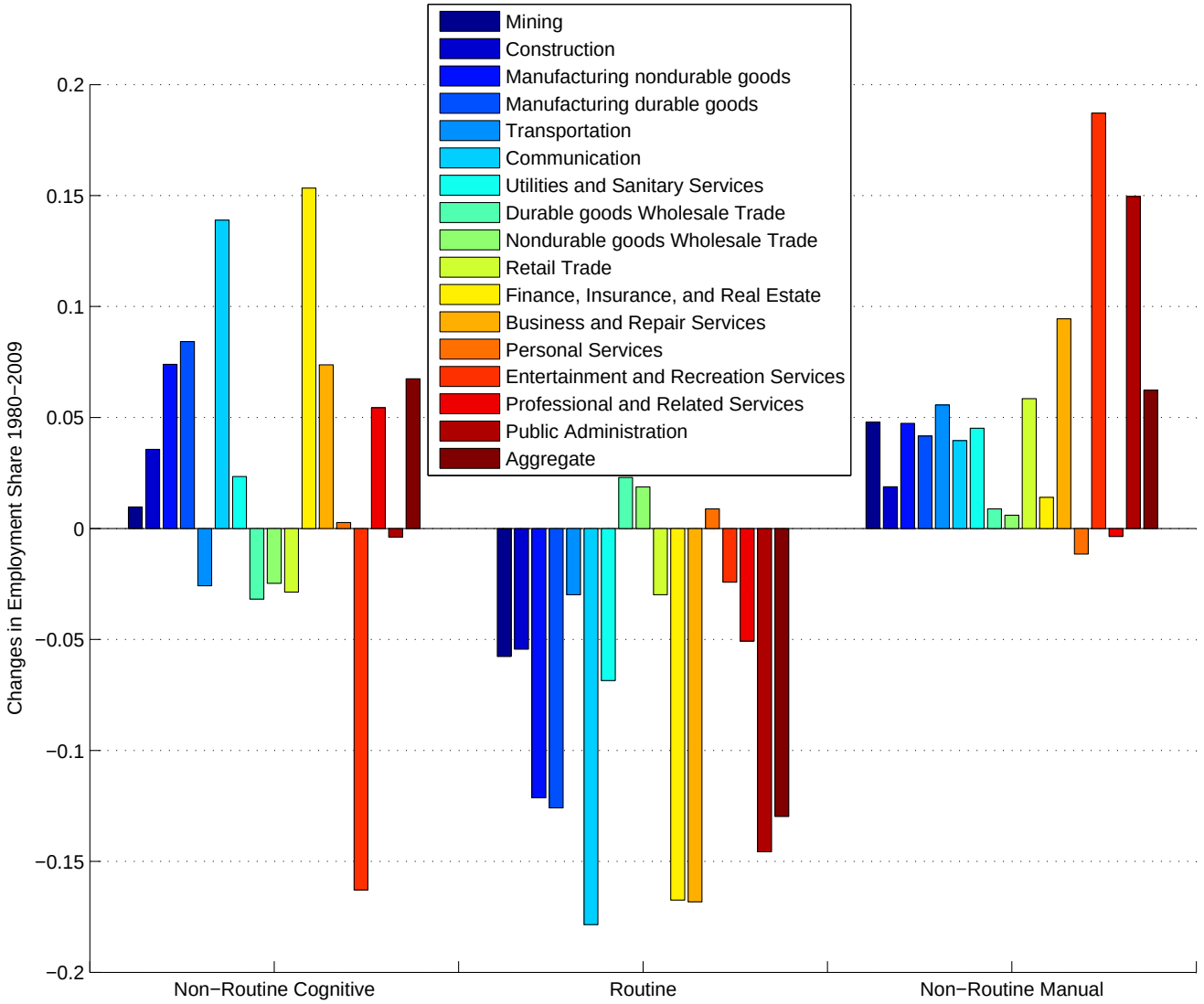

Figure 1.1: Changes in Employment Share by Industry between 1980 and 2009

Note: The horizontal axis denotes three occupational groups (each occupational group includes 16 industries and one aggregate variable) and the vertical axis denotes the change in employment share of a specific occupational group in each industry between 1980 and 2009.
Source: The U.S. Census.

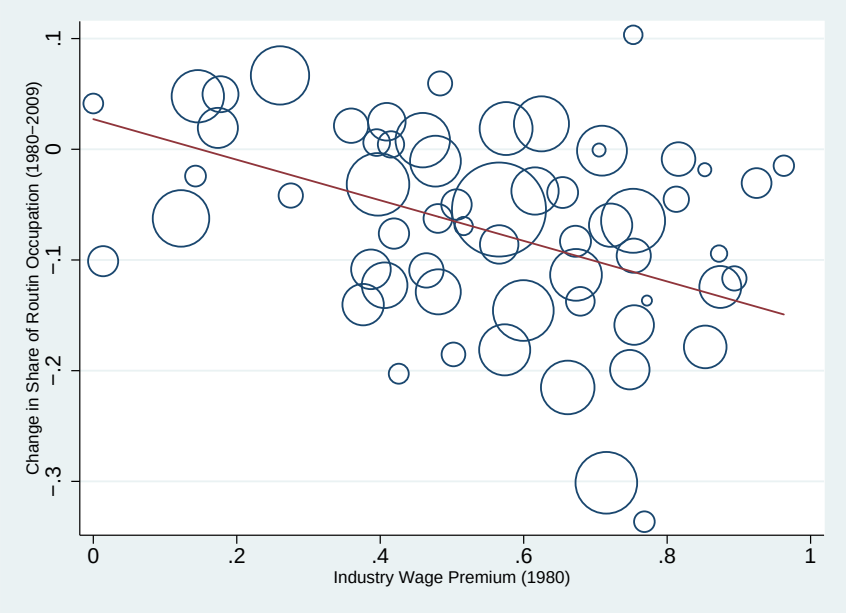

Figure 1.2: Job Polarization and Interindustry Wage Differentials
Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The U.S. Census and American Community Survey (ACS).

In order to understand the relationship between job polarization and interindustry wage differentials, we develop a two-sector neoclassical growth model and then solve the model analytically. As usually assumed in the job polarization literature, firms can use Information, Communication, and Technology (ICT, henceforth) capital, which is assumed to be a relative substitute for workers who perform routine tasks (routine workers) and a relative complement to workers who perform non-routine tasks (non-routine workers). The main predictions from our model are as follows. Firstly, job polarization is more evident in the high-wage industries. In our model, the relative wage structure across industries is assumed to be 'rigid' because of some industry specific factors.[3] Hence, some firms pay higher wages than other firms for observationally identical workers. As a result, firms with a high wage premium seek alternative methods to cut production cost instead of changing wages: they replace labor with other production factors, such as capital. When a firm changes its labor demand, however, the effect is not even across different workers: tasks performed by routine workers are more easily codifiable or computerized, and hence

[3]In the appendix, we derive the rigid interindustry wage structure as an equilibrium outcome, which does not change the predictions of the model.

they are more affected by a firm's dynamic decision to replace labor with capital.[4] As the price of capital becomes lower due to investment-specific technological changes, high-wage firms rent more capital than low-wage firms because they are more willing to cut high production costs. As a consequence, high-wage firms reduce relative demand for routine workers more, resulting in different degrees of job polarization across industries. Second prediction of our model, which is consistent with the first prediction, is that the growth rate of capital per routine worker is higher in the high-wage industries, since firms in such industries have more incentives to replace routine workers with capital.

We then test these predictions using U.S. Census and EU KLEMS[5] data. Several findings emerge from the empirical analysis. Firstly, we find that the average growth rate of routine employment between 1980 and 2009 decreased by 0.42 percent when the initial industry wage premium in 1980 rose by 10 percent, which is strictly greater than the estimates for non-routine occupations in absolute terms. In other words, job polarization was more apparent in the high-wage industries. We also confirm that ICT capital per worker grew more rapidly in high-wage industries; as the initial industry wage premium increased by 10 percent, the annualized growth rate of ICT capital per worker between 1980 and 2007 increased by 0.35 percent. We further find that the estimate for non-ICT capital per worker is much lower than the estimate for ICT capital per worker. This is consistent with non-ICT capital being a complement to all types of workers.

This study contributes to the existing literature on job polarization by aiding understanding of heterogeneity in job polarization across industries and its mechanism. This paper provides the first evidence that polarized employment is connected with interindustry wage differentials using a simple two-sector model and an empirical analysis of the theoretical predictions.

The paper is organized as follows. Section 2 introduces two key concepts, interindustry wage differentials and job polarization, and then explains the link between them, with reviews of related papers. We then propose a two-sector model with its predictions in Section 3, which formalizes the story suggested in Section 2. Section 4 describes the data, while Section 5 presents

[4]Offshoring is another possibility, as Goos, Manning, and Salomons (2013) and Oldenski (2012) show.
[5]KLEMS stands for capital (K), labor (L), energy (E), materials (M), and service inputs (S).

empirical tests of the model's predictions. Section 6 concludes.

2 Link between Job Polarization and Interindustry Wage Differentials

In this section, we introduce interindustry wage differentials and job polarization in detail, with reviews of related studies, and explain the link between them.

2.1 Interindustry Wage Differentials

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 so puzzling from the perspective of competitive labor market equilibrium theory, it is useful to consider two workers with the same observable socio-economic characteristics (including education, age, race, occupation, region, and sex), but who work in different industries. Then, wages should be (at least in the long run) the same between the two workers in equilibrium. If wages differ, a worker in a low-wage industry will attempt to find a job in a high-wage industry; in equilibrium, this increases (resp. decreases) labor supply to high- (resp. low-) wage industries, and hence wages will be equalized in a competitive labor market. This notion, however, of a competitive labor market is not supported by the data; for instance, a worker employed in the petroleum-refining industry earned about 40 percent more than a worker employed in the leather-tanning and finishing industry in 1984 after controlling for all observables (Krueger and Summers (1988)). On top of that, the wage dispersion is not a transitory perturbation from the competitive equilibrium. To demonstrate this, we compute the industry wage premia in 1980 and 2009 separately with a typical wage equation, which regresses log wage over various socio-economic characteristics and industry fixed effects, and draw a scatter plot of the two sets of industry fixed effects in Figure 2.1. It then becomes apparent that industries that paid relatively high wages in 1980 also paid high wages in 2009, which implies that the structure of interindustry wage differentials is highly persistent. We also find, as Dickens and Katz (1987) show, that an

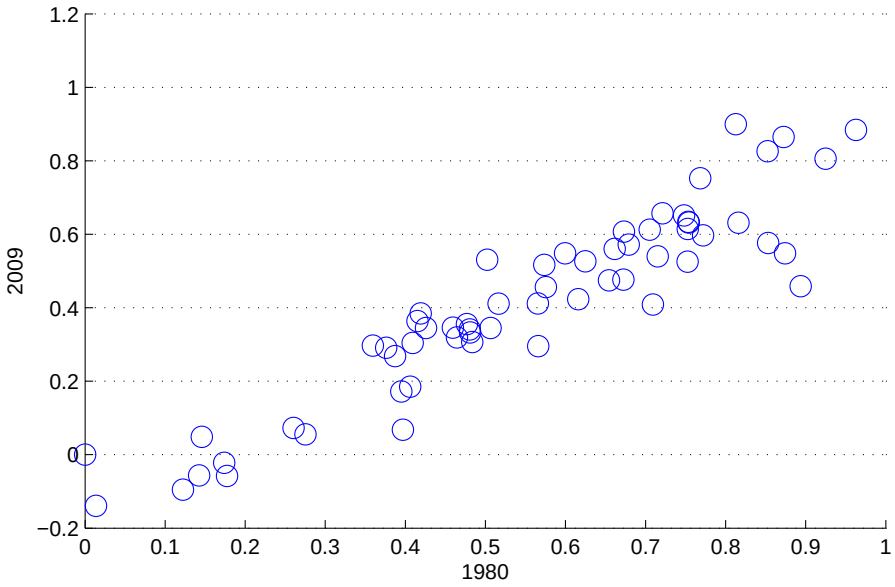

Figure 2.1: Persistency of Interindustry Wage Differentials: Comparison between 1980 and 2009
Source: The U.S. Census and American Community Survey (ACS).

industry variable has been a consistently important factor in explaining wage differentials.[6]

Since the focus of our paper is to study the 'consequences' of interindustry wage differentials, we simply point out that both our model and empirical results are based on non-competitive labor market theories of industry wage premia, not on the competitive labor market theory.[7] While there have been many studies focusing on the causes of interindustry wage differentials, to our knowledge, there exists only one paper, Borjas and Ramey (2000), which studies their consequences. Borjas and Ramey (2000) find that industries that paid relatively high wages

[6]We run the wage regression (5.1) for different periods (1980, 1990, 2000, and 2009) and compute the explanatory power of the wage equation with and without industry dummies, following Dickens and Katz (1987). Results are reported in Table B.4. In particular, 4 percent to 16 percent of the wage variation is explained by industry. The sum of the explanatory power reported in the second and third row is not equal to the value reported in the first row since industries and covariates are not exactly orthogonal (Dickens and Katz (1987)). Interestingly, the explanatory power attributable to the industry is very stable and substantial over time, which implies that industry should be considered as an important factor in explaining wages.

[7]For example, 'unobserved ability of workers' (Murphy and Topel (1987)) is consistent with the competitive equilibrium theory. Krueger and Summers (1988), Borjas and Ramey (2000), and Blackburn and Neumark (1992), however, 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, we focus on non-competitive models. These theories include the rent-sharing model (Nickell and Wadhwani (1990), Borjas and Ramey (2000) and Montgomery (1991)) and the efficiency wage model (Walsh (1999) and Alexopoulos (2006)).

to workers in 1960 experienced (1) lower employment growth, and (2) a higher capital-labor ratio growth and higher labor productivity growth between 1960 and 1990. Our findings on the heterogenous effects of firms' dynamic responses to interindustry wage differentials distinguish our paper from that of Borjas and Ramey (2000); while they focus on the 'average' effect of interindustry wage differentials on workers, our findings emphasize the importance of considering heterogenity across different workers (occupations) in studies of the labor market.

2.2 Job Polarization To be consistent with the job polarization literature, including Autor (2010), Acemoglu and Autor (2011), and Cortes (2014), we classify occupations into three groups as follows:

- Non-routine cognitive occupations: Managers, Professionals, and Technicians.
- Routine occupations: Sales, 'Office and administration', 'Production, crafts, and repair' and 'Operators, fabricators, and laborers'.
- Non-routine manual occupations: Protective services, 'Food preparation, building and grounds cleaning', and 'Personal care and personal services'.

Using the March Current Population Study (CPS) between 1971 and 2010,[8][9] we plot Figure 2.2 to show job polarization graphically: while the employment share of non-routine cognitive (henceforth cognitive) and non-routine manual (henceforth manual) occupations have grown over time, that of routine occupations has decreased.

One intuitive reason behind job polarization, which is also important to understand our findings, is that the skill (task) content of each occupation is different. Among the three groups, routine occupations are the easiest to replace by ICT capital, as demonstrated by Autor, Levy, and Murnane (2003); the tasks that workers with routine occupations perform are easier to codify than other tasks because the tasks have routine procedures. Meanwhile, cognitive and manual

[8]Data were extracted from the IPUMS website: http://cps.ipums.org/cps (see King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick (2010)).

[9]We apply the method of 'conversion factors' to obtain consistent aggregate employment series. See Shim and Yang (2013) for detailed discussion on the method of conversion factors.

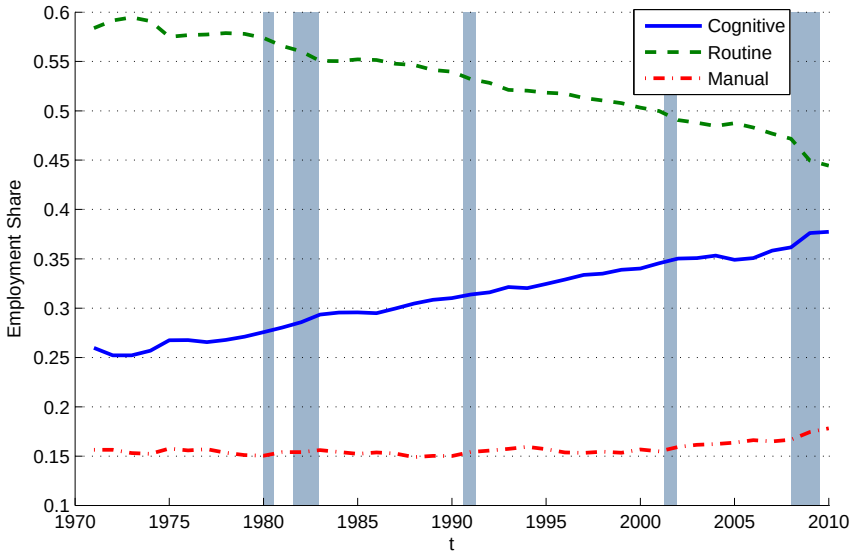

Figure 2.2: Job Polarization
Note: The shaded regions are the official NBER recession dates.
Source: The March CPS.

occupations are not easily replaced by ICT capital. For instance, business decisions of managers (cognitive occupations) cannot be replaced by technology; introduction of technology, such as advanced software, does not substitute for these managers, rather it is a complement to their tasks. In addition, people involved in cooking, or cleaning buildings (manual occupations) cannot be directly replaced by machines; these jobs require humans to do non-routine manual tasks. Instead, a great portion of the tasks that a bank clerk performs, which are included in routine occupations, are easily replaced by an ATM; deposits and withdrawals are routine tasks, and machines can perform these tasks more efficiently than humans. Hence, these jobs disappear over time as the economy experiences rapid technological progress in ICT-type capital.[10] Consistent with this story, Figure 2.3 shows that investment-specific technological changes have mainly occurred for ICT capital rather than for other types of capital so that the relative price of ICT capital has declined more rapidly since 1970.[11]

[10] As we mentioned earlier, 'offshorability' is also higher for routine occupations than for cognitive and manual occupations. Most of the service jobs (manual occupations) are not tradable and occupations that require non-routine cognitive tasks are not easily offshored while factories can be relatively easily relocated to foreign countries.

[11] The timing that the growth rate of investment-specific technological changes increases does not perfectly match the occurrence of job polarization, which is usually said to be after 1980. Consistently with this timing

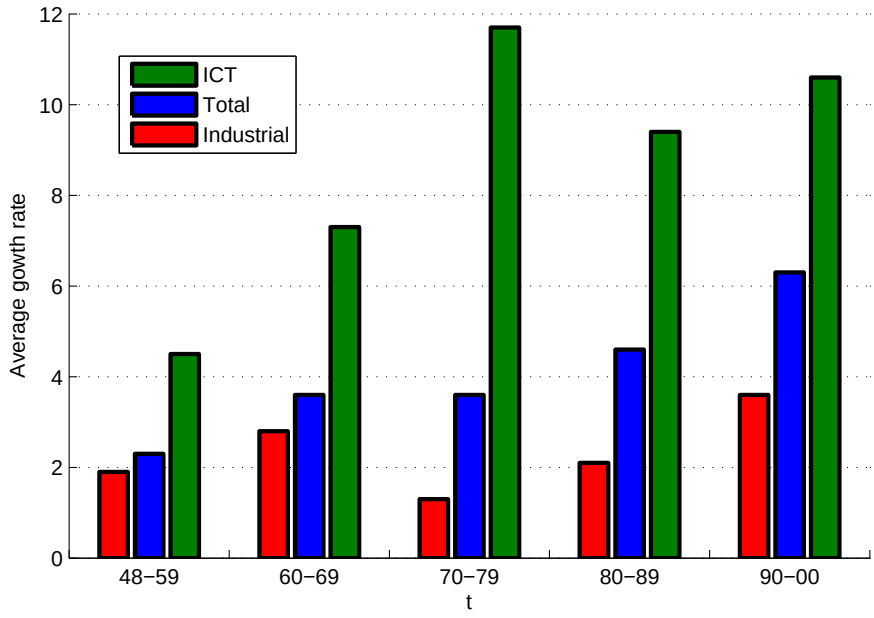

Figure 2.3: Growth Rate of Investment-Specific Technological Changes
Source: Data from Cummins and Violante (2002).

A few papers have studied the possibility of heterogenous job polarization across industries.[12] Acemoglu and Autor (2011) argue that changes in industrial composition do not play an important role in job polarization. Jaimovich and Siu (2013) and Foote and Ryan (2012) note that job polarization may be more pronounced in the construction and manufacturing industries. While Autor, Levy, and Murnane (2003) and Goos, Manning, and Salomons (2013) also consider possible differences in job polarization across industries, they do not consider wage differentials as the source of heterogeneity. Rather, they assume different production functions across industries. Michaels, Natraj, and Reenen (2013) is also relevant to our study: they show that industries with a high growth rate of ICT capital exhibit more pronounced job polarization in terms of the shifting of wage bills from middle-educated workers to highly-educated workers. Our paper, however, differs from that of Michaels, Natraj, and Reenen (2013) in two ways. Firstly, they consider different education groups while we instead consider different occupation groups. This

problem, we show in Section 5.3 that job polarization also occurred, while the magnitude was small, before 1980.

[12]Some recent papers, including Mazzolari and Ragusa (2013), Autor, Dorn, and Hanson (2013a) and Autor, Dorn, and Hanson (2013b), analyze job polarization at the local labor market level.

distinction makes a difference in the subsequent analysis since 'employment' polarization is not observed when we use educational attainment to classify workers.[13] Secondly, while Michaels, Natraj, and Reenen (2013) found a positive relationship between the growth rate of ICT capital and the degree of job polarization, they do not link them to interindustry wage differentials.

2.3 Job Polarization and Interindustry Wage Differentials: Link Our key contribution is to understand the role of interindustry wage differentials and the different 'task content' of occupations. Cost of labor is the product of wage and employment, and it is not possible for high-wage firms to reduce the wage gap with low-wage firms because of the rigid wage structure by which they are constrained. As a consequence, the only way to respond to a high labor cost is to adjust employment over time and this can be achieved by hiring alternative production factors, as Borjas and Ramey (2000) found.

In particular, as technology improves, the price of ICT capital becomes lower, and firms with incentives to adjust employment will decrease relative demand for routine workers by replacing them with ICT capital. As a result, firms in a high-wage industry will experience more evident job polarization as the demand for routine workers declines more in these firms. In addition, the ICT capital-labor ratio rises by a greater amount than in a low-wage industry since more ICT capital is introduced to substitute for routine workers.

In summary, our hypothesis on the different degrees of job polarization across industries is as follows. Since firms cannot adjust wages relative to those paid by other firms as they would wish to do, they dynamically substitute labor with capital. In particular, routine occupations will decrease more intensively because they can be replaced easily by ICT capital, which results in heterogenous job polarization across industries. We formalize this hypothesis in Section 3, and test it with the data in Section 5.[14]

[13] In Figure B.1, we plot the employment series by each educational group, following Michaels, Natraj, and Reenen (2013).

[14] In the sense that different market environments make firms behave differently across industries, our paper is close to Alder, Lagakos, and Ohanian (2013). Contrary to our paper, however, Alder, Lagakos, and Ohanian (2013) do not consider initial wage differentials as the source of the differences. Rather, the difference they take into account is a lack of competition in labor and output markets. Furthermore, they do not examine possible heterogenous effects of labor market changes due to firms' dynamic decisions on different types of workers. Acemoglu and Shimer (2000) is also relevant to our paper; they show with a searching model how *ex-ante*

3 Model

In this section, we present a two-sector neoclassical growth model and analyze properties of the steady-state equilibrium. While our model is highly stylized, it provides clear predictions that are testable with data.

We first sketch the structure of the economy. In order to capture features of job polarization, we assume that there are two types of tasks, where the first type is the 'non-routine' task (workers who perform non-routine tasks will be called non-routine workers) and the second type is the 'routine' task (routine workers).[15] As is usually assumed in the job polarization literature,[16] capital is a relative substitute for workers who perform routine tasks, while it is a relative complement to workers who perform non-routine tasks. In this sense, capital considered in our model can be interpreted as ICT capital. In order to generate interindustry wage differentials, we assume that industry 1 pays higher wages, by some exogenous factors, than industry 2.[17] This assumption, which is the key in our model, is innocuous for our purpose as long as the rigid wage structure across industries originates from non-competitive theories.[18]

We then provide comparative statics of the steady-state equilibrium by changing the parameter that governs the relative price of capital. We show that while both industries experience job polarization, the share of non-routine over routine workers, which measures the degree of job polarization in our model, increases more in the high-wage industry when the relative price of capital declines. We also show that the heterogeneity in the degree of job polarization across

equivalent firms optimally choose different technologies and wages. While the underlying idea is similar, they also do not consider that the strategy of the firm can affect different workers disproportionately.

[15] One might further decompose non-routine workers into cognitive and manual workers; given, however, that these workers have similar roles in the production function (both workers are relative complements to capital) and their behavior is almost the same (the wage and employment relative to routine-workers increase for both workers over time), we choose to use only two types of workers in the model for simplicity of discussion. This is also the same strategy used by Beaudry, Green, and Sand (2013) and Jaimovich and Siu (2013).

[16] See Autor, Levy, and Murnane (2003), Autor and Dorn (2013), and Cortes (2014), for instance.

[17] For instance, in Appendix A.1, we consider labor unions as the source of interindustry wage differentials.

[18] For example, one might argue that the 'initial' interindustry wage differentials arise from high capital-labor ratio in some industries due to industrial characteristics, which is in line with competitive theories. However, this theory does not coincide with data as is documented in Section 5 and Borjas and Ramey (2000); over the last several decades, the capital-labor ratio has risen more in high-wage industries. This implies that wage differentials should have been widened, which is not supported by data.

industries increases in the industry wage premium. In addition, the capital-routine worker ratio rises more in the high-wage industry when the relative price of capital decreases.

3.1 Setup

3.1.1 Household We consider an environment in which a representative household consists of identical workers, whose total hours supplied to the labor market are denoted by n_t.[19]

There is an infinitely lived representative household in the economy that solves the following deterministic maximization problem:

$$\max_{\{c_t,k_{t+1},x_t,n_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \left[\log c_t + \theta(\bar{n} - n_t)\right] \tag{3.1}$$

subject to

$$(1)\ c_t + x_t = w_t n_t + r_t k_t + \pi_t$$
$$(2)\ k_{t+1} = (1-\delta)k_t + q_t x_t$$

where $\theta > 0$ is a constant, $k_0 > 0$ is given, $\bar{n} > 0$ is total hours with which a household is endowed, and π_t is a lump-sum transfer from the labor broker that is described below.

The period t income can be used to purchase consumption goods, c_t, or used to generate investment goods, x_t, with the technology q_t. Hence, higher q_t means that the technology to generate investment goods improves; more investment goods can be generated with the same income and consumption. We sometimes refer to $1/q_t$ as the relative price of capital. We normalize the price of the final good to 1. In addition, r_t and $\delta \in [0,1]$ are the rental cost and the depreciation rate of capital, respectively. In addition, equation (2) is the law of motion for capital that a household owns and rents to firms. The household supplies labor at wage rate w_t. Detailed discussions on wage rates are provided in the next section.[20]

[19] The assumption on the representative household is made in order to avoid the distributional issue that arises from different wage rates across industries and types of workers.

[20] We assume that the utility is linear in hours worked in order to make clear predictions and to avoid the problem that the labor market may not clear when labor supply is inelastic under the existence of the industry wage premium.

The key optimality condition for the household problem is given as follows:[21]

$$\frac{c_{t+1}}{c_t} = \beta \left[q_t r_{t+1} + (1-\delta)\frac{q_t}{q_{t+1}} \right] \tag{3.2}$$

We focus on comparative statics in the steady state, and therefore we set $c_t = c_{t+1}$ and $q_t = q_{t+1}$ and obtain a relationship between r and q as follows.

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{q} \tag{3.3}$$

The rental cost of capital (r) is strictly decreasing in q; that is, the steady state level of capital can be sustained with less investment when the technology, q, is more efficient. Hence, less demand for capital lowers the rental rate of capital.

3.1.2 Labor Market The labor market is assumed to be intermediated by a labor broker that receives hours worked from the household and allocates them across industries 1 and 2 and routine and non-routine occupations.[22] Let h_{it} (resp. $\tilde{h}_{it}$) be the hours of non-routine (resp. routine) workers supplied to industry i. We further define w_{it} (resp. $\tilde{w}_{it}$) to be the wage rate of non-routine (resp. routine) workers employed industry i.

To capture the industry wage differentials observed in the data, we assume that the wage in industry 1 is higher than that of industry 2 by a factor $\lambda > 0$[23] so that

[21] There is another optimality condition for labor supply, $w_t = \theta c_t$, which we abstract from here since it is not relevant for our analysis.

[22] Or equivalently, one can assume rationing in the labor market so that only some fractions of workers can be employed in the high-wage industry. Households then collect total labor income as a sum of labor income from all workers, as discussed in Alder, Lagakos, and Ohanian (2013). All of these features are to obtain equilibrium in which all firms employ positive hours.

[23] Since we are more interested in the consequences of the industry wage premium, in this paper, we do not analyze the source of these differentials. Instead, our model postulates that firms in some sectors face a higher 'wage markup' by some exogenous factors. We take the stance that the source of interindustry wage differentials does not come from unobserved heterogeneity across workers; we assume *ex-ante* identical workers. There are several ways to introduce the industry wage premia. For instance, one might consider the efficiency wage model as in Alexopoulos (2006), by assuming that the detection rate of shirking is heterogenous across industries; the value of matching is different across industries, as in Montgomery (1991). Instead, we can also assume that there is a labor union in industry 1 but not in industry 2, which is discussed in Appendix A.1. In the appendix, we assume that there is a labor union in each industry and a firm in the particular industry can hire workers only through the labor union of the industry where the monopoly power of labor unions are heterogenous across industries. Then, the above equation (3.4) can be derived as an equilibrium condition.

Therefore, we can interpret the labor market environment used in our model as a parsimonious way to generate

$$w_{1t} = (1+\lambda)w_{2t} \text{ and } \tilde{w}_{1t} = (1+\lambda)\tilde{w}_{2t} \tag{3.4}$$

As non-routine occupations[24] require more complex skills of a worker, the broker sets the following wage rule to compensate the skill differences across occupations:[25]

$$w_{it} = \chi \tilde{w}_{it} \tag{3.5}$$

where $\chi > 1$ measures the compensation to the occupations that require relatively complex skills.

The broker compensates the hours supplied by the household at the lowest wage in the market that corresponds to the wage of a routine worker in industry 2.[26] It then allocates the hours according to the demand of firms in the two industries given the assumed wage differentials and wage rule. The additional wage income received by the broker on the hours supplied to industry 1 is rebated to the household as a lump-sum transfer:

$$\pi_t = \tilde{w}_{2t}(\lambda\chi h_{1t} + \chi h_{2t} + \lambda\tilde{h}_{1t}) \tag{3.6}$$

3.1.3 Final Goods-Producing Firms The final good, which can be either consumed or used to purchase investment at the price $1/q_t$, is assumed to be produced by a firm that utilizes two intermediate goods. The problem of this firm, which operates in a perfectly competitive market, is given by:

$$\max_{y_{1t}, y_{2t}} y_t - p_{1t}y_{1t} - p_{2t}y_{2t} \tag{3.7}$$

subject to the CES aggregator

$$y_t = \left[y_{1t}^{1-\nu} + y_{2t}^{1-\nu}\right]^{\frac{1}{1-\nu}}$$

wage differentials across industries and λ captures the heterogeneity across industries.

[24] Here, we focus on cognitive occupations.

[25] Or equivalently, we can assume that there are two types of workers that constitute a household and leisure is linear in both types of workers, which yields identical results.

[26] One can set a different wage rule without changing equilibrium properties; for example, $w_t = w_{1t}$ is also possible but then the household should pay back the remaining labor income to the broker.

where $\nu \in [0, 1)$. Hence, the elasticity of demand for each intermediate good is $\frac{1}{\nu}$.

The demand for intermediate goods in industries 1 and 2 is then given by

$$p_{it} = \left(\frac{y_t}{y_{it}}\right)^{\nu} \tag{3.8}$$

which is the usual form of the inverse demand function for each intermediate good.[27]

3.1.4 Intermediate Goods-Producing Firms We assume that the intermediate goods market is perfectly competitive so that a firm's profit will be zero in equilibrium. Each firm produces an output by utilizing two types of workers and capital. A firm in industry i solves the following static profit maximization problem:

$$\max_{\{k_{it}, h_{it}, \tilde{h}_{it}\}} p_{it} y_{it} - w_{it} h_{it} - \tilde{w}_{it} \tilde{h}_{it} - r_t k_{it} \tag{3.9}$$

subject to

$$y_{it} = h_{it}^{\alpha} \left(\tilde{h}_{it}^{\mu} + k_{it}^{\mu}\right)^{\frac{1-\alpha}{\mu}}$$

where $\mu \in (0, 1)$, $\alpha \in (0, 1)$.

Following Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006), and Autor and Dorn (2013), we assume a CES production function. Notice that the elasticity of substitution between non-routine workers and total routine task input is 1, while the elasticity of substitution between a routine worker and capital is $\frac{1}{1-\mu} > 1$, since $\mu > 0$. Thus, as Autor and Dorn (2013) point out, capital is a *relative substitute* for workers who perform routine tasks and is a *relative complement* to workers who perform non-routine tasks. Hence, capital in our model is ICT capital. Notice that if $\mu = 1$, each input that performs a routine task is a perfect substitute for each other. Once the output, y_{it}, is produced, it is sold to the final goods-producing firm at p_{it}.

Optimality conditions for the firm's optimization problem are given as follows:

[27] One can show easily that the zero-profit condition holds under the above first-order condition (3.8).

$$\frac{w_{it}}{p_{it}} = \alpha \frac{y_{it}}{h_{it}} \tag{3.10}$$

$$\frac{\tilde{w}_{it}}{p_{it}} = (1-\alpha)\frac{\tilde{h}_{it}^{\mu}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu}} \frac{y_{it}}{\tilde{h}_{it}} \tag{3.11}$$

$$\frac{r_t}{p_{it}} = (1-\alpha)\frac{k_{it}^{\mu}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu}} \frac{y_{it}}{k_{it}} \tag{3.12}$$

Each equation shows that the remuneration of factors takes the form of shares, which is the property from the CRS production function. In particular, the first (resp. second) equation means that the real wage that a worker performing non-routine (resp. routine) tasks receives should be equal to the marginal product of the worker. The last equation, similarly, means that the real rental cost of capital should be equal to the marginal product of capital. As usual, demand for each input is a decreasing function of the factor price. In order to understand the role of changes in the price of capital, we divide equation (3.11) by (3.12):

$$\frac{\tilde{w}_{it}}{r_t} = \left(\frac{k_{it}}{\tilde{h}_{it}}\right)^{1-\mu} \tag{3.13}$$

This equation implies that capital per routine worker increases as the rental cost decreases because capital is a relative substitute for routine workers, and firms will replace routine workers with capital as the relative cost of utilizing capital becomes lower. In order to gain an intuition into how q is related to this property, we use the steady-state property that r and q are inversely related, as discussed earlier. An increase in q means that less investment is enough to maintain the steady-state capital level, so that demand for capital would be lower, which results in a lower rental cost of capital.

One can further check that capital per routine worker is always higher in a high-wage industry, which arises from the fact that high-wage firms can lower production costs by employing more capital than low-wage firms. Notice that this equilibrium property is consistent with empirical facts reported by Dickens and Katz (1987) and theoretical predictions provided by Alexopoulos

(2006) and Acemoglu and Shimer (2000).

3.1.5 Competitive Equilibrium A competitive equilibrium of this economy consists of quantities[28] $\{c_t, k_{it}, h_{it}, \tilde{h}_{it}, k_{it+1}, y_{it}, n_t\}_{t=0}^{\infty}$ and prices $\{p_{it}, r_t, w_{it}\}_{t=0}^{\infty}$ for $i \in \{1, 2\}$ such that, given prices, (1) a household chooses an optimal allocation plan $\{c_t, k_{t+1}, n_t\}_{t=0}^{\infty}$ that solves the utility maximization problem (3.1), (2) an intermediate firm optimally chooses a factor demand schedule $\left\{k_{it}, h_{it}, \tilde{h}_{it}\right\}_{t=0}^{\infty}$ that maximizes the firm's profit (3.9), (3) a final goods-producing firm chooses optimal demand for each intermediate good to satisfy equation (3.8), and (4) all markets clear:

$$k_{t+1} = q_t(y_t - c_t) + (1 - \delta)\, k_t \tag{3.14}$$

$$h_{1t} + h_{2t} + \tilde{h}_{1t} + \tilde{h}_{2t} = n_t \tag{3.15}$$

$$k_{1t} + k_{2t} = k_t \tag{3.16}$$

We list the whole equilibrium conditions in Appendix A.2.1.

3.2 Predictions of the Model: Steady-State Analysis In this section, we provide predictions of the model by studying the comparative statics of steady state equilibrium in which $q_t = q_{t+1}$ over time. In order to obtain analytical tractability that provides clear predictions of the model, we assume $\nu = 0$; i.e., intermediate goods are perfect substitutes, and hence $p_{1t} = p_{2t} = 1$. In Appendix A.2.2, we provide equilibrium conditions for the steady state when values of parameters are not specified.

Since we are interested in how the changes in the price of capital due to investment-specific technological changes affect the two industries differently, we conduct the comparative statics exercise by analyzing the behavior of the steady-state economy when there is a change in q. While we only consider two industries, the analysis can be extended easily to $n > 2$ industries.

The next proposition is the collection of predictions of the model when q rises. This is

[28] We implicitly reduce the number of variables here, such as output and investment.

introduced to capture the fact that the relative price of (ICT) capital has declined over time; one can think of the steady-state economy as the U.S economy in the beginning of 1980, and then there was a rise in q so that the new steady state is the U.S. economy in 2010. We first define s_i as follows.

$$s_i = \frac{h_i}{\tilde{h}_i} \tag{3.17}$$

This term measures the usage of non-routine workers relative to routine workers. Then, job polarization in our model indicates the situation in which s_i increases. Next, we define κ_i as follows:

$$\kappa_i = \frac{k_i}{\tilde{h}_i} \tag{3.18}$$

Hence, κ is the capital-routine worker ratio.

Proposition 1 (Job Polarization: Connection to Interindustry Wage Differentials)**.** *The following results hold in the steady state:*

1. *The capital-routine worker ratio increases in both industries when the price of capital declines, while it rises more in the high-wage industry. In addition, the difference between industries increases in the wage premium (λ) and substitutability between capital and routine workers (μ). Formally,*

$$\frac{d\kappa_1}{dq} = (1+\lambda)^{\frac{1}{1-\mu}} \frac{d\kappa_2}{dq} > 0 \tag{3.19}$$

2. *Job polarization happens in both industries when the price of capital declines. Formally,*

$$\frac{ds_i}{dq} = \frac{\alpha}{\chi(1-\alpha)} \frac{d\kappa_i^{\mu}}{dq} > 0 \tag{3.20}$$

3. *The change in the employment share of non-routine over routine workers in industry* 1 *is greater than that in industry* 2 *when the price of capital declines; i.e., job polarization*

is more evident in the high-wage industry. In addition, the difference in the degree of job polarization across industries increases in the wage premium (λ) and substitutability between capital and routine workers (μ). Formally,

$$\frac{ds_1}{dq} = (1+\lambda)^{\frac{\mu}{1-\mu}} \frac{ds_2}{dq} \tag{3.21}$$

Proof. See Appendix A.3. □

First of all, it is a natural consequence of the model that firms try to use capital more than routine workers when the price of capital declines, because capital and routine workers are substitutes. One can show that capital per routine worker rises more as the substitutability, μ, rises. In addition, the first part of the proposition shows that firms that are constrained to pay a higher wage markup use capital more intensively in production, and hence the capital-routine worker ratio grows more in those firms. The difference across industries increases in λ; as the firm should pay more to workers, its incentive to utilize capital increases, which results in more rapid growth in the capital-routine worker ratio than in firms that can pay less to workers.

The second part of Proposition 1 shows that, consistent with previous models on job polarization, including Autor and Dorn (2013), Autor, Levy, and Murnane (2003), and Cortes (2014), a decline in the price of capital is one of the critical factors in job polarization. The last part of the proposition is another key prediction of our model: the non-routine share of hours (employment) grows more in the high-wage industry since new technology (utilizing capital) is adopted more aggressively by the firms that face high labor costs, as discussed in the first part of the proposition. Furthermore, the difference in the degree of job polarization across industries increases in λ, the parameter that governs the industry wage premium, which shows the importance of the industry wage premium in explaining heterogeneous aspects of job polarization across industries.

We finally note that the first and the last part of the proposition together provide a theoretical background to the findings by Michaels, Natraj, and Reenen (2013). They find that the degree of job polarization is positively correlated with the growth rate of ICT capital, but they do not provide a clear explanation as to why this relationship holds in the data. Our model shows

that it is interindustry wage differentials that systematically affect their finding; the high-wage industry substitutes routine workers with ICT capital more aggressively to cut production costs, and hence the progress of job polarization is more evident in this industry.

3.3 Tests of Predictions

In what follows, we empirically test the predictions from the model presented in Proposition 1. We first introduce two data sets to be used in the empirical analysis in Section 4. Then, in Section 5, we analyze if the predictions are consistent with the data.

In order to test the prediction that κ_i (capital-routine worker ratio) grows more in the high-wage industry when the price of capital declines, we instead consider ICT capital per worker because the EU KLEMS data do not include information about occupations of workers. This provides, however, the same information as the proposition in the following sense; the capital-(total) labor ratio is $k_i/(h_i + \tilde{h}_i)$ and this can be decomposed into two parts as $\kappa_i \cdot \frac{1}{s_i+1}$. In the model, the first term increases more but the second term decreases more in the high-wage industry when q increases. Hence, if we can observe a positive relationship between the growth of ICT capital per worker and the initial industry wage premium, it implies that κ_i grows more in the high-wage industry, which is consistent with the prediction of the model.

Furthermore, in the empirical analysis, we compute the growth rate of employment for each occupational group, and compare the coefficients of the regression over the initial wage premium when evaluating the main prediction of the model (the last part of Proposition 1), which basically conveys the same information as the proposition; if the growth rate is lower in routine occupations than in non-routine occupations, which is an alternative way of defining job polarization, s_i will increase as the price of ICT capital decreases.

4 Data

There are two main sources of data for this paper: (1) the decennial Census and American Community Survey (henceforth, ACS) data,[29] and (2) the EU KLEMS data. Following Borjas

[29]Data were extracted from the Integrated Public Use Microdata Series (henceforth, IPUMS) website: https://usa.ipums.org/usa (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010)).

and Ramey (2000) and Acemoglu and Autor (2011), we use the 1960, 1970, 1980, 1990, and 2000 Census and the 2006, 2007, and 2009 ACS. As Acemoglu and Autor (2011) note, the relatively large sample size of the Census data makes fine-grained analysis within detailed demographic groups possible.[30] We drop farmers (and related industries) and the armed forces. Age is restricted to 16 - 64 and we only consider persons employed in wage-and-salary sectors. Table B.1 in Appendix B describes the industry classification used in the analysis.

The second data set, EU KLEMS, has information on value added, labor, and capital for various industries in many developed countries, including the U.S.. The EU KLEMS is useful since it provides detailed information on capital: in the data, capital is divided into two parts, ICT capital and non-ICT capital, so we can analyze the roles of different types of capital in a firm's behavior. In particular, we use U.S. data between 1980 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 industries to be consistent between the Census and the EU KLEMS data. Table B.2 in Appendix B describes the industry classification for the EU KLEMS data used in the analysis.

In order to overcome the inconsistency problem of occupation codes due to the frequent changes in occupation coding in the CPS and to construct a consistent occupation series,[31] we use the 'occ1990dd classification system', following Dorn (2009).

5 Empirical Analysis

Two key predictions of the model to be tested in this section are as follows: When the relative price of capital $(1/q_t)$ declines,

1. Job polarization occurs in all industries but is more apparent in the industries that paid a relatively high wage premium to workers.

2. (ICT) capital per (routine) worker grows more in high-wage industries.

[30] 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.

[31] For detailed discussion on the inconsistency issue, see Dorn (2009) and Shim and Yang (2013).

As mentioned earlier, we test the second prediction of the model with ICT capital per worker instead of ICT capital per routine worker, which does not change the main concept of Proposition 1.

In order to test the model's predictions, we first estimate industry wage premia as follows.

$$\log w_{hit} = X_{hit}\beta_t + \omega_{it} + \varepsilon_{hit} \tag{5.1}$$

where w_{hit} is the wage rate of worker h in industry i in Census year t; X_{hit}, a vector of socio-economic characteristics, includes the worker's age (there are five age groups: 16-24, 25-34, 35-44, 45-54, or 55-64), educational attainment (there are five educational groups: less than nine years, nine to 11 years, 12 years, 13 to 15 years, or at least 16 years of schooling), race (indicating if the worker is African-American[32]), sex, and region of residence (indicating in which of the nine Census regions the worker lives). We also control for three occupation dummies (cognitive, routine, and manual occupation groups). ω_{it}, an industry fixed effect, measures the industry wage premia.

The result of equation (5.1) in 1980 is reported in Table B.3 and the coefficients are estimated to be consistent with the usual intuition: 1. African-Americans earn less, 2. wages are strictly increasing in education, and 3. wages also rise in ages until workers reach prime age, and then decrease slightly. After we obtain the estimated coefficients for 60 industry fixed effects from equation (5.1), $\hat{\omega}_{it}$, we estimate the second-stage regression as follows:

$$\Delta y_{ijt} = \theta_j \hat{\omega}_{it} + \eta_{ijt} \tag{5.2}$$

where y_{ijt} is the variable of interest such as employment of occupation group j in industry i.[33] Δy_{ijt} is the annualized (average) growth rate of y_{ijt} between period t and $t+k$, and $j \in \{cognitive, routine, manual\}$. The average growth rate is $\Delta y_{ijt} = \left(\log(y_{ij,t+k}) - \log(y_{ijt})\right)/k$. We estimate equation (5.2) separately for cognitive, routine, and manual occupations.

[32]Further classification is not possible in our data.
[33]In this case, $y_{ijt} = k_{it}/N_{it}$, since capital is not occupation-specific.

Note that we use the estimated value, $\hat{\omega}_{it}$, as a regressor in the second-stage regression, which raises a concern about the generated regressor problem. In particular, it is possible that the error term in equation (5.2) is heteroscedastic. In order to address this issue, we weigh the regression by the initial (i.e., 1980) employment of each industry. In addition, the large sample size of the Census data weakens the generated regressor problem - there are at least $1,000$ observations in each cell of occupation j in industry i in Census year t.[34] Furthermore, in order to address the potential endogeneity of the wage premium and to account for the generated regressor problem, we also use the previous decade's estimated industry wage premium as an instrumental variable (IV).

5.1 Job Polarization: Link to initial wage premium? In this section, we test the first prediction of the model: firms' dynamic responses to interindustry wage differentials have caused different degrees of job polarization across industries. Suppose that, contrary to our argument, there is no link between interindustry wage differentials and job polarization. Then, the coefficients on $\hat{\omega}_{it}$ estimated by equation (5.2) would not differ from each other, i.e., the subsequent employment growth of each occupational group does not react differently to interindustry wage differentials. If our hypothesis is right, however, we should observe $|\theta_r| > |\theta_c|, |\theta_m|$ and $\theta_r < 0$, where r are routine, c are cognitive, and m are manual occupations, respectively.

Figures 5.1 to 5.3 show graphically how initial industry wage premia are related to the subsequent employment growth of each occupational group. The horizontal axis is the 1980 industry wage premium, which is estimated using equation (5.1). The vertical axis denotes the average employment growth rate of each occupational group by industry between 1980 and 2009. We can observe that the slope of the fitted line is the steepest in Figure 5.2, which supports the prediction of the model that firms with high wages changes their demand for labor more dramatically and it mostly affects routine workers. Interestingly, Figure 5.3 shows that there is no relationship between initial industry wage premia and subsequent employment growth in manual occupations. We will return to this issue later.

The main empirical finding based on equation (5.2) is reported in Table 5.1. The first row

[34]For more detailed discussion on the generated regressor problem, see Wooldridge (2001).

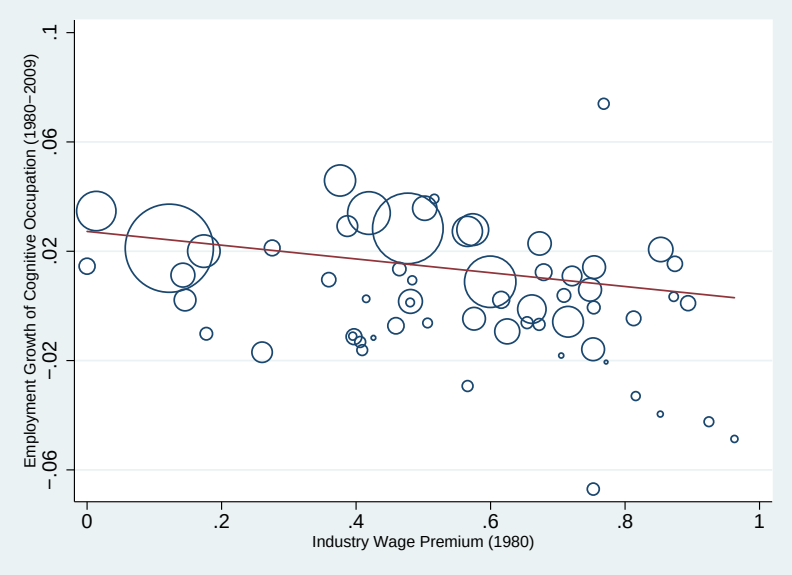

Figure 5.1: Dynamic Responses of Firms to Interindustry Wage Differentials - Cognitive Occupations

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The U.S. Census and American Community Survey (ACS).

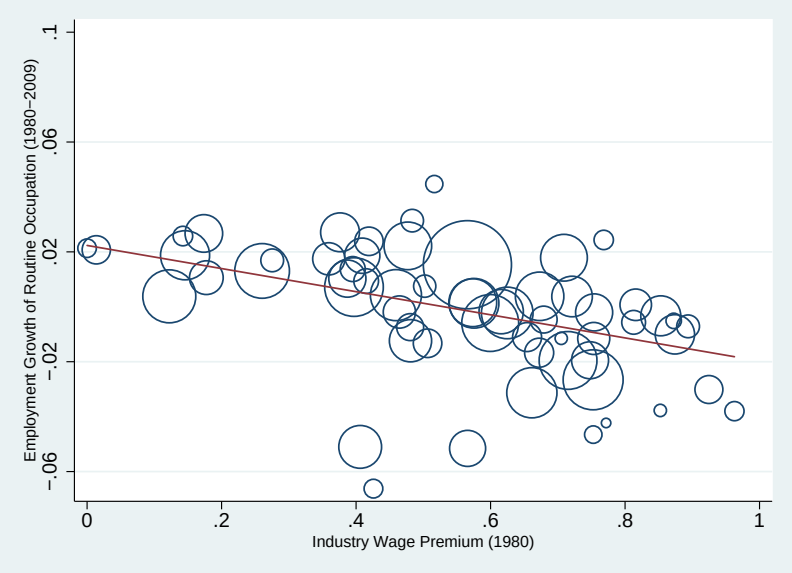

Figure 5.2: Dynamic Responses of Firms to Interindustry Wage Differentials - Routine Occupations

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The U.S. Census and American Community Survey (ACS).

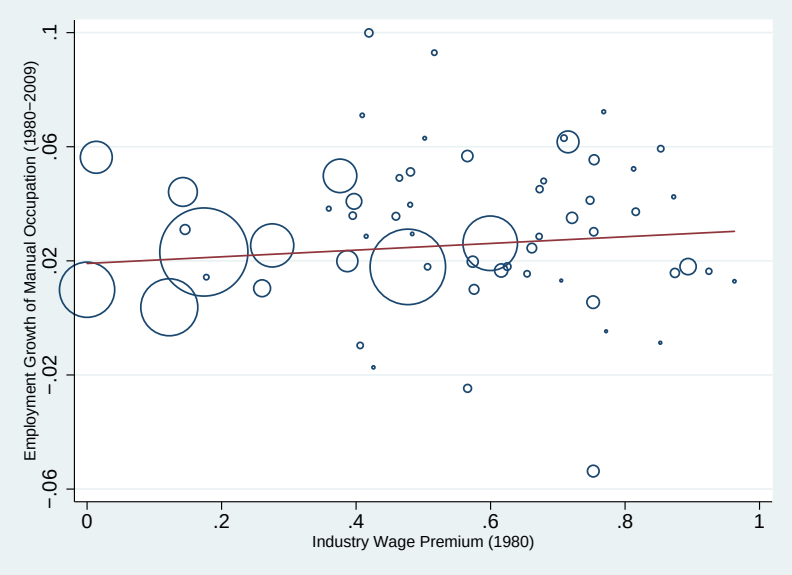

Figure 5.3: Dynamic Responses of Firms to Interindustry Wage Differentials - Manual Occupations

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The U.S. Census and American Community Survey (ACS).

reproduces Borjas and Ramey (2000) for a different period, 1980-2009, where the dependent variable is the average (annualized) growth rate of aggregate employment for industry i. In the second, third, and fourth rows, we report the estimation of equation (5.2), where the dependent variable is the average growth rate of employment for occupation j in industry i between 1980 and 2009.

When estimating equation (5.2) for each occupation, the initial industry wage premium does not vary by occupations: i.e., in this case the industry wage premium ($\hat{\omega}_{i,1980}$) does not depend on occupations. In this sense, the regression results reported in Table 5.1 reveal how 'average' industry wage premia affect different occupational groups in a distinct manner.

The IV estimates are also reported in Table 5.1. Both the ordinary least squares (henceforth, OLS) and IV regressions yield similar coefficients, which implies that measurement errors in the estimated $\hat{\omega}_{it}$ and the generated regressor problem are not severe. The estimate reported in the first row confirms the robustness of the main finding of Borjas and Ramey (2000) in the sense that their finding is also observed in a different period.[35] Firms with high initial industry wage

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

Table 5.1: Estimates of Employment Growth by Occupation Groups (1980-2009)

	OLS		IV	
Occupation Groups	Coefficient	R-Squared	Coefficient	R-Squared
Total	$-0.0381^{***}(0.0073)$	0.24	$-0.0331^{***}(0.0069)$	0.24
Cognitive Occupations	$-0.0252^{***}(0.0071)$	0.14	$-0.0197^{***}(0.0066)$	0.13
Routine Occupations	$-0.0421^{***}(0.0090)$	0.21	$-0.0412^{***}(0.0086)$	0.21
Manual Occupation	0.0117(0.0137)	0.03	$0.0206^{*}(0.0114)$	0.13

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The instrument is the previous decade's (i.e., 1970) industry wage premium.
3. The sample size is 60.
4. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

premia see larger reductions in demand for labor over time, which is in sharp contradiction to the competitive equilibrium theory. The annualized growth rate of total employment between 1980 and 2009 decreased by 0.38 percent when the initial industry wage premium in 1980 increased by 10 percent. For the competitive equilibrium theory to be supported by data, the estimated coefficients should be positive, but the results in Table 5.1 show the opposite sign.

The estimated coefficients reported in the second to fourth rows in Table 5.1 are consistent with Figures 5.1 to 5.3. The average growth rate of routine employment between 1980 and 2009 decreased by 0.42 percent when the initial industry wage premium in 1980 increased by 10 percent, while the average growth rate of cognitive employment decreased by 0.25 percent. That is, the coefficient for the routine occupation group is negative and the highest in absolute value. The coefficient for the cognitive occupation group is also negative, and is still statistically significant, while it is much smaller than the coefficient for the routine occupation group. Furthermore, the OLS estimate confirms that the initial industry wage premium does not have any significant impact on the subsequent employment growth rate of the manual occupation group, as we observe from Figure 5.3.

We test if these coefficients are significantly different from each other. The test statistics reported in Table 5.2 confirm our hypothesis; at the 5 percent significance level, θ_r is not equal to either θ_c or θ_m[36], and hence the firm's response to the initial industry wage premium is not

[36] θ_r is greater than θ_c in absolute terms and hence, θ_r is different from θ_m from the second row of the table.

uniform across different occupations. In summary, routine occupations are more affected by the firm's decreasing labor demand than are the cognitive and manual occupation groups. Our findings re-emphasize the importance of recognizing the heterogeneity of workers (occupations) in studies of the labor market.

Table 5.2: Differences between Coefficients (1980-2009)

	p-value (OLS)	p-value (IV)
Null: $\theta_c = \theta_r$	0.042	0.008
Null: $\theta_m = \theta_c$	0.007	0.000

Note: To test whether the coefficients in Table 5.1 are significantly different from each other, we pool cognitive, routine, and manual occupational data and estimate the coefficients for the interaction terms of routine occupation x industry wage premium and manual occupation x industry wage premium (omitting the interaction terms of cognitive occupation x industry wage premium) in one regression (where standard errors are clustered by industry) instead of running a regression separately for cognitive, routine, and manual occupations.

One might raise concerns that the results might be exaggerated by the great recession that occurred at the end of 2007, which disproportionately affected employment of routine occupations (Jaimovich and Siu (2013)). In order to address this issue, we estimate the same regression with a sample period between 1980 and 2007, which is reported in Table 5.3. The results are almost identical to those reported in Table 5.1: the subsequent employment growth of routine occupations between 1980 and 2007 is still decreasing in the initial industry wage premium and its coefficient is the greatest in absolute terms. In Table B.5, we also conduct the same exercise with a sample period between 1980 and 2006 and the results are largely unaffected by this change.

Table 5.3: Estimates of Employment Growth by Occupation Groups (1980-2007)

	OLS		IV	
Occupation Groups	Coefficient	R-Squared	Coefficient	R-Squared
Total	$-0.0431^{***}(0.01)$	0.23	$-0.0369^{***}(0.0093)$	0.22
Cognitive Occupations	$-0.0259^{***}(0.0083)$	0.12	$-0.0195^{***}(0.0076)$	0.11
Routine Occupations	$-0.0412^{***}(0.0097)$	0.18	$-0.0387^{***}(0.0095)$	0.18
Manual Occupations	$-0.0005(0.0154)$	0.00	$0.0105(0.0136)$	0.00

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The instrument is the previous decade's (i.e., 1970) industry wage premium.
3. The sample size is 60.
4. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In addition, as a robustness check for using the same industry wage premium for different occupation groups, we also consider an occupation-specific industry wage premia, denoted as ω_{ijt}, which is the wage premium of occupation j in industry i. Suppose that routine occupations are paid more highly than cognitive and manual occupations in the high-wage industry. Then, it becomes natural for firms in this industry to reduce their demand for routine occupations simply because they are paid more than other occupations; we call this narrative the 'relative price' explanation. The 'task-based' explanation may not be appropriate if the relative price explanation is true (while the property of tasks required by routine occupations may enhance the firm's dynamic responses to interindustry wage differentials, it may not be of the first order). In order to address these issues, we estimate the following alternative wage equation:

$$\log w_{hit} = X_{hit}\beta_t + \underbrace{\omega_{it} \times \psi_{jt}}_{=\omega_{ijt}} + \varepsilon_{hit} \tag{5.3}$$

where ω_{it} is the industry fixed effect and ψ_{jt} is the occupation fixed effect. Thus, $\omega_{it} \times \psi_{jt}$ is the interaction of each industry premium and each occupation dummy. We call this the 'occupation-specific industry wage premium'. In this alternative wage equation, we do not include the own fixed effect terms - ω_{it} and ψ_{jt}. By regressing the above equation, we obtain information about the extent to which an occupation group in a specific industry earns more than the same occupation group employed in other industries, and this also allows for within-industry comparisons of the wage premia.

Figure 5.4 depicts occupation-specific industry wage premia by industry. The horizontal axis denotes industries in order of size of the average industry wage premium. In order to see how the average industry wage premium (ω_{it}) and the occupation-specific industry wage premium (ω_{ijt}) are related, we sort industries by the initial industry wage premium in ascending order. To the left, there are low-wage industries, such as hotels and lodging places, and to the right, there are high-wage industries, such as mining or investment. All values are estimated in 1980, which is the reference year of our study.

Figure 5.4 shows that the occupation-specific industry wage premium rises almost monoton-

ically in the average industry wage premia for cognitive and routine occupation groups, while there is much variation in the manual occupation-specific industry wage premium. This is one of the reasons that the effect of the average industry wage premium on the manual occupations is almost negligible; even when firms face relatively higher industry wage premia, firms may not pay high wages to workers who perform manual tasks; i.e., even in the high-wage industries, people employed in manual occupations are not paid much relative to those employed in low-wage industries. For example, the 'security, commodity brokerage, and investment companies industry' (on the right in Figure 5.4) paid manual occupation workers less than quite a few other industries. As a result, the wage pressure from the manual occupation group is not large for firms compared to that for other occupation groups. Therefore, firms have less incentive to decrease their labor demand for manual occupations when facing high wages, which is represented by the insignificant coefficient reported in Table 5.1.

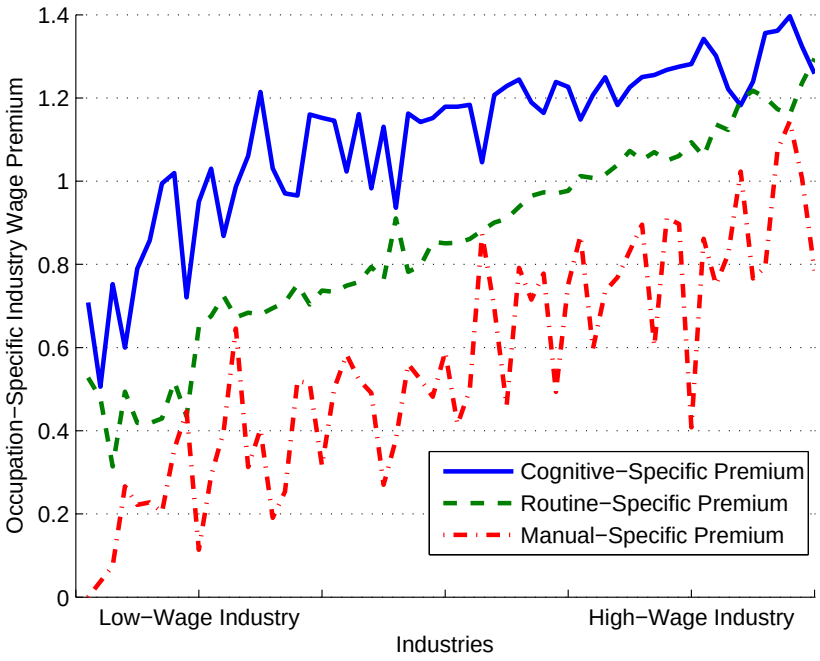

Figure 5.4: Occupation-Specific Industry Wage Premium

Note: We order industry by the industry wage premium obtained by equation (5.1).
Source: The U.S. Census and American Community Survey (ACS).

Note again that the findings in Table 5.1 offer two explanations. The first is the 'task content'

explanation: as routine jobs can be easily replaced by other production factors, demand for routine occupations is more sensitive to the initial industry wage premium. The second argument is the 'relative price' explanation: if the routine occupations are paid more than other groups after we control for industry, firms would decrease their demand for the routine occupation group since this group is actually the most expensive production factor. The latter explanation weakens our preferred story that links job polarization and interindustry wage differentials. Figure 5.4, however, shows that the 'relative price' explanation is not supported by the data: in any industry, we observe that $\omega_{ict} > \omega_{irt} > \omega_{imt}$, which means that the cognitive occupations are paid the most, followed by the routine and manual occupations. Hence, we can exclude the possibility that the subsequent employment growth of routine occupations is lower than other occupation groups because they were paid relatively more than other groups.[37]

As a robustness check, we estimate the same second-stage regression with a different dependent variable, the changes in employment share of occupation groups. As shown in Table 5.1, the employment growth of routine occupations has been lower than that of cognitive and manual occupations for the last 30 years. As a result, the employment share of routine occupations has declined while the share of at least one of either the cognitive or manual occupations has increased. Thus, we should observe that (1) the change in employment share of routine occupations is negatively related to the initial industry wage premium and, (2) the change in employment share of cognitive or manual occupations is (weakly) positively related to the initial industry wage premium. In estimating equation (5.2), we set $\Delta y_{ijt} = es_{ij,t+k} - es_{ijt}$, where es_{ijt} is the employment share of occupation j in industry i at t, where the number of industries is 60 and $t = 1980$. Table 5.4 summarizes the results of the alternative estimation. IV estimates are also reported in Table 5.4. The overall result is, not surprisingly, quite similar.

Firstly, the employment share of routine occupations decreases more in industries with a high

[37]One interesting finding is that the slope of the line in Figure 5.4 is steeper for routine occupations than for cognitive occupations. In the end, the gap between the cognitive occupation-specific industry wage premium and routine occupation-specific industry premium becomes almost zero. This fact implies that while cognitive occupations are paid more than routine occupations, there is a tendency for high-wage industries to actually pay relatively more for the routine occupations than low-wage industries. This feature may have a 'price' effect on our estimates, but given that the level of the cognitive occupation-specific industry wage premium is highest for any industry, we do not analyze this further, since its effect may be limited.

Table 5.4: Estimates of Employment Share by Occupation Groups (1980-2009)

	OLS		IV	
Occupation Groups	Coefficient	R-Squared	Coefficient	R-Squared
Cognitive Occupations	0.0076(0.0802)	0.00	0.0119(0.0808)	0.00
Routine Occupations	-0.1833^{***}(0.0572)	0.19	-0.2421^{***}(0.0599)	0.16
Manual Occupations	0.1306(0.0960)	0.13	0.1813^{**}(0.0797)	0.11

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The instrument is the previous decade's (i.e., 1970) industry wage premium.
3. The sample size is 60.
4. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

initial wage premium, which is consistent with the fact that the subsequent employment growth of the routine occupation group decreases in the initial industry wage premium during 1980-2009. Secondly, the coefficient for manual occupations is now much greater than zero in both the OLS and IV regressions, while the coefficient for cognitive occupations is estimated to be almost zero. This is because (1) the negative responsiveness of the employment growth of cognitive occupations to the initial industry wage premium was not large compared to that of routine occupations, and (2) there was basically no correlation between the subsequent employment growth of manual occupations and the initial industry wage premium. Similarly to Table 5.2, we find that the coefficient for routine occupations is statistically different to that for cognitive occupations.

5.2 Has ICT capital been substituted for workers? We now test the second prediction of our model: ICT capital per worker grows more in high-wage industries than in the low-wage industries. In addition, we also test if the growth rate of ICT capital per worker is different from that of non-ICT capital per worker. If non-ICT capital is general-purpose capital when compared to ICT capital, which substitutes for routine workers, the coefficients from the regression would be lower for non-ICT capital per worker than for ICT capital per worker.

Notice that the growth rate of the capital level may not be negatively related to the initial industry wage premium. If the size of an industry shrinks as labor demand decreases, capital demand itself might also decrease. If the rate at which the demand for capital decreases is lower

than the rate at which the demand for labor decreases, the resulting capital-labor ratio grows in the industry wage premium.

For the analysis, we use the EU KLEMS database. We restrict our attention to U.S. data between 1980 and 2007. Since it provides information on 29 industries, we recompute the initial industry wage premium in 1980 by reclassifying the Census 60 industries into 29 industries.[38] Details on the classification can be found in Table B.2. Each capital series (capital, ICT capital, and non-ICT capital) is real fixed capital stock based on 1995 prices. In order to obtain capital per worker series, we divide capital by employment for each industry where employment variable is also provided by EU KLEMS. We first show graphical evidence and then formally test the prediction of the model.

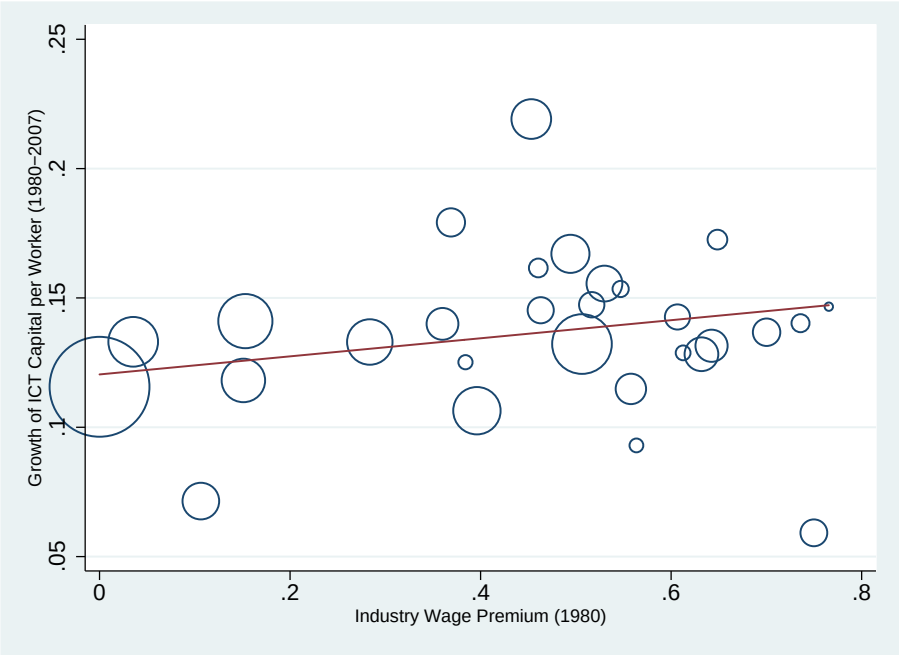

Figure 5.5: ICT Capital per Worker to Initial Industry Wage Premium (1980-2007)

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The EU KLEMS and The U.S. Census.

Our figures confirm our hypothesis. Firstly, Figure 5.5 shows a positive relationship between the initial industry wage premium in 1980 and the subsequent annualized growth rate of ICT

[38]EU KLEMS also provides data with more detailed industry classifications, with more than 50 industries (using the SIC Industry classification) between 1977 and 2005. We, however, do not use this classification, since we need to classify industries in a discretionary manner.

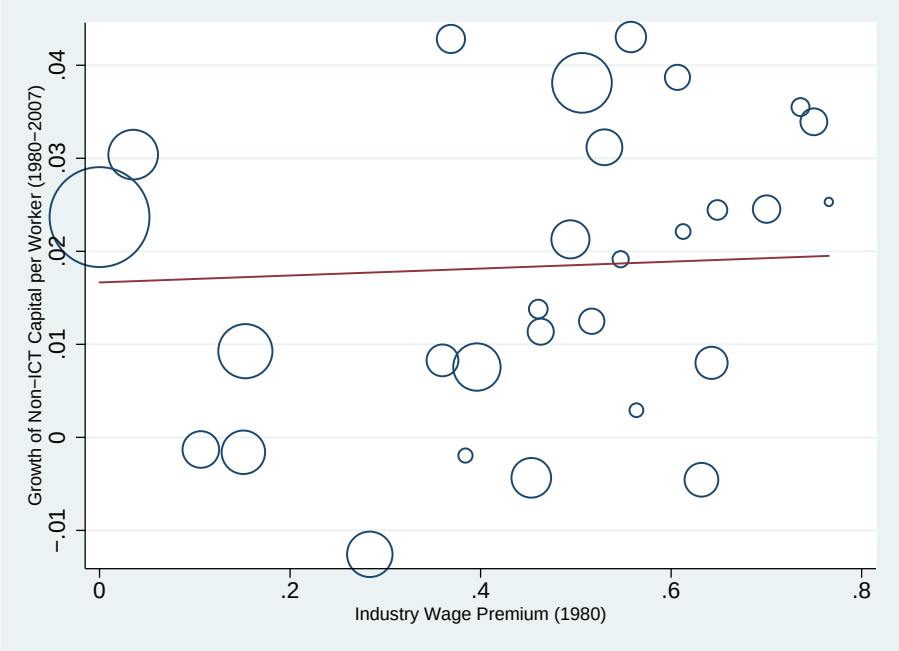

Figure 5.6: Non-ICT Capital per Worker to Initial Industry Wage Premium (1980-2007)

Note: The size of a circle denotes the employment level of each industry in 1980.
Source: The EU KLEMS and The U.S. Census.

capital per worker between 1980 and 2007. It supports our theory that firms increase demand for ICT capital in order to substitute (certain types of) workers because of the wage burden. Figure 5.6, however, suggests that changes in non-ICT capital per worker between 1980 and 2007 may not be precisely related to interindustry wage differentials.

For the complete analysis, we estimate equation (5.4).

$$\Delta y_{it} = \theta \hat{\omega}_{it} + \eta_{it} \tag{5.4}$$

where y_{it} is capital per worker or capital level or employment in industry i at time t.

The OLS and IV results are reported in Table 5.5, which are quite similar. Before we discuss the main result, we first focus on the last row, in which the dependent variable is the average employment growth rate. The estimate using the EU KLEMS data is similar to the coefficient obtained from the Census data (See Table 5.1), which confirms the robustness of our findings.

The relevant coefficients for different types of capital are presented in the first three rows.

Table 5.5: Estimates of Capital, Productivity, and Employment Growth (1980-2007)

	OLS		IV	
Dependent	Coefficient	R-Squared	Coefficient	R-Squared
Capital/Worker	0.0145(0.0134)	0.05	0.0138(0.0139)	0.05
ICT Capital/Worker	0.0350^{*}(0.0190)	0.09	0.0400^{***}(0.0171)	0.09
Non-ICT Capital/Worker	0.0037(0.0136)	0.00	0.0030(0.0144)	0.004
Capital	-0.0201^{*}(0.0110)	0.10	−0.0181(0.0114)	0.10
ICT Capital	0.0004(0.0217)	0.00	0.0081(0.0204)	0.000
Non-ICT Capital	-0.0308^{***}(0.0107)	0.25	-0.0289^{***}(0.0115)	0.25
Output	−0.0055(0.0089)	0.01	−0.0044(0.0087)	0.01
Labor Productivity	0.0290^{***}(0.0089)	0.22	0.0275^{***}(0.0091)	0.22
Employment	-0.0345^{***}(0.0076)	0.27	-0.0319^{***}(0.0072)	0.27

Note: 1. Both the EU KLEMS and the Census data are used for the estimation.
2. The regressions are weighted by each industry's initial (i.e., 1980) employment.
3. The instrument is the previous decade's (i.e., 1970) industry wage premium.
4. The sample size is 29.
5. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
6. Labor productivity is obtained by dividing output by workers in each industry.
7. Capital and output are real variables.

As the initial industry wage premium increased by 10 percent, the annualized growth rates of aggregate ICT capital per worker, ICT capital per worker, and non-ICT capital per worker between 1980 and 2007 increased by 0.14 percent, 0.35 percent, and 0.03 percent, respectively. As expected, we confirm the relationship among the coefficients as follows: $\theta_{ICT} > \theta_{Aggregate} > \theta_{non-ICT}$. Furthermore, only θ_{ICT} is statistically significant. Hence, we conclude that firms respond dynamically to wage pressure by increasing demand for ICT capital, but not all types of capital, because only ICT capital can be replaced with routine workers. This finding is consistent with Michaels, Natraj, and Reenen (2013). They show that job polarization is more evident in industries that experience higher ICT capital growth; in so doing, they treat ICT capital growth as an exogenous change given to each industry without providing an answer as to why some industries have experienced rapid ICT capital growth while others have not. Hence, our finding makes a unique contribution to this literature by showing that the asymmetric rises in ICT capital (per worker) across industries over the last 30 years may be the result of the endogenous responses of firms to interindustry wage differentials. Some industries exhibit more apparent job

polarization since firms in these industries have higher incentives to hire more ICT capital in production than firms in other industries, and the incentives increase in the initial industry wage premium that the industry encountered.

In this sense, our finding provides evidence of '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. Acemoglu and Autor (2011) also point out the possibility that directed technology changes may have contributed to job polarization during the past 30 years. Our findings suggest that an environment of interindustry wage differentials has generated the different degrees of job polarization across industries.

The fourth to the sixth rows in Table 5.5 confirm our earlier discussions and they are also consistent with other estimation results. Firstly, both capital and non-ICT capital decrease in the initial industry wage premium; firms with a relatively high initial wage premium demand less capital because they want to reduce the firm's size. Together with the fact that these industries also decrease demand for labor, capital per worker and non-ICT capital per worker seem not to respond to interindustry wage differentials. ICT capital, however, is not affected by the initial industry wage premium because it plays an important role in a firm's subsequent behavioral changes; as a result, ICT capital per worker rises more in industries with a high initial industry wage premium.

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

5.3 Job Polarization and Interindustry Wage Differentials before 1980 Interindustry wage differentials have been observed to have been occurring even prior to 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 whether or not the job polarization is also observed for the period prior to 1980; our theory explaining the heterogenous aspects of job polarization across industries is based on firms' dynamic responses to interindustry wage differ-

entials, and hence the occurrence of heterogenous job polarization should be observed whenever an industry wage premium exists and alternative technology to replace (routine) workers is available. To address this issue, Figure 5.7 shows the changes in employment share of each occupation group across industries, between 1960 and 1980. We still observe that the employment share of routine occupations decreased in most industries, which suggests the possibility of the existence of job polarization during 1960-1980, although its extent is smaller: overall, the employment share of the routine occupation group decreased by about 5 percent between 1960 and 1980, while it decreased by more than 10 percent between 1980 and 2009.

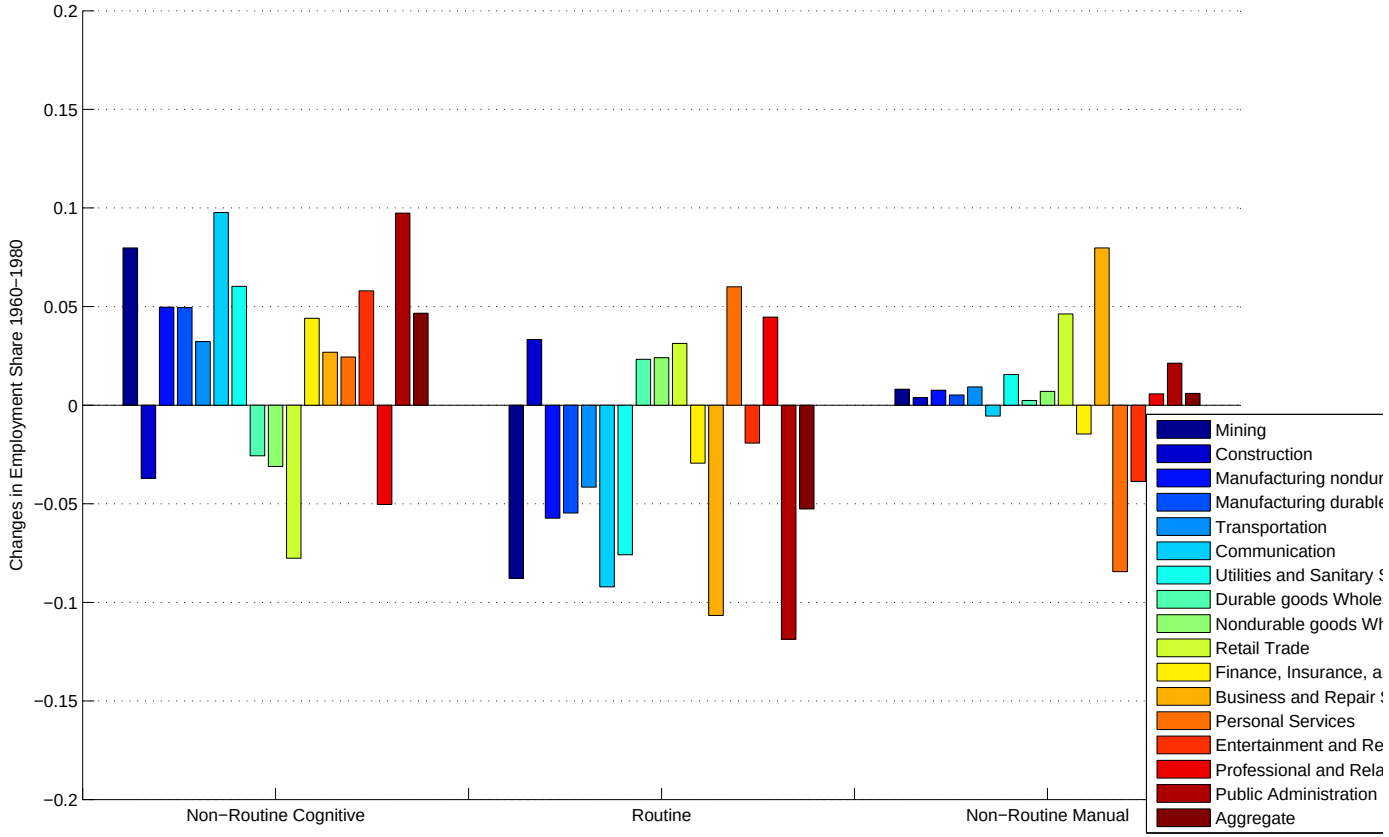

Figure 5.7: Changes in Employment Share by Occupation across Industries between 1960 and 1980

Note: The horizontal axis denotes three occupation groups (each occupation group includes 16 industries and one aggregate variable) and the vertical axis denotes the change in employment share of a specific occupation group in each industry between 1960 and 1980.

Source: The U.S. Census.

Again, we estimate equation (5.2) for the period between 1960 and 1980. We first estimate the wage equation (5.1) with the 1960 Census data to obtain the industry wage premium in 1960. In Table 5.6, we compare the OLS estimates for the two different periods.[39] The estimated coefficients for the earlier period (1960-1980) are reported in the first two columns and those for the latter period (1980-2009) are reported in the last two columns, which are repeated from Table 5.1 for comparison.

Table 5.6: Estimates of Employment Growth by Occupation Groups (1960-1980 and 1980-2009)

	1960-1980		1980-2009	
Occupation Groups	Coefficient	R-Squared	Coefficient	R-Squared
Total	−0.0178(0.0284)	0.03	−0.0381***(0.0073)	0.24
Cognitive Occupations	0.0053(0.0151)	0.00	−0.0252***(0.0071)	0.14
Routine Occupations	−0.0303**(0.0122)	0.10	−0.0421***(0.0090)	0.21
Manual Occupations	0.0595***(0.0077)	0.03	0.0117(0.0137)	0.03

Note: 1. The regressions are weighted by each industry's initial employment.
2. The sample size is 60.
3. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

While the coefficient for the total employment growth rate between 1960 and 1980 is not significantly different from zero, the coefficient for the routine occupation group is negative and still significantly different from zero. This indicates that firms with a high initial industry wage premium in 1960 responded to this situation by decreasing demand for routine occupations relative to other occupations. The magnitude of the responsiveness (θ_r) is, however, much lower than that of the latter period and the explanatory power drops by half, indicating that the dynamic responses of firms with a high initial industry wage premium in 1980 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-replacing technological changes, and (2) increased offshoring opportunities since the 1980s. Among the three occupation categories, only the routine occupations are

[39]The IV regressions show the same results, and hence we omit them here.

replaced easily either by (ICT) capital or by offshoring (Goos, Manning, and Salomons (2013)). Thus, for firms to adjust their labor demand dynamically, they need to change their demand for routine occupations. Consider an extreme case in which neither of the two options are available to firms. If firms could not access technologies that perform routine tasks, these firms would not change the demand for labor. Hence, changes in labor demand would not differ across different industries if firms could not replace workers. Suppose now, instead, that firms can either buy ICT capital because its price has become lower, or they can offshore some tasks to foreign countries. Then, labor demand for routine occupations will decline more (or its growth rate will be lower) for firms with high industry wage premia. Hence, both of these changes, which are usually argued to have become available or accessible to firms since the 1980s (Acemoglu and Autor (2011) and Jaimovich and Siu (2013)), made it easier for firms to decrease their demand for routine occupations. As a result, the heterogenous aspect of job polarization across industries becomes more evident in the latter period.

6 Conclusion

Over the past decades, employment has become polarized in the U.S., with composition of the labor force shifting away from routine occupations towards both cognitive and manual occupations. In this paper, we show that the degree of job polarization is different across industries and identify the factor that causes this phenomenon by demonstrating that the job polarization is connected with wide dispersion in wages across industries.

In particular, we analyze how the market responds to the interindustry wage structure with a two-sector neoclassical growth model; the model predicts that a high-wage industry would increase the capital-routine worker ratio more than a low-wage industry when the rental cost of capital declines and hence job polarization is more evident in this industry. We then empirically test the predictions of our model. Our findings can be explained as dynamic responses of firms to interindustry wage differentials; firms that paid high industry wage premia responded to wage pressures by replacing routine workers with ICT capital. Therefore, the heterogenous aspect of job polarization across industries was the result of optimal responses of industries to existing

interindustry wage differentials.

This paper aids understanding of heterogeneity in job polarization across industries, presenting the underlying mechanism and empirical regularities that reveal the relationship between job polarization and the wage structure of industries, which have not been studied before. In addition, similarly to Borjas and Ramey (2000), our paper raises a question about the validity of the competitive labor market theory where flows of workers across industries provide an equilibrating mechanism for wages. Instead, our findings indicate that firms respond endogenously to the rigid wage structure by replacing routine workers with capital, and hence the mechanism for the competitive labor market may not work.

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A Appendix: Model

A.1 Unions: Microfoundation to Interindustry Wage Differentials

In this appendix, we develop a labor market environment in which the wage structure given in equation (3.4) is derived endogenously.

In particular, we adopt the labor market environment usually used in the New Keynesian literature, as in Smets and Wouters (2007) and Erceg, Henderson, and Levin (2000). We assume that a firm can buy labor only through a labor union. Notice that the existence of a labor union is assumed only for convenience of the model; the key here is that the wage of a particular industry can be different from the wages of other industries. One might have a concern, in addition, that unionization in the U.S. is too small to be considered; according to recent estimates, only about 8 percent of U.S. private-sector workers are covered by a union agreement (Taschereau-Dumouchel (2012)). As Taschereau-Dumouchel (2012) shows in his paper, however, the 'threat' of forming

a labor union can still have an impact on a firm's decisions in equilibrium, and hence it is not problematic to assume the existence of a union and its effect on wages. In addition, as we pointed out earlier, a union itself is not an essential feature of our model; one can adopt alternative labor market structures so long as they can generate wages different from the ones determined in the competitive labor market. For instance, one might consider an efficiency wage model, as in Alexopoulos (2006), by assuming that the detection rate of shirking is heterogenous across industries. Instead, one might assume that the value of matching is different across industries, as in Montgomery (1991). Under the setup of our model, λ^i captures the differences across industries. Therefore, we can interpret the labor market environment used in our model as a reduced-form way to generate wage differentials across industries.

To showcase the importance of different levels of market power of labor unions, we assume for now that both industries have labor unions and a firm in industry $i \in \{1, 2\}$ buys labor only from the labor union of the same industry. In addition, we allow possible differences in wage rates across non-routine and routine workers employed in the same industries, which does not change the main results. Later in this section, we assume that the labor union of industry 2 does not have market power, so that it is equivalent to the competitive labor market environment. The labor market is organized as follows. Firstly, the labor market (broker) supplies workers to the labor union of each industry at w_{ijt}, where $i \in \{1, 2\}$ and $j \in \{NR, R\}$. The labor union unpacks the labor into different varieties, $H^j_{it}(l)$, $l \in [0, 1]$, and sells them at wage rate $w^j_{it}(l)$. In so doing, the union acts as a monopolist for each single variety. The different labor varieties are purchased by perfectly competitive intermediaries, called labor packers. They produce aggregate labor for each task j according to the CES (Dixit-Stiglitz) production function:

$$H^j_{it} = \left[\int_0^1 \left(H^j_{it}(l) \right)^{\frac{1}{1+\lambda^i}} dl \right]^{1+\lambda^i}$$

where λ^i, the wage markup in industry i, measures the market power of the union. We assume that the wage markup is the same across different occupations (tasks). Notice that if $\lambda^i = 0$, the labor union does not have any market power, so that wages will be determined by the competitive labor market.

The labor bundle H_{it}^j is then sold to the firm at a given price w_{it}^j. The cost minimization of labor packers yields the following labor demand equation:

$$H_{it}^j(l) = \left(\frac{w_{it}^j(l)}{w_{it}^j} \right)^{-\frac{1+\lambda^i}{\lambda^i}} H_{it}^j \tag{A.1}$$

and the wage aggregator $w_{it}^j = \left[\int_0^1 \left(w_{it}^j(l) \right)^{-\frac{1}{\lambda^i}} dl \right]^{-\lambda^i}$. Furthermore, the zero profit condition of the labor packers yields $w_{it}^j H_{it}^j = \int_0^1 w_{it}^j(l) H_{it}^j(l) dl$.

Now we consider the labor union's problem:

$$\max_{w_{it}^j(l)} d_{it}^j(l) = \left(w_{it}^j(l) - w_{ijt} \right) H_{it}^j$$

subject to the labor demand equation (A.1). By substituting the constraint into the objective function, the labor union's problem reduces to $\left(w_{it}^j(l) - w_{ijt} \right) \left(\frac{w_{it}^j(l)}{w_{it}^j} \right)^{-\frac{1+\lambda^i}{\lambda^i}} H_{it}^j$. Differentiating with respect to $w_{it}^j(l)$ yields:

$$\begin{aligned} H_{it}^j(l) - \frac{1+\lambda^i}{\lambda_w^i} \left(w_{it}^j(l) - w_{ijt} \right) \frac{H_{it}^j(l)}{w_{it}^j(l)} &= 0 \\ \Leftrightarrow \lambda^i w_{it}^j(l) &= \left(1+\lambda^i \right) \left(w_{it}^j(l) - w_{ijt} \right) \end{aligned} \tag{A.2}$$

Hence,

$$w_{it}^j(l) = \left(1+\lambda^i \right) w_{ijt}$$

Note that in a symmetric equilibrium, $w_{it}^j(l) = w_{it}^j$, and hence,

$$w_{it}^j = \left(1+\lambda^i \right) w_{ijt} \tag{A.3}$$

Therefore, with $\lambda > 0$, a labor union collects more labor income from firms and resulting profits (dividends) will be given back to households as a lump-sum transfer.

From now on, we will assume $\lambda^1 > \lambda^2 = 0$, and hence the labor union in industry 2 does not have any market power. This implies $w_{2t}^j = w_{2jt}$ and the indifference condition for positive employment for both industries yields:

$$w_{1t}^j = \left(1 + \lambda^1\right) w_{2t}^j \tag{A.4}$$

These are interindustry wage differentials in our economy: while workers are identical, a worker employed in industry 1 earns more than the other worker hired in industry 2.

A.2 Equilibrium Conditions

A.2.1 Non-Steady State In this section, we present the set of equilibrium conditions that characterize the definition of competitive equilibrium:

$$\frac{c_{t+1}}{c_t} = \beta \left[q_t r_{t+1} + (1-\delta) \frac{q_t}{q_{t+1}} \right] \tag{A.5}$$

$$w_t = \theta c_t = w_{2t} \tag{A.6}$$

$$w_{it} = \chi \tilde{w}_{it} \tag{A.7}$$

$$p_{it} = \left(\frac{y_t}{y_{it}} \right)^{\nu} \tag{A.8}$$

$$y_t = \left[\sum_{i=1}^{2} y_{it}^{1-\nu} \right]^{\frac{1}{1-\nu}} \tag{A.9}$$

$$\lim_{T \to \infty} \beta^T \frac{k_{T+1}}{c_T} = 0 \tag{A.10}$$

$$w_{1t} = (1+\lambda) w_{2t} \tag{A.11}$$

$$y_{it} = h_{it}^{\alpha}\left(\tilde{h}_{it}^{\mu} + k_{it}^{\mu}\right)^{\frac{1-\alpha}{\mu}} \tag{A.12}$$

$$\frac{w_{it}}{p_{it}} = \alpha\frac{y_{it}}{h_{it}} \tag{A.13}$$

$$\frac{\tilde{w}_{it}}{p_{it}} = (1-\alpha)\frac{\tilde{h}_{it}^{\mu}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu}}\frac{y_{it}}{\tilde{h}_{it}} \tag{A.14}$$

$$\frac{r_t}{p_{it}} = (1-\alpha)\frac{k_{it}^{\mu}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu}}\frac{y_{it}}{k_{it}} \tag{A.15}$$

$$k_{t+1} = q_t(y_t - c_t) + (1-\delta)\,k_t \tag{A.16}$$

$$h_{1t} + h_{2t} + \tilde{h}_{1t} + \tilde{h}_{2t} = n_t \tag{A.17}$$

$$k_{1t} + k_{2t} = k_t \tag{A.18}$$

where $i = 1, 2$.

A.2.2 Steady State In this section, we present the set of equilibrium conditions of the steady-state equilibria when $q_t = q$ for all t:

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{q} \tag{A.19}$$

$$w = \theta c = w_2 \tag{A.20}$$

$$p_i = \left(\frac{y}{y_i}\right)^{\nu} \tag{A.21}$$

$$y = \left[\sum_{i=1}^{2} y_i^{1-\nu}\right]^{\frac{1}{1-\nu}} \tag{A.22}$$

$$w_i = \chi \tilde{w}_i \tag{A.23}$$

$$w_1 = (1+\lambda) w_2 \tag{A.24}$$

$$y_i = h_i^{\alpha}\left(\tilde{h}_i^{\mu} + k_i^{\mu}\right)^{\frac{1-\alpha}{\mu}} \tag{A.25}$$

$$\frac{w_i}{p_i} = \alpha \frac{y_i}{h_i} \tag{A.26}$$

$$\frac{\tilde{w}_i}{p_i} = (1-\alpha)\frac{\tilde{h}_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}}\frac{y_i}{\tilde{h}_i} \tag{A.27}$$

$$\frac{r}{p_i} = (1-\alpha)\frac{k_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}}\frac{y_i}{k_i} \tag{A.28}$$

$$c + \frac{\delta}{q}k = y \tag{A.29}$$

$$h_1 + h_2 + \tilde{h}_1 + \tilde{h}_2 = n \tag{A.30}$$

$$k_1 + k_2 = k \tag{A.31}$$

where $i = 1, 2$.

Equilibrium conditions (A.19) and (A.20) are from the household's problem, equilibrium conditions (A.21) and (A.22) are from the final goods-producing firms' problem, (A.25) to (A.28)

are from the firm's problem, (A.23) and (A.24) are wage rules, and (A.29) through (A.31) are market-clearing conditions. One can show easily that the household budget constraint is redundant (Walras' law).

A.3 Appendix: Proof of Proposition 1 We first obtain the following equations by dividing equation (A.26) (equations (A.27) and (A.28)) for industry 1 by equation (A.26) (equations (A.27) and (A.28)) for industry 2 and apply the wage structure given in equation (A.24):

$$1+\lambda = \frac{y_1}{y_2}\frac{h_2}{h_1} \tag{A.32}$$

$$1+\lambda = \frac{y_1}{y_2}\frac{\tilde{h}_2^{1-\mu}}{\tilde{h}_1^{1-\mu}}\frac{\tilde{h}_2^{\mu}+k_2^{\mu}}{\tilde{h}_1^{\mu}+k_1^{\mu}} \tag{A.33}$$

$$\frac{y_1}{y_2} = \frac{k_1^{1-\mu}}{k_2^{1-\mu}}\frac{\tilde{h}_1^{\mu}+k_1^{\mu}}{\tilde{h}_2^{\mu}+k_2^{\mu}} \tag{A.34}$$

Combining equations (A.33) and (A.34), we obtain the following relationship:

$$\frac{k_1}{\tilde{h}_1} = \phi\frac{k_2}{\tilde{h}_2} \tag{A.35}$$

where $\phi = (1+\lambda)^{\frac{1}{1-\mu}} > 1$. For simplicity of notation, we let $\kappa_i = \frac{k_i}{\tilde{h}_i}$ in what follows. Hence, the above equation is now $\kappa_1 = \phi\kappa_2$.

We then combine equations (A.27) and (A.28) to obtain the following equation:

$$\tilde{w}_i = r\kappa_i^{1-\mu} \tag{A.36}$$

Recall that q and r are inversely related (see equation (A.19)) and hence a higher q implies a lower r. Accordingly, in what follows, we conduct comparative statics with respect to r for convenience, while we report the comparative statics with respect to q in the main text. We first differentiate equation (A.36) with respect to r:

$$\frac{d\tilde{w}_i}{dr} = \kappa_i^{1-\mu} + r(1-\mu)\kappa_i^{-\mu}\frac{d\kappa_i}{dr} \tag{A.37}$$

Note that $\frac{d\tilde{w}_1}{dr} = (1+\lambda)\frac{d\tilde{w}_2}{dr}$ and $\frac{d\kappa_1}{dr} = \phi\frac{d\kappa_2}{dr}$ from the wage structure and equation (A.35). Then, we can solve for $\frac{d\kappa_2}{dr}$, whose expression is given as follows:

$$\frac{d\kappa_2}{dr} = -\frac{\kappa_2}{r(1-\mu)} < 0 \tag{A.38}$$

As a result, as one can expect from the substitutability between routine workers and capital, a lower rental cost of capital accelerates capital deepening (in terms of the capital-routine worker ratio). In addition, $\frac{d\kappa_1}{dr} = \phi\frac{d\kappa_2}{dr} < \frac{d\kappa_2}{dr} < 0$ implies that capital deepens more in the high-wage industry; the high-wage industry tries to find a way to reduce labor cost, and the reduction of the price of capital provides the incentive for the high-wage industry to rent more capital in order to replace routine workers more than the low-wage industry.

We define $s_i = \frac{h_i}{\tilde{h}_i}$. This measures, as discussed in the main text, the share of non-routine workers over routine workers. If s_i is increasing, it means that more non-routine workers are employed for given numbers (hours) of routine workers and hence it can be interpreted as job polarization. In order to study the effect of changes in r (and hence q) on job polarization, we combine equations (A.26) and (A.27):

$$\frac{1}{\chi} = \frac{1-\alpha}{\alpha}\frac{s_i}{1+\kappa_i^{\mu}} \tag{A.39}$$

Notice that the left-hand side of the above equation is constant at $1/\chi$ while κ_i increases as r decreases. As a result, it should be the case that $\frac{ds_i}{dr} < 0$. Formally,

$$\frac{ds_i}{dr} = \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_i^{\mu-1}\frac{d\kappa_i}{dr} = \frac{\alpha}{\chi(1-\alpha)}\frac{d\kappa_i^{\mu}}{dr} < 0 \tag{A.40}$$

Hence, as the price of capital decreases, job polarization occurs in both industries.

Now, we compare the degree of job polarization across industries. Notice that the degree of job polarization is apparent in the high-wage industry if $|\frac{ds_1}{dr}| > |\frac{ds_2}{dr}|$. We use equation (A.40)

and the relationship $\kappa_1 = \phi\kappa_2$:

$$\begin{aligned}\frac{ds_1}{dr} &= \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_1^{\mu-1}\frac{d\kappa_1}{dr} \\ &= \frac{\alpha}{\chi(1-\alpha)}\mu\phi^{\mu-1}\kappa_2^{\mu-1}\phi\frac{d\kappa_2}{dr} = \phi^{\mu}\frac{ds_2}{dr}\end{aligned} \tag{A.41}$$

Hence, $|\frac{ds_1}{dr}| > |\frac{ds_2}{dr}|$ since $\phi > 1$ and $\mu > 0$.

The above equation shows clearly that the degree of job polarization becomes greater in the high-wage industry when r decreases. Suppose instead that $\lambda = 0$, so that there is no industry wage premium. Then, it is clear that $\frac{ds_1}{dr} = \frac{ds_2}{dr}$, and hence job polarization is of the same magnitude across industries. As a result, the heterogeneity in the progress of job polarization across industries increases in λ, which is consistent with our intuition.

B Appendix: Additional Tables and Figures

Table B.1: Census Industry Classification

Number	Industry	IND1990 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. Numbers 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 B.2: EU KLEMS Industry Classification

Number			Industry	IND1990 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 storage 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 B.3: OLS Estimates of the Wage Regression in 1980

Variable	Coefficient	Variable	Coefficient
Female	−0.5413(0.0009)	Cognitive Occupation	0.4892(0.0030)
Age1	1.0227(0.0035)	Routine Occupation	0.2267(0.0029)
Age2	1.5225(0.0035)	Manual 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	−0.5575(0.0020)	Region4	−0.0188(0.0023)
Edu2	−0.4799(0.0017)	Region5	−0.0045(0.0020)
Edu3	−0.2689(0.0013)	Region6	−0.0612(0.0024)
Edu4	−0.2418(0.0014)	Region7	−0.0011(0.0022)
Edu5	0 (Omitted)	Region8	0 (Omitted)
African-American	−0.0842(0.0014)	Region9	0.0665(0.0021)
R-Squared	.4045	Observations	4,307,598

Notes:
1. Robust standard errors are reported in parentheses.
2. The Census data are used for the estimation.
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 18-24, 25-34, 35-44, 45-54, and 55-64, respectively.
5. Edu1 to Edu5 correspond to worker has fewer than nine years, nine to 11 years, 12 years, 13 to 15 years, and at least 16 years of schooling, respectively.

Table B.4: Source of Wage Variation (R-Squared)

	1980	1990	2000	2009
Total	0.40	0.42	0.42	0.43
Industry Only	0.14	0.14	0.13	0.16
Covariates Only	0.36	0.37	0.38	0.38
Observations	4,307,598	4,940,215	5,530,409	1,202,671

Note: 1. 1980, 1990, and 2000 data are from the Census and 2009 data are from the ACS.
2. The first row is the explanatory power (R^2) of the wage regression when individual characteristics (including ages, education, etc. (see Section 5 for detail)) and 60 industries are all controlled for. The second row is the explanatory power of the wage equation when industry dummies are the only independent variables and the third row is that of the wage equation when only covariates are considered as independent variables.

Table B.5: Estimates of Employment Growth by Occupation Groups (1980-2006)

	OLS	
Occupation Groups	Coefficient	R-Squared
Total	$-0.0432^{***}(0.0103)$	0.22
Cognitive Occupations	$-0.0257^{***}(0.0083)$	0.12
Routine Occupations	$-0.0417^{***}(0.0099)$	0.18
Manual Occupations	$-0.0017(0.0159)$	0.000

Note: 1. The regressions are weighted by each industry's initial (i.e., 1980) employment.
2. The sample size is 60.
3. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.6: Occupation-Specific Industry Wage Premia in 1980

Industry	Average	Cognitive	Routine	Manual	Industry	Average	Cognitive	Routine	Manual
1	0.8524(.0097)	1.1828(.0181)	1.1954(.0111)	1.0234(.0660)	31	0.8938(.0060)	1.3965(.0104)	1.1606(.0071)	1.1442(.0131)
2	0.9627(.0073)	1.2585(.0173)	1.2947(.0079)	0.7852(.0838)	32	0.5164(.0090)	1.1424(.0159)	0.7964(.0105)	0.5229(.0478)
3	0.8128(.0063)	1.3019(.0094)	1.1361(.0075)	0.7512(.0539)	33	0.8531(.0049)	1.2388(.0069)	1.2174(.0056)	0.7661(.0343)
4	0.7051(.0101)	1.1480(.0250)	1.0123(.0112)	0.8694(.0600)	34	0.7212(.0049)	1.1831(.0069)	1.0390(.0056)	0.7687(.0170)
5	0.5656(.0045)	1.1518(.0065)	0.8544(.0052)	0.4819(.0194)	35	0.6248(.0048)	1.2285(.0067)	0.9098(.0055)	0.4597(.0304)
6	0.6158(.0050)	1.2072(.0080)	0.9004(.0057)	0.6949(.0155)	36	0.5755(.0049)	1.1837(.0073)	0.8610(.0056)	0.4987(.0237)
7	0.7718(.0121)	1.3420(.0231)	1.0594(.0137)	0.8614(.0673)	37	0.4835(.0071)	1.1310(.0135)	0.7634(.0080)	0.2699(.0810)
8	0.5659(.0053)	1.1789(.0108)	0.8505(.0059)	0.5900(.0231)	38	0.2603(.0048)	1.0194(.0077)	0.5185(.0056)	0.3553(.0129)
9	0.4061(.0052)	1.2145(.0127)	0.6792(.0058)	0.4035(.0305)	39	0.3969(.0050)	1.0609(.0098)	0.6838(.0056)	0.3128(.0157)
10	0.7534(.0055)	1.2674(.0098)	1.0496(.0063)	0.9124(.0270)	40	0.4593(.0050)	1.1522(.0093)	0.7371(.0057)	0.3153(.0291)
11	0.4809(.0053)	0.9827(.0079)	0.7939(.0061)	0.4910(.0312)	41	0.1773(.0062)	0.9946(.0122)	0.4295(.0070)	0.2041(.0419)
12	0.7540(.0049)	1.2752(.0065)	1.0607(.0058)	0.8968(.0180)	42	0.3595(.0063)	0.9503(.0120)	0.6492(.0071)	0.1138(.0522)
13	0.8724(.0074)	1.3563(.0116)	1.2011(.0088)	0.7933(.0530)	43	0.1737(.0045)	0.8572(.0068)	0.4181(.0067)	0.2277(.0054)
14	0.6543(.0057)	1.2446(.0097)	0.9382(.0065)	0.7914(.0289)	44	0.1457(.0055)	0.7895(.0092)	0.4188(.0063)	0.2218(.0246)
15	0.4259(.0079)	1.1603(.0254)	0.7035(.0085)	0.5134(.0522)	45	0.5735(.0046)	1.1792(.0057)	0.8521(.0055)	0.4151(.0188)
16	0.5063(.0062)	1.1625(.0143)	0.7820(.0070)	0.5604(.0337)	46	0.7683(.0079)	1.2815(.0138)	1.0938(.0092)	0.4082(.0575)
17	0.4804(.0063)	1.1613(.0142)	0.7575(.0070)	0.5229(.0458)	47	0.6730(.0048)	1.2383(.0066)	0.9704(.0055)	0.4936(.0294)
18	0.6722(.0057)	1.1642(.0109)	0.9782(.0064)	0.7780(.0346)	48	0.3871(.0058)	1.8683(.0095)	0.7241(.0072)	0.3979(.0107)
19	0.7525(.0046)	1.2502(.0065)	1.0509(.0052)	0.8954(.0150)	49	0.3762(.0051)	1.0299(.0068)	0.6757(.0066)	0.2917(.0085)
20	0.7152(.0045)	1.2500(.0059)	1.0159(.0053)	0.7358(.0184)	50	0.4092(.0063)	1.0308(.0142)	0.6946(.0069)	0.1908(.0574)
21	0.6614(.0046)	1.1896(.0060)	0.9648(.0054)	0.7154(.0199)	51	0.4151(.0083)	0.9705(.0219)	0.7090(.0090)	0.2536(.0820)
22	0.8742(.0050)	1.3618(.0079)	1.1730(.0057)	1.0748(.0178)	52	0.00(Omitted)	0.7086(.0120)	0.5276(.0102)	0.00(Omitted)
23	0.7480(.0048)	1.2259(.0061)	1.0781(.0057)	0.8322(.0241)	53	0.2753(.0061)	0.7207(.0132)	0.4343(.0093)	0.4462(.0078)
24	0.6790(.0056)	1.2268(.0075)	0.9771(.0067)	0.7521(.0330)	54	0.1425(.0063)	0.5998(.0098)	0.4938(.0104)	0.2662(.0091)
25	0.4644(.0061)	1.1455(.0109)	0.7338(.0069)	0.5019(.0339)	55	0.4770(.0043)	1.0231(.0052)	0.7489(.0056)	0.5829(.0054)
26	0.9247(.0055)	1.3237(.0100)	1.2363(.0061)	1.0065(.0281)	56	0.5021(.0069)	0.9358(.0106)	0.9103(.0080)	0.3791(.0700)
27	0.3950(.0072)	0.9870(.0161)	0.6723(.0080)	0.6458(.0297)	57	0.1223(.0044)	0.7527(.0052)	0.3141(.0058)	0.0750(.0062)
28	0.7092(.0051)	1.2070(.0107)	1.0078(.0057)	0.5972(.0350)	58	0.0137(.0053)	0.5056(.0066)	0.4788(.0078)	0.0374(.0092)
29	0.8159(.0054)	1.2214(.0120)	1.1231(.0060)	0.8248(.0256)	59	0.4192(.0052)	0.9655(.0062)	0.7514(.0076)	0.5198(.0276)
30	0.7528(.0094)	1.2554(.0170)	1.0699(.0108)	0.6032(.0541)	60	0.5995(.0043)	1.0453(.0054)	0.8814(.0054)	0.8729(.0057)

Note: 1. Industry numbers follow B.1. Standard errors are in parentheses.
2. Average is the industry wage premium estimated from equation (5.1) and cognitive, routine, and manual are the occupation-specific industry wage premia estimated from equation (5.3). We normalize the industry wage premium.

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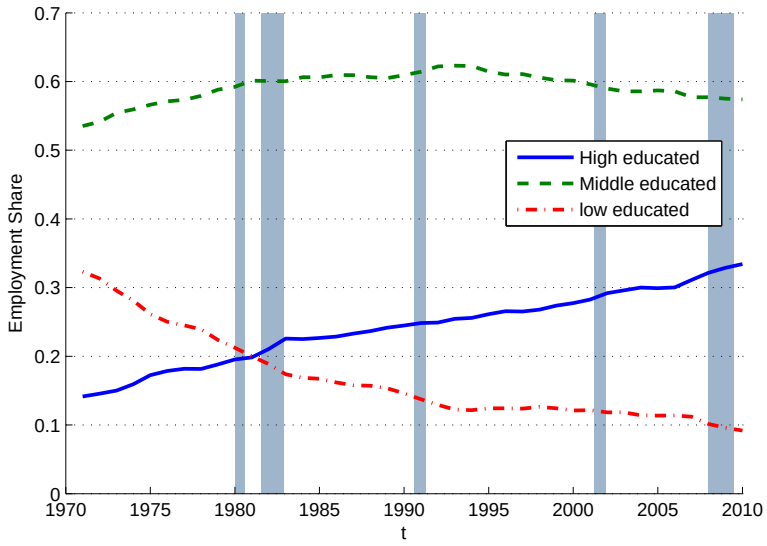

Figure B.1: Job Polarization: Education

Note: 1. Low-educated workers are high school dropouts, middle-educated workers are ones with high a school diploma or with some colleges, and highly-educated workers possess at least a college degree.
2. One can readily observe that, contrary to Figure 2.2, 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 highly-educated workers. Thus, the classification of workers by occupation may be more appropriate in studies of job polarization.
Source: The March CPS between 1971-2010.