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

Myungkyu Shim[‡] Hee-Seung Yang[§]

Abstract

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 high wage premia than in industries that did not. With a simple neoclassical firm model, we show that this phenomenon can be explained as firms' optimal responses to interindustry wage differentials: firms with high wage premia are more likely to replace routine workers with capital. As a result, high-wage industries have experienced slower employment growth of routine workers than low-wage industries, which led to heterogeneity in job polarization across industries.

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[‡]School of Economics, Shanghai University of Finance and Economics, mkshim@mail.shufe.edu.cn

[§]Department of Economics, Monash University, heeseung.yang@monash.edu

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 (2014)), the extent of job polarization differs across industries (see Autor, Levy, and Murnane (2003); Goos, Manning, and Salomons (2014); and Michaels, Natraj, and Reenen (2014)). 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 in 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.

[1] As emphasized by Autor (2010), Goos, Manning, and Salomons (2009), and Michaels, Natraj, and Reenen (2014), 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 (CPS).

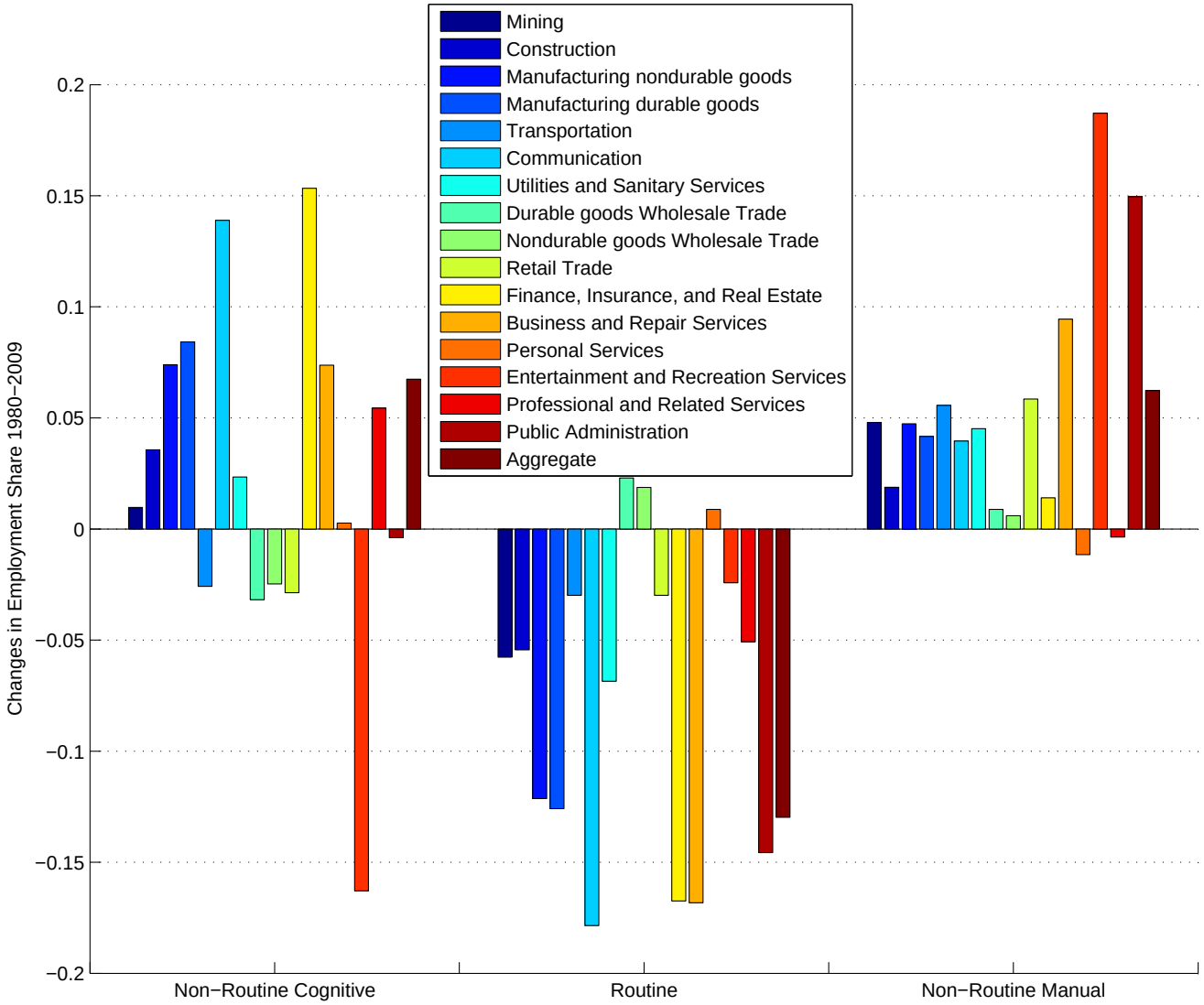

Figure 1.1: Changes in Employment Share by Industry between 1980 and 2009

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.

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. In order to understand the relationship between job polarization and interindustry wage differentials, we develop a simple partial equilibrium model.[3] As usually assumed in the job polarization literature, information, communication, and technology (ICT, henceforth) capital 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. First, 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: some firms pay higher wages than other firms to observationally identical workers.[4] 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 ICT capital. When a firm changes its labor demand, however, the effect is not even across workers: tasks performed by routine workers are more easily codifiable or computerized, and hence they are more affected by a firm's dynamic decision to replace labor with capital.[5] As the relative price of capital decreases, firms in a high-wage industry are more likely to replace routine workers with capital than firms in a low-wage industry because they have greater incentives to cut high production costs, which results in different degrees of job polarization across industries. The 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

[3]Predictions are the same when we consider the general equilibrium model introduced in the Supplementary Online Appendix B.1.

[4]We can derive the rigid interindustry wage structure as an equilibrium outcome, which does not change the predictions of the model. For instance, the existence of labor unions with different negotiation powers across the industries can endogenously generate the rigid interindustry wage structure. The derivation of this result is available upon request.

[5]Offshoring is another possibility, as Goos, Manning, and Salomons (2014) and Oldenski (2014) show.

capital.

We then test these predictions using U.S. Census and EU KLEMS[6] data. Several findings emerge from the empirical analysis. First, we find that the average (annualized) 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 paper has three major contributions. First, our study contributes to the existing literature on job polarization by aiding understanding of heterogeneity in job polarization across industries and its mechanism. Particularly, we provide the first evidence that polarized employment is connected with interindustry wage differentials using a simple model and an empirical analysis of the theoretical predictions. Second, this paper provides additional evidence to the literature on firms' optimal responses to the labor market structure (Acemoglu (2002) and Caballero and Hammour (1998)). Lastly, our results support the non-competitive view of the labor market in explaining the industry wage premium, adding to the literature and discussion on interindustry wage differentials.

The paper is organized as follows. Section 2 introduces two key concepts, interindustry wage differentials and job polarization, and explains the link between them with reviews of related literature. We then propose a simple model with its predictions in Section 3, which formalizes the hypothesis suggested in Section 2. Section 4 describes the data, and Section 5 presents empirical tests of the model's predictions. Section 6 concludes.

[6]KLEMS stands for capital (K), labor (L), energy (E), materials (M), and service inputs (S).

2 Link between Job Polarization and Interindustry Wage Differentials

2.1 Interindustry Wage Differentials Persistent dispersion in wages across industries (i.e., the existence of "interindustry wage differentials") has been one of the most challenging subjects in 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 socioeconomic characteristics (including education, age, gender, race, region, and occupation) but who work in different industries. The competitive labor market theory predicts that the 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 the high- (resp. low-) wage industry, 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 even after controlling for all observables (Krueger and Summers (1988)). In addition, 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 using a typical wage equation, which regresses log wages over various socioeconomic characteristics and industry fixed effects, and present a scatter plot of the two sets of industry fixed effects in Figure 2.1. It 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 industry variable has been a consistently important factor in explaining wage differentials.[7]

[7] 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). The results are reported in Table A.2. In particular, 4 percent to 16 percent of the wage variation is explained by industry. Interestingly, the explanatory power attributable to the industry is very stable and substantial over

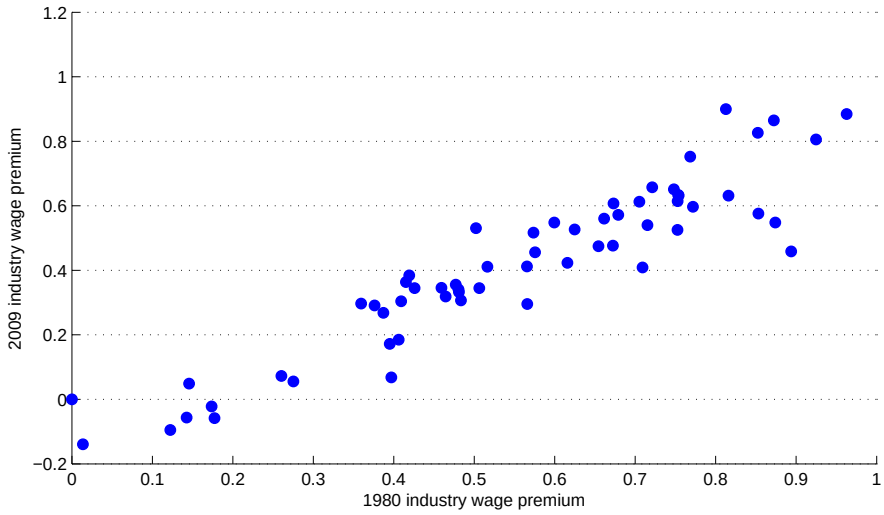

Figure 2.1: Persistency of Interindustry Wage Differentials: Comparison between 1980 and 2009

Note: We omit the industry ("hotels and lodging places") that has the lowest value of estimated coefficients in the wage regression of 1980 so that every other coefficient for industry dummies has a positive sign.
Source: The U.S. Census and American Community Survey (ACS).

Our paper studies the "consequences" of interindustry wage differentials, and, given that the wage dispersion is a persistent phenomenon, 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.[8] 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), that studies their consequences. Borjas and Ramey (2000) find that industries that paid relatively high wages to workers in 1960 experienced (1) lower employment growth and (2) higher capital-labor ratio growth and higher labor productivity growth between 1960 and 1990. While they focus on the "average" effect of interindustry wage differentials on workers, our findings emphasize the importance of considering heterogeneity across different workers (occupations) in studies of the

time, which implies that industry should be considered as an important factor in explaining wages.

[8]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. In addition, predictions of the competitive labor market model are inconsistent with the empirical facts (See Supplementary Online Appendix B.3). Based on these observations, we focus on non-competitive models, which 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)).

labor market, distinguishing our paper from Borjas and Ramey (2000).

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

- 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 CPS between 1971 and 2010,[9,10] 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 most easily replaced by ICT capital, as demonstrated by Autor, Levy, and Murnane (2003); the tasks that routine workers perform are easier to codify than other tasks because the tasks have routine procedures. Meanwhile, cognitive and manual occupations are not easily replaced by ICT capital. For instance, business decisions of managers (cognitive occupations) cannot be replaced by technology; introduction of new 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 (manual occupations) cannot be directly replaced by machines; these jobs require humans to perform non-routine manual tasks. In contrast, a

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

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

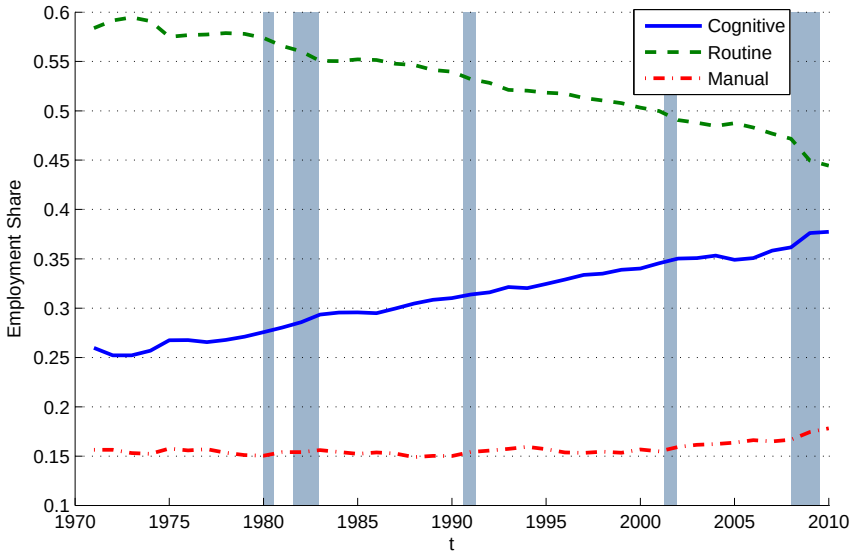

Figure 2.2: Job Polarization
Note: The shaded regions are the official NBER recession dates.
Source: The March CPS.

great portion of the tasks that a bank clerk performs 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 have disappeared over time as the economy has experienced rapid technological progress in ICT capital.[11] Consistent with this story, Cummins and Violante (2002) show 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.[12]

A few papers have studied the possibility of heterogenous job polarization across industries.[13] Acemoglu and Autor (2011) argue that changes in industrial composition do not play an important role in job polarization. Jaimovich and Siu (2014) and Foote and Ryan (2014) note that job

[11] 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 cognitive tasks are not easily offshored while factories can be relatively easily relocated to foreign countries.

[12] The period in which 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 problem, we show in Section 5.4 that job polarization also occurred before 1980, while the magnitude was smaller than the one after 1980.

[13] 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.

polarization may be more pronounced in the construction and manufacturing industries. While Autor, Levy, and Murnane (2003) and Goos, Manning, and Salomons (2014) 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 (2014) 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 Michaels, Natraj, and Reenen (2014) in two ways. First, they consider different education groups while we consider different occupation groups. This distinction makes a difference in the subsequent analysis since "employment" polarization is not observed when we use educational attainment to classify workers.[14] Second, while Michaels, Natraj, and Reenen (2014) found a positive relationship between the growth rate of ICT capital and the degree of job polarization, they are silent about why some industries experienced the high growth of ICT capital, which is in contrast studied in our paper.

2.3 Link between Job Polarization and Interindustry Wage Differentials

The industry wage dispersion, as well as the different "task content" of occupations, is a key mechanism to understand the heterogeneity in job polarization across industries. Cost of labor is the product of wage and employment, and it is hard for high-wage firms to reduce wages because they are constrained by the rigid wage structure. As a consequence, the only way to respond to the high labor cost is to adjust employment over time, which can be achieved by hiring alternative production factors, as Borjas and Ramey (2000) found.

In particular, as technology improves, the relative price of ICT capital becomes lower, and firms with incentives to adjust employment will reduce 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 in a high-wage industry rises by a greater amount than in

[14] In Figure A.1, we plot the employment series by each educational group, following Michaels, Natraj, and Reenen (2014).

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.[15] We formalize this hypothesis in Section 3, and test it with the data in Section 5.

3 The Model

In this section, we present a firm's profit maximization problem and analyze properties of the steady-state equilibrium. While our model is highly stylized and is a partial equilibrium model, it has two advantages. First, it provides clear predictions that are testable with data. Second, the predictions of the model are exactly preserved to the general equilibrium model, which is introduced in Supplementary Online Appendix B.1.

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; "non-routine" tasks (workers who perform non-routine tasks will be called non-routine workers) and "routine" tasks (routine workers).[16] As is usually assumed in the job polarization literature[17], capital is a relative substitute for routine workers, while it is a relative complement to non-routine workers. In this sense, the capital

[15] 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* equivalent firms optimally choose different technologies and wages. Lastly, Caballero and Hammour (1998) show how the appropriability of labor can distort the incentives of the firms so that firms choose technology in favor of capital in the long run. While the underlying ideas are similar to ours, both of the papers do not consider the possibility that the strategy of the firm can affect different workers disproportionately.

[16] 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), 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 (2014).

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

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. 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 study firms' responses to different industry wage premia when the relative price of capital to wages declines. In particular, we find that while both firms 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 because the capital-routine worker ratio rises more in that industry when the relative price of capital decreases.

3.1 Setup: A firm's Problem

We assume that the 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:

$$\max_{\{k_{it},h_{it},\tilde{h}_{it}\}} p_{it}y_{it} - w_{it}h_{it} - \tilde{w}_{it}\tilde{h}_{it} - r_t k_{it} \tag{3.1}$$

subject to

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

where $\mu \in (0,1)$ and $\alpha \in (0,1)$. h_{it} (resp. $\tilde{h}_{it}$) denotes hours of non-routine (resp. routine) workers supplied to industry i and w_{it} (resp. $\tilde{w}_{it}$) is the corresponding wage rate. We assume that labor is infinitely supplied as firms would like to hire and capital is rent at the competitive international market at rate r, which can possibly vary due to investment-specific technology changes.

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

[18] In Supplementary Online Appendix B.3, we provide a simple competitive model where its predictions are exactly opposite to the predictions of our model.

between non-routine workers and total routine inputs is 1, while the elasticity of substitution between routine workers and capital is $\frac{1}{1-\mu} > 1$, since $\mu > 0$. As a result, as Autor and Dorn (2013) point out, capital is a *relative substitute* for routine workers and a *relative complement* to non-routine workers. Hence, capital in our model is ICT capital.

A final remark on the firm's problem is that the implications of our model are still preserved even when we assume heterogenous production functions (different α and μ) across industries under some conditions on exogenous industry wage premia.[19] Hence, we will maintain the assumption that production functions are the same across industries in this paper in order to clearly show the relationship between industry wage premium and job polarization.

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

$$\frac{w_{it}}{p_{it}} = \alpha \frac{y_{it}}{h_{it}} \tag{3.2}$$

$$\frac{\tilde{w}_{it}}{p_{it}} = (1-\alpha)\frac{\tilde{h}_{it}^{\mu}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu}}\frac{y_{it}}{\tilde{h}_{it}} \tag{3.3}$$

$$\frac{r_t}{p_{it}} = (1-\alpha)\frac{k_{it}^{\mu}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu}}\frac{y_{it}}{k_{it}} \tag{3.4}$$

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 non-routine (resp. routine) worker 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 (3.3) by (3.4):

$$\frac{\tilde{w}_{it}}{r_t} = \left(\frac{k_{it}}{\tilde{h}_{it}}\right)^{1-\mu} \tag{3.5}$$

[19]For the high-wage industry to experience more pronounced job polarization, the industry wage premium should be high enough. Details of the results with heterogenous production functions are available upon request.

This equation implies that capital per routine worker increases as the relative rental cost over routine workers 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 capture the industry wage differentials observed in the data, we assume that the wage in industry 1 is higher than that in industry 2 by a factor $\lambda > 0$[20] so that

$$w_{1t} = (1+\lambda)w_{2t} \text{ and } \tilde{w}_{1t} = (1+\lambda)\tilde{w}_{2t} \tag{3.6}$$

One can further check that capital per routine worker is always higher in a high-wage firm, which arises from the fact that it can lower production costs by employing more capital than the 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).

Demand for goods are given by $y_t = \left[y_{1t}^{1-\nu} + y_{2t}^{1-\nu}\right]^{\frac{1}{1-\nu}}$ so that the individual inverse demand function can be derived as $p_{it} = \left(\frac{y_t}{y_{it}}\right)^{\nu}$.

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 order to obtain analytical tractability, we assume $\nu = 0$; i.e., goods are perfect substitutes, and hence $p_{1t} = p_{2t} = 1$.[21]

Since we are interested in how changes in the ratio of wage rates for routine workers and

[20] 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 arise 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. Then, equation (3.6) can be derived as an equilibrium condition. Results with (1) labor unions and (2) compensating wage differentials (hedonic approach), which do not change any of the results reported in this paper, are available upon request.

In this sense, we can interpret the labor market environment used in our model as a parsimonious way to generate wage differentials across industries and λ captures the heterogeneity across industries.

[21] In Appendix B.2.2, we provide the equilibrium conditions for the steady state of the general equilibrium model when values of parameters are not specified.

the rental price of capital ($\tilde{w}/r$) affect the two industries differently, we conduct the comparative statics exercise by analyzing the behavior of the steady-state economy when there is an exogenous change in r so that $\tilde{w}/r$ varies. For a clear comparison between industries, we focus on how the increase in $\tilde{w}_2/r$, the relative wage of routine workers over capital price in the low-wage industry, affects job polarization in each industry. While we only consider two industries (firms), the analysis can be extended easily to $n > 2$ industries (firms).

The next proposition is the collection of predictions of the model when $\tilde{w}/r$ rises. An increase in $\tilde{w}/r$ is 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 an exogenous decline in r so that the new steady state is the U.S. economy in 2010. We first define s_i as follows:

$$s_i = \frac{h_i}{\tilde{h}_i} \tag{3.7}$$

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:

$$\kappa_i = \frac{k_i}{\tilde{h}_i} \tag{3.8}$$

Hence, κ is the capital-routine worker ratio.

Proposition 3.1 (Job Polarization: Connection to Interindustry Wage Differentials)**.** *Suppose that $\tilde{w}_i/r$ increases in all industries. Then the following results hold in the steady state:*

1. *The capital-routine worker ratio increases in both industries, 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,*

$$\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} = (1+\lambda)^{\frac{1}{1-\mu}} \frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} > 0 \tag{3.9}$$

2. *Job polarization occurs in both industries. Formally,*

$$\frac{ds_i}{d\frac{\tilde{w}_2}{r}} = \frac{\alpha}{\chi(1-\alpha)} \frac{d\kappa_i^{\mu}}{d\frac{\tilde{w}_2}{r}} > 0 \tag{3.10}$$

where $\chi = w_i/\tilde{w}_i$.

3. *The change in the employment share of non-routine over routine workers in industry* 1 *is greater than that in industry* 2*; 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,*

$$\frac{ds_1}{d\frac{\tilde{w}_2}{r}} = (1+\lambda)^{\frac{\mu}{1-\mu}} \frac{ds_2}{d\frac{\tilde{w}_2}{r}} \tag{3.11}$$

Proof. See Appendix A.1. □

First of all, it is a natural consequence of the model that firms try to use capital more than routine workers when the relative 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, the parameter that governs the industry wage premium; as firms should pay more to workers, their incentive to utilize capital increases, which results in more rapid growth of the capital-routine worker ratio in those firms than in firms that can pay less.

The second part of Proposition 3.1 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 relative price of capital over routine workers 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, 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 (2014). 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 Theory to Empirics

In what follows, we empirically test the predictions from the model presented in Proposition 3.1. We first introduce two data sets in Section 4 and then analyze if the proposed mechanism works in the data in Section 5.

In order to test the prediction that κ_i (capital-routine worker ratio) grows more in the high-wage industry when the relative price of capital declines, we instead consider ICT capital per worker because the EU KLEMS data, which have information on capital, 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 $\tilde{w}/r$ 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 3.1), 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 relative price of ICT capital over routine workers decreases.

4 Data

There are two main sources of data for this paper: (1) the decennial Census and ACS data,[22] and (2) the EU KLEMS data. Following Borjas 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.[23] 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 A.2 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 A.2 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,[24] we use the "occ1990dd classification system", following Dorn (2009).

[22]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)).

[23]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.

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

5 Empirical Analysis

In this section, we test two key predictions of the model: When the relative rental cost of capital over routine workers ($r/\tilde{w}$) 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.

As mentioned in Section 3.3, in order to test the second prediction, we use ICT capital per worker instead of ICT capital per routine worker, which does not change the main concept of Proposition 3.1.

First, we 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 (five age groups: 16−24, 25−34, 35−44, 45−54, or 55−64), educational attainment (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), gender, and region of residence (indicating in which of the nine Census regions the worker lives).[25] We also control for three occupation dummies (cognitive, routine, or manual occupations). ω_{it}, an industry fixed effect, measures the industry wage premia.

The result of equation (5.1) in 1980 is reported in Table A.1.[26] 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:

[25] Controlling for state dummies does not change the results much.

[26] The estimated coefficients are consistent with the usual intuition: 1. wages are strictly increasing in education, 2. wages also rise in ages until workers reach their prime age, and then decrease slightly, and 3. African-American earns less.

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

where y_{ijt} is the variable of interest such as employment of occupation group j in industry i. $\Delta y_{ijt,t+k}$ is the annualized (average) growth rate of y_{ijt} between periods t and $t+k$, and $j \in \{cognitive, routine, manual\}$.[27] We estimate equation (5.2) separately for cognitive, routine, and manual occupations.

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.[28] Furthermore, in order to address the potential endogeneity of the wage premium, we use the previous decade's estimated industry wage premium as an instrumental variable (IV).

5.1 Job Polarization and Initial Industry Wage Premia

In this section, we test if firms' dynamic responses to interindustry wage differentials have really 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 $\hat{\omega}_{it}$ in equation (5.2) would not differ from each other; i.e., the subsequent employment growth of each occupational group does not react differently to industry wage premia. If our hypothesis is right, however, we should observe $|\theta_r| > |\theta_c|, |\theta_m|$ and $\theta_r < 0$, where r, c, and m indicate routine, cognitive, and 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 industry wage premia in 1980, 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

[27] That is, $\Delta y_{ijt,t+k} = (\log(y_{ij,t+k}) - \log(y_{ijt}))/k$.

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

can observe that the slope of the fitted line is negative and the steepest in the case of routine occupations (Figure 5.2), which supports the prediction of the model that firms facing high wages reduce their demand for routine workers more. Interestingly, Figure 5.3 shows that there is a weaker (positive) relationship between initial industry wage premia and subsequent employment growth in manual occupations. We will return to this issue later in Section 5.3.

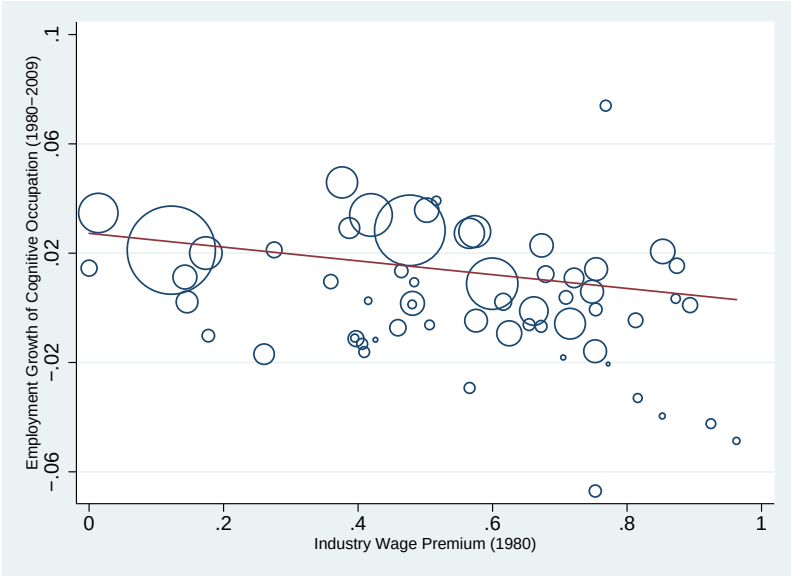

Figure 5.1: Dynamic Responses of Firms to Interindustry Wage Differentials-Cognitive Occupations

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

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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

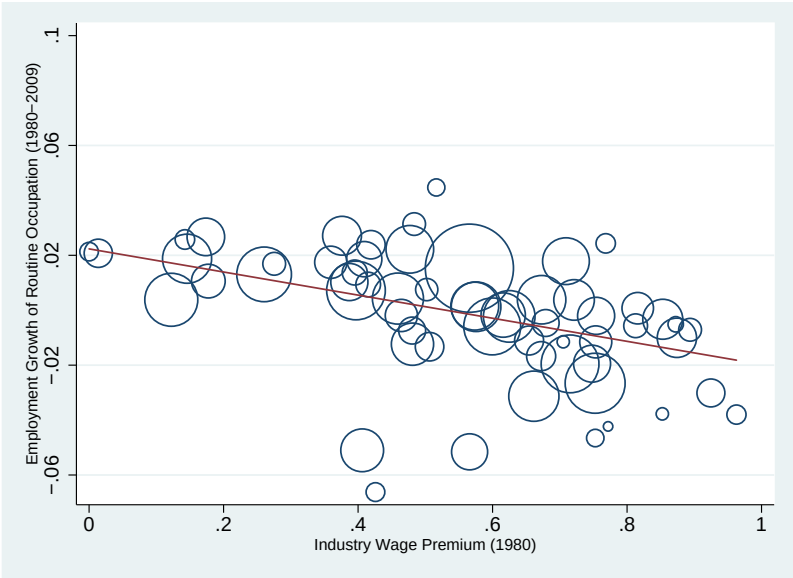

Figure 5.2: Dynamic Responses of Firms to Interindustry Wage Differentials-Routine Occupations

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

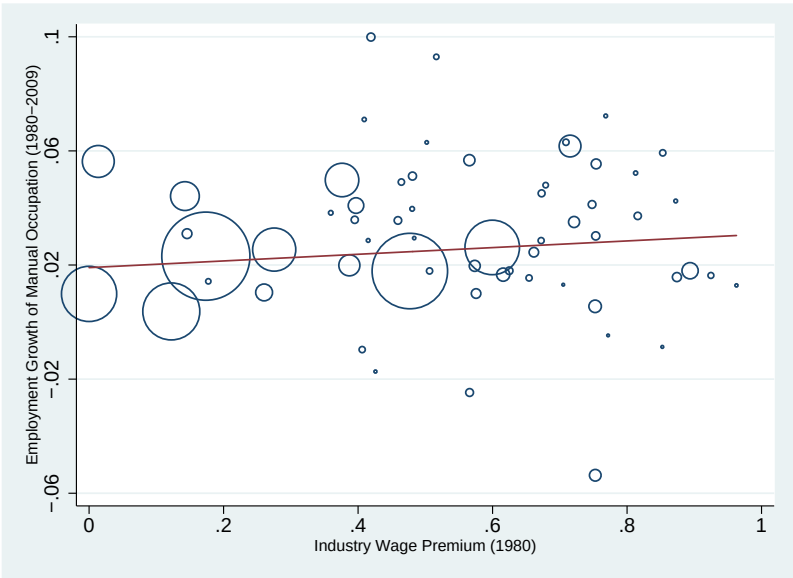

Figure 5.3: Dynamic Responses of Firms to Interindustry Wage Differentials-Manual Occupations

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

reproduces Borjas and Ramey (2000) for a different period, where the dependent variable is the

annualized growth rate of aggregate employment for industry i.[29] The estimate confirms the robustness of the main result of Borjas and Ramey (2000) in the sense that their finding is also observed for a later period. Firms with high initial industry wage premia see larger reductions in demand for labor over time, which is in sharp contradiction to the competitive equilibrium theory. For the competitive equilibrium theory to be supported by data, the estimated coefficients should be positive, but the result in Table 5.1 shows the opposite sign.

In the remaining 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 ($\hat{\omega}_{i,1980}$) does not depend on occupation. In this sense, the results in Table 5.1 reveal how "average" industry wage premia affect different occupational groups in a distinct manner.

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 that 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 initial industry wage premium has a positive relationship with the subsequent employment growth rate of the manual occupation group and the OLS estimate is not significant. In summary, routine occupations are more affected by the firm's decreasing labor demand than are the cognitive and manual occupation groups. The IV estimates are also reported in Table 5.1. Both the 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.[30]

One might raise a concern that the results might be exaggerated by the great recession that occurred at the end of 2007, which disproportionately affected the employment of routine occupations (Jaimovich and Siu (2014)). In order to address this issue, we estimate the same regression with a sample period between 1980 and 2007, which is reported in Table 5.2. The

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

[30] We test if these coefficients are significantly different from each other; at the 5 percent significance level, θ_r is not equal to either θ_c or θ_m, and hence the firm's response to the initial industry wage premium is not uniform across different occupations.

results are similar to those reported in Table 5.1: the subsequent employment growth of routine occupations between 1980 and 2007 still decreases in the initial industry wage premium and its coefficient is the greatest in absolute terms.[31] In addition, one might argue that the heterogeneity in job polarization might be driven by part-time workers as they are more likely to be affected by firms responses to wage pressure and more likely to have routine occupations. In Table A.3, we conduct the same exercise with a sample of full-time workers only and the results are largely unaffected.

Table 5.2: 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Another possible concern about our estimates obtained from equation (5.2) is that there might be other industry-specific factors that could affect the subsequent employment growth of each occupation group. We tested the robustness of our results to the inclusion of various industry-specific factors: share of routine workers in industry i in 1980, capital per worker and ICT capital per worker in industry i in 1980[32], and union membership rate in industry i in 1983.[33] The estimation results are reported in Table 5.3.[34]

We find that the inclusion of the various industrial factors does not alter our results in Table 5.1. In fact, it increases the differences between the coefficients of routine workers and non-routine workers. Hence, our main results are robust to the addition of other industry-specific

[31]Estimates with a sample period between 1980 and 2006 are also similar to the main results.
[32]Capital is only available for 29 industries in EU KLEMS data; thus, we assigned those industries to 60 industries by matching industry codes.
[33]Union data at industry level are available only from 1983.
[34]We discuss in detail why the first two variables are included in the regression in Section 5.3.

Table 5.3: OLS Estimates of Employment Growth by Occupation Groups (1980−2009): Including Industry-Specific Variables

	Cognitive	Routine	Manual
Industry wage premium	−0.0010	−0.0339**	0.0068
Routine share	−0.0393***	−0.0085	0.0269*
Capital per worker	0.0000**	0.0000**	0.0000
ICT capital per worker	0.0005***	0.0003**	0.0011**
Union membership (1983)	−0.0418***	−0.0192	−0.0564***
R^2	0.52	0.26	0.29

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

factors. The results also show that union membership seems to affect employment growth of non-routine occupations only, even though the higher union membership rate might put more pressure for firms. This might be because routine workers are mostly covered by unions until the 1990s and unions might prevent firms from replacing them with capital.

As the last 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 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 $\Delta y_{ijt,t+k} = es_{ij,t+k} - es_{ijt}$, where es_{ijt} is the employment share of occupation j in industry i at Census year t, where the number of industries is 60. Table 5.4 summarizes the results of the alternative estimation.

First, the employment share of routine occupations decreases more in industries with a high initial wage premium, which is consistent with the previous results in Table 5.1. Second, 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

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 weak correlation between the subsequent employment growth of manual occupations and the initial industry wage premium.

5.2 Substitution of ICT Capital for Workers

We now analyze if 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, the coefficients from the regression would be lower in magnitude for non-ICT capital per worker than for ICT capital per worker. Notice that the growth rate of capital level may 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. Since it provides information on employment and capital in 29 industries, we recompute the initial industry wage premium in 1980 by reclassifying the Census 60 industries into 29 industries.[35] Each capital series (capital, ICT capital, and non-ICT capital) is real fixed capital stock based on 1995 prices. In order to obtain

[35]Details on the classification can be found in Supplementary Online Appendix Table B.2.

capital per worker series, we divide capital by employment for each industry. We first show graphical evidence of our argument.

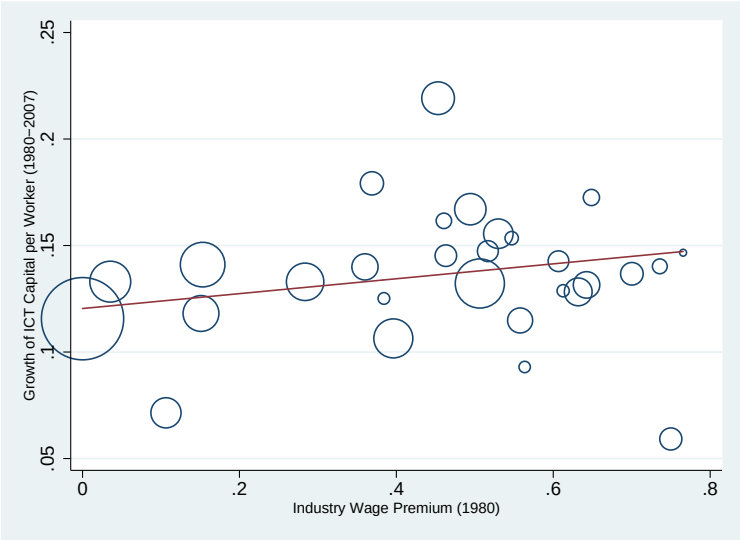

Figure 5.4: ICT Capital per Worker to Initial Industry Wage Premium (1980−2007)

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

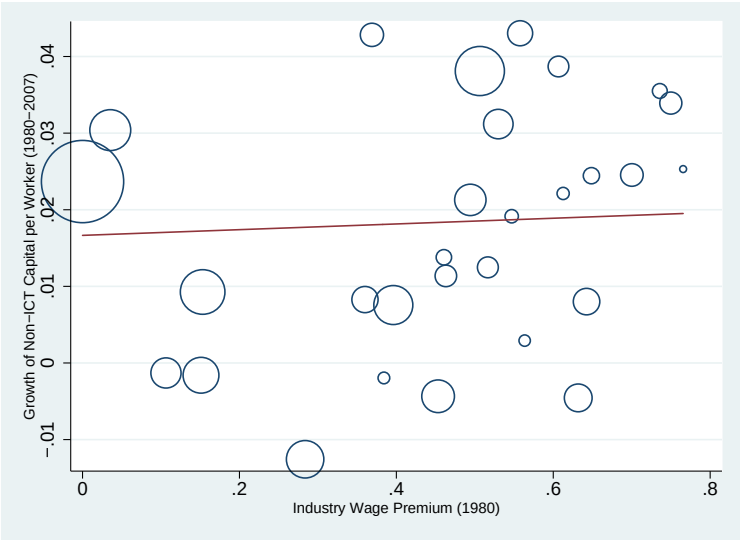

Figure 5.5: Non-ICT Capital per Worker to Initial Industry Wage Premium (1980−2007)

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

The figures confirm our hypothesis. First, Figure 5.4 shows a positive relationship between the industry wage premium in 1980 and the subsequent annualized growth rate of ICT capital

per worker between 1980 and 2007. Figure 5.5, 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 (5.3).

$$\Delta y_{it,t+k} = \theta \hat{\omega}_{it} + \eta_{it} \tag{5.3}$$

where y_{it} is capital per worker, capital level, or employment in industry i at time t. The OLS and IV results, which are quite similar, are reported in Table 5.5. Before we discuss the main result, we 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.

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.

The relevant coefficients for different types of capital are presented in the first three rows. As the initial industry wage premium increased by 10 percent, the annualized growth rates of aggre-

gate 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 a substitute for routine workers. Our finding makes a unique contribution to the 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.

In this sense, our finding provides supporting evidence of "directed technology changes" suggested by Acemoglu (2002) and the role of different appropriability between production factors by Caballero and Hammour (1998): 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. First, 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 do not seem 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 Competing Theories: Robustness Check of Our Theory

In this section, we discuss three alternative theories that might explain our findings and show that the competing theories are not consistent with the data.

5.3.1 Price Effect: Were Routine Workers Paid the Highest?

As the first competing theory, one can argue that it was the routine workers that were paid the highest in 1980; hence, firms had an incentive to replace them with other production factors not because routine workers can be easily substituted for capital.

Note that the main findings in Table 5.1 offer two possible 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, firms would decrease their demand for the routine occupation group since this group is actually the most expensive production factor (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).

To check which explanation fits better, we consider an occupation-specific industry wage premium, denoted as ω_{ijt}, which is the wage premium of occupation j in industry i, in the following alternative wage equation:

$$\log w_{hit} = X_{hit}\beta_t + \underbrace{\omega_{it} \times \psi_{jt}}_{=\omega_{ijt}} + \varepsilon_{hit} \tag{5.4}$$

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 dummy 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 5.6 depicts occupation-specific industry wage premia by industry. 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 average 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. Figure 5.6 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 of the relative price explanation.[36]

Figure 5.6 also shows that the occupation-specific industry wage premium rises almost monotonically 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 not negative and almost negligible; even when firms face relatively higher average industry wage premia, firms may not pay high wages to manual workers. For example, the "security, commodity brokerage, and investment companies industry" (on the right in Figure 5.6) paid manual workers less than quite a few other industries did. As a result, the wage pressure from the manual occupation group is not as large as the pressure from other occupation groups. Therefore, firms have less incentive to decrease their labor demand for manual occupations when facing high wages.

5.3.2 Level Effect: Heterogeneity in relative importance of routine workers

The correlation between the employment share of routine workers in 1980 and the industry wage premium in 1980 is strictly positive. For instance, the manufacturing industry had a higher

[36]One interesting finding is that the slope of the line in Figure 5.6 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.

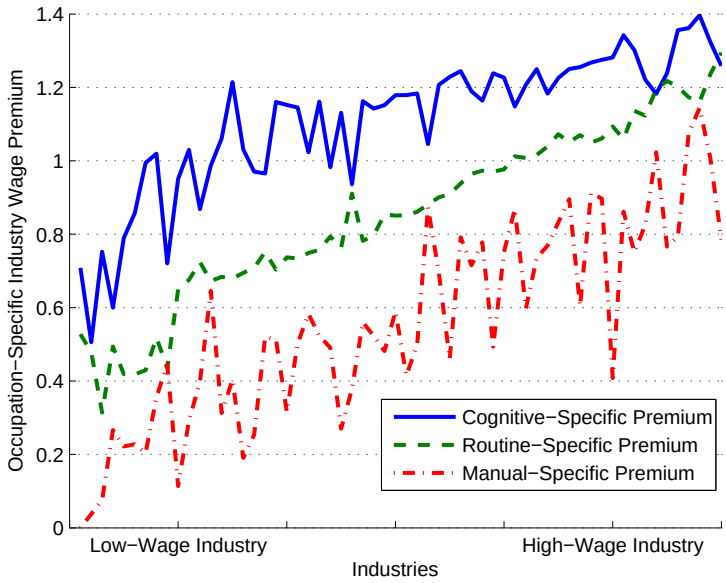

Figure 5.6: Occupation-Specific Industry Wage Premium

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

share of routine workers than other industries in 1980 and it paid relatively higher wages to workers because it faced higher unionization rates. The second competing theory is based on this observation: as the relative price of capital declines, the high-wage industries would experience more replacement of routine workers because they employed routine workers more intensively in 1980, i.e., the "level effect" is a dominant reason why the job polarization was more evident in the high-wage industries.

We test this hypothesis by replacing the initial industry wage premium with the initial employment share of routine workers in the main equation (5.2). The result in Table 5.6 does not support the level effect: when we estimate the effect of the initial share of routine workers on the employment growth of each occupation, the coefficient for routine occupations is rather smaller in absolute value than the coefficient for cognitive occupations. Therefore, we are able to rule out the level effect of initial share of routine workers.

5.3.3 Wage premium as outcome of high capital/labor ratio

As a last alternative theory, it can be argued that the high wage premium was the consequence of high capital-labor

Table 5.6: OLS Estimates of Employment Growth by Occupation Groups (1980−2009): Level Effect

Occupation Groups	Coefficient	R-squared
Total	$-0.0353^{***}(0.0075)$	0.30
Cognitive Occupations	$-0.0362^{***}(0.0071)$	0.33
Routine Occupations	$-0.0238^{**}(0.0116)$	0.07
Manual Occupations	$0.0236^{**}(0.0103)$	0.09

Note: The main regressor is the employment share of routine workers in 1980 instead of the initial industry wage premium.

ratio in 1980, which is basically based on competitive labor market theories. Capital-intensive industries might pay higher wages in 1980 because their labor productivity was high. Hence, as the price of capital declines, those industries might adopt more capital. As a result, more (routine) workers might have been replaced by (ICT) capital in capital-intensive industries.

However, this theory is at odds with data in two respects. First, it is not consistent with the long-run trend of an industry wage premium. If this theory is correct, the dispersion of industry wage premium should have further increased because the (ICT) capital-labor ratio increased more in high-wage industries as in Table 5.5. However, industry wage dispersion has slightly decreased (see Borjas and Ramey (2000)). Second, we again estimate the main equation (5.2) by replacing the initial industry wage premium with the initial ICT capital-labor ratio.[37] The result in Table 5.7 shows that the last theory is not consistent with the data: the effect of capital-labor ratio in 1980 is almost zero. In addition, the estimation result in Table 5.3 shows that our finding is not affected by the factors that we discussed in this section.

Table 5.7: OLS Estimates of Employment Growth by Occupation Groups (1980−2009): Capital-Labor Ratio

Occupation Groups	Coefficient	R-squared
Total	$-0.0000537(0.0000793)$	0.00
Cognitive Occupations	$0.0000821(0.0000693)$	0.00
Routine Occupations	$-0.0000846(0.0000976)$	0.00
Manual Occupations	$0.0015398^{*}(0.0008162)$	0.03

Note: The main regressor is the capital-labor ratio in 1980 instead of the initial industry wage premium.

[37]Results do not change when we use initial (general) capital-labor ratio.

5.4 Job Polarization and Interindustry Wage Differentials before 1980 Interindustry wage differentials have been observed 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 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 differentials, and hence the heterogenous job polarization should be observed whenever interindustry wage differentials exist and alternative technology to replace routine workers is available. Figure 5.7 shows the changes in employment share of each occupation group across industries between 1960 and 1980. We can observe that the employment share of routine occupations decreased in most industries, which suggests the possibility of the existence of job polarization during the earlier period, although its extent is less than in the later period: 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.

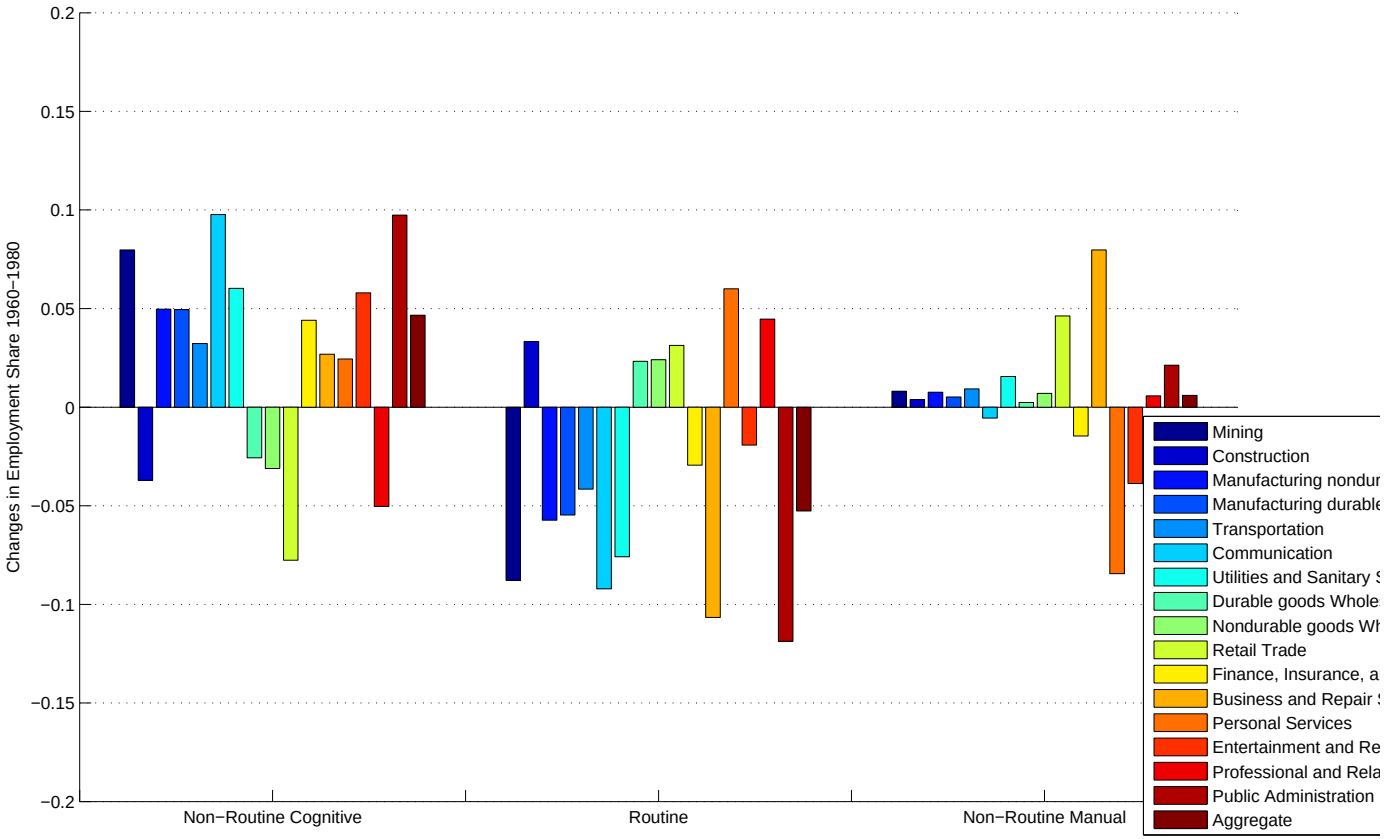

Figure 5.7: Changes in Employment Share by Occupation across Industries between 1960 and 1980

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 5.8, we compare the OLS estimates for the two different periods.[38] 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 5.8: 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 significantly different from zero. This indicates that firms with a high initial industry wage premium in 1960 also responded to the wage pressure 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. 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 easily replaced either by ICT capital or by offshoring (Goos, Manning, and Salomons (2014)). Both of these changes, which are usually argued to have become available or accessible to firms

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

since the 1980s (Acemoglu and Autor (2011) and Jaimovich and Siu (2014)), 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 simple neoclassical firm model;the model predicts that when the relative rental cost of capital over routine workers declines, the capital-routine worker ratio would increase more in a high-wage industry than in a low-wage industry, and hence, job polarization is more evident in a high-wage industry. We then empirically analyze if our suggested mechanism works in the data. Our findings can be explained as dynamic responses of firms to interindustry wage differentials; firms that paid high industry wage premia responded to the wage pressure 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

A.1 Proof of Proposition 3.1

We first list the equilibrium conditions for the firm's problem in the steady state.

$$w_1 = (1+\lambda)w_2 \text{ and } \tilde{w}_1 = (1+\lambda)\tilde{w}_2 \tag{A.1}$$

$$y_i = h_i^{\alpha}\left(\tilde{h}_i^{\mu} + k_i^{\mu}\right)^{\frac{1-\alpha}{\mu}} \tag{A.2}$$

$$\frac{w_i}{p_i} = \alpha\frac{y_i}{h_i} \tag{A.3}$$

$$\frac{\tilde{w}_i}{p_i} = (1-\alpha)\frac{\tilde{h}_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}}\frac{y_i}{\tilde{h}_i} \tag{A.4}$$

$$\frac{r}{p_i} = (1-\alpha)\frac{k_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}}\frac{y_i}{k_i} \tag{A.5}$$

We first obtain the following equations by dividing equation (A.3) (equations (A.4) and (A.5)) for industry 1 by equation (A.3) (equations (A.4) and (A.5)) for industry 2 and apply the wage structure given in equation (A.1):

$$1+\lambda = \frac{y_1}{y_2}\frac{h_2}{h_1} \tag{A.6}$$

$$1+\lambda = \frac{y_1}{y_2}\frac{\tilde{h}_2^{1-\mu}}{\tilde{h}_1^{1-\mu}}\frac{\tilde{h}_2^{\mu} + k_2^{\mu}}{\tilde{h}_1^{\mu} + k_1^{\mu}} \tag{A.7}$$

$$\frac{y_1}{y_2} = \frac{k_1^{1-\mu}}{k_2^{1-\mu}}\frac{\tilde{h}_1^{\mu} + k_1^{\mu}}{\tilde{h}_2^{\mu} + k_2^{\mu}} \tag{A.8}$$

Combining equations (A.7) and (A.8), we obtain the following relationship:

$$\frac{k_1}{\tilde{h}_1} = \phi \frac{k_2}{\tilde{h}_2} \tag{A.9}$$

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.4) and (A.5) to obtain the following equation:

$$\frac{\tilde{w}_i}{r} = \kappa_i^{1-\mu} \tag{A.10}$$

We first differentiate equation (A.10) with respect to $\frac{\tilde{w}_i}{r}$:

$$\frac{d\kappa_i}{d\frac{\tilde{w}_i}{r}} = \frac{\kappa_i^{\mu}}{1-\mu} > 0 \tag{A.11}$$

Hence,

$$\begin{aligned} \frac{d\kappa_1}{d\frac{\tilde{w}_1}{r}} &= \frac{\kappa_1^{\mu}}{1-\mu} = \frac{(\phi\kappa_2)^{\mu}}{1-\mu} = \phi^{\mu}\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} \\ \Leftrightarrow \frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} &= \phi\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} \end{aligned} \tag{A.12}$$

The last step comes from $\tilde{w}_1 = (1+\lambda)\tilde{w}_2$.

As a result, as one can expect from the substitutability between routine workers and capital, a lower relative rental cost of capital accelerates capital deepening (in terms of the capital-routine worker ratio). In addition, $\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} = \phi\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} > \frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} > 0$ 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 relative 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 $\frac{\tilde{w}_i}{r}$ on job polarization, we combine equations (A.3) and (A.4):

$$\frac{1}{\chi} = \frac{1-\alpha}{\alpha}\frac{s_i}{1+\kappa_i^{\mu}} \tag{A.13}$$

Here we use the fact that $\frac{\tilde{w}_i}{w_i}$ is the same across industries due to (A.1) and define $\frac{\tilde{w}_i}{w_i}$ as $1/\chi$. Notice that the left-hand side of the above equation is constant at $1/\chi$ while κ_i increases as $\frac{\tilde{w}_i}{r}$ increases. As a result, it should be the case that $\frac{ds_i}{d\frac{\tilde{w}_i}{r}} > 0$. Formally,

$$\frac{ds_i}{d\frac{\tilde{w}_i}{r}} = \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_i^{\mu-1}\frac{d\kappa_i}{d\frac{\tilde{w}_i}{r}} = \frac{\alpha}{\chi(1-\alpha)}\frac{d\kappa_i^{\mu}}{d\frac{\tilde{w}_i}{r}} > 0 \tag{A.14}$$

Hence, as the relative rental cost of capital over routine workers 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 $\frac{ds_1}{d\frac{\tilde{w}_1}{r}} > \frac{ds_2}{d\frac{\tilde{w}_2}{r}}$. We use equation (A.14), the relationship $\kappa_1 = \phi\kappa_2$, and $\tilde{w}_1 = (1+\lambda)\tilde{w}_2$:

$$\begin{aligned}\frac{ds_1}{d\frac{\tilde{w}_2}{r}} &= \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_1^{\mu-1}\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} \\ &= \frac{\alpha}{\chi(1-\alpha)}\mu\phi^{\mu-1}\kappa_2^{\mu-1}\phi\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} = \phi^{\mu}\frac{ds_2}{d\frac{\tilde{w}_2}{r}}\end{aligned} \tag{A.15}$$

Hence, $\frac{ds_1}{d\frac{\tilde{w}_1}{r}} > \frac{ds_2}{d\frac{\tilde{w}_2}{r}}$ 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 $\frac{\tilde{w}_2}{r}$ increases. Suppose instead that $\lambda = 0$, so that there is no industry wage premium. Then, it is clear that $\frac{ds_1}{d\frac{\tilde{w}_1}{r}} = \frac{ds_2}{d\frac{\tilde{w}_2}{r}}$, 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.

A.2 Additional Tables and Figures

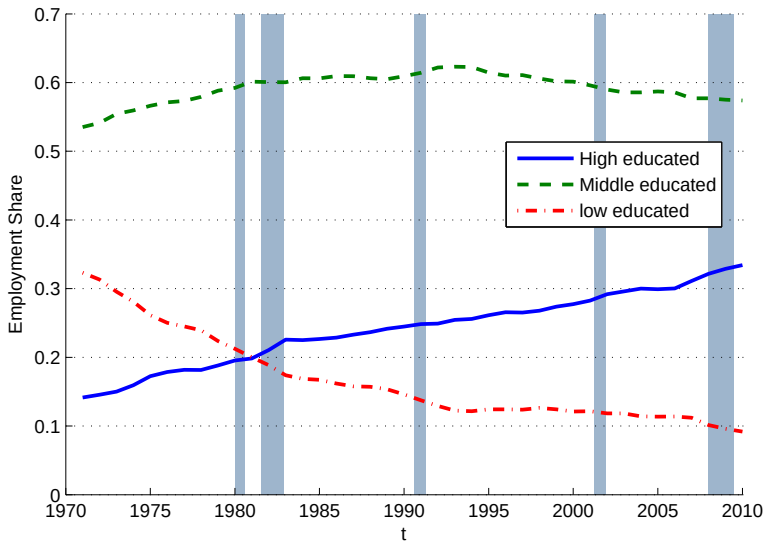

Figure A.1: Job Polarization: Education

Note: 1. Low-educated workers are high school dropouts, middle-educated workers are ones with a high school diploma or with some college education, 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 high-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.

Table A.1: 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 workers with fewer than nine years, nine to 11 years, 12 years, 13 to 15 years, and at least 16 years of schooling, respectively.

Table A.2: 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 and education (see Section 5 for details)) 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.
3. 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)).

Table A.3: OLS Estimates of Employment Growth by Occupation Groups, Full-Time Workers Only (1980−2009)

Occupation Groups	Coefficient	R-squared
Total	$-0.0427^{***}(0.0078)$	0.26
Cognitive Occupations	$-0.0272^{***}(0.0067)$	0.15
Routine Occupations	$-0.0461^{***}(0.0098)$	0.20
Manual Occupations	$0.0091(0.0124)$	0.02

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Supplementary Online Appendix (Not for Publication)

B.1 Full Equilibrium Model: Setup

In this section, we present the full two-sector neoclassical growth model whose predictions about the behaviors of the firms are exactly the same as those of the partial equilibrium model analyzed in Section 3.

B.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.[39]

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

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

subject to

$$(1)\ c_t + x_t = w_t n_t + r_t k_t + \pi_t$$

$$(2)\ k_{t+1} = (1-\delta)k_t + q x_t$$

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. Hence, higher q 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 $1/q$ 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.

[39] 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.

Detailed discussions on wage rates are provided in the next section.[40]

The key optimality condition for the household problem is given as follows:[41]

$$\frac{c_{t+1}}{c_t} = \beta \left[q r_{t+1} + (1 - \delta) \right] \tag{B.2}$$

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

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{q} \tag{B.3}$$

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.

B.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.[42] 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 in industry i.

As discussed in the main text, the industry wage differentials observed in the data are captured by assuming that the wage in industry 1 is higher than that in industry 2 by a factor $\lambda > 0$ so that

$$w_{1t} = (1 + \lambda) w_{2t} \text{ and } \tilde{w}_{1t} = (1 + \lambda) \tilde{w}_{2t} \tag{B.4}$$

[40] 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.

[41] 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.

[42] 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.

As non-routine occupations[43] require more complex skills of a worker, the broker sets the following wage rule to compensate the skill differences across occupations:[44]

$$w_{it} = \chi \tilde{w}_{it} \tag{B.5}$$

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.[45] 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:

$$\pi_t = \tilde{w}_{2t}(\lambda\chi h_{1t} + \chi h_{2t} + \lambda \tilde{h}_{1t}) \tag{B.6}$$

B.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:

$$\max_{y_{1t}, y_{2t}} y_t - p_{1t} y_{1t} - p_{2t} y_{2t} \tag{B.7}$$

subject to the CES aggregator

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

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

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

[43] Here, we focus on cognitive occupations.

[44] 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.

[45] 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.

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

which is the usual form of the inverse demand function for each intermediate good.[46]

B.1.4 Intermediate Goods-Producing Firms This is equivalent to the firm's problem we introduced in Section 3.1. Once the output, y_{it}, is produced, it is sold to the final goods-producing firm at p_{it}.

B.1.5 Equilibrium An equilibrium of this economy consists of quantities[47] and prices[48] 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 (B.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 (3.1), (3) a final goods-producing firm chooses optimal demand for each intermediate good to satisfy equation (B.8), and (4) all markets clear:

$$k_{t+1} = q(y_t - c_t) + (1-\delta)\, k_t \tag{B.9}$$

$$h_{1t} + h_{2t} + \tilde{h}_{1t} + \tilde{h}_{2t} = n_t \tag{B.10}$$

$$k_{1t} + k_{2t} = k_t \tag{B.11}$$

B.2 Equilibrium Conditions

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

$$\frac{c_{t+1}}{c_t} = \beta\left[q_t r_{t+1} + (1-\delta)\frac{q_t}{q_{t+1}}\right] \tag{B.12}$$

[46] One can show easily that the zero-profit condition holds under the above first-order condition (B.8).
[47] $\{c_t, k_{it},\ h_{it}, \tilde{h}_{it}, k_{t+1}, y_{it}, n_t\}_{t=0}^{\infty}$
[48] $\{p_{it}, r_t, w_{it}\}_{t=0}^{\infty}$ for $i \in \{1, 2\}$

$$w_t = \theta c_t = w_{2t} \tag{B.13}$$

$$w_{it} = \chi \tilde{w}_{it} \tag{B.14}$$

$$p_{it} = \left(\frac{y_t}{y_{it}}\right)^{\nu} \tag{B.15}$$

$$y_t = \left[\sum_{i=1}^{2} y_{it}^{1-\nu}\right]^{\frac{1}{1-\nu}} \tag{B.16}$$

$$\lim_{T\to\infty} \beta^T \frac{k_{T+1}}{c_T} = 0 \tag{B.17}$$

$$w_{1t} = (1+\lambda) w_{2t} \tag{B.18}$$

$$y_{it} = h_{it}^{\alpha} \left(\tilde{h}_{it}^{\mu} + k_{it}^{\mu}\right)^{\frac{1-\alpha}{\mu}} \tag{B.19}$$

$$\frac{w_{it}}{p_{it}} = \alpha \frac{y_{it}}{h_{it}} \tag{B.20}$$

$$\frac{\tilde{w}_{it}}{p_{it}} = (1-\alpha) \frac{\tilde{h}_{it}^{\mu}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu}} \frac{y_{it}}{\tilde{h}_{it}} \tag{B.21}$$

$$\frac{r_t}{p_{it}} = (1-\alpha) \frac{k_{it}^{\mu}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu}} \frac{y_{it}}{k_{it}} \tag{B.22}$$

$$k_{t+1} = q_t(y_t - c_t) + (1-\delta)\, k_t \tag{B.23}$$

$$h_{1t} + h_{2t} + \tilde{h}_{1t} + \tilde{h}_{2t} = n_t \tag{B.24}$$

$$k_{1t} + k_{2t} = k_t \tag{B.25}$$

where $i = 1, 2$.

B.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:

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{q} \tag{B.26}$$

$$w = \theta c = w_2 \tag{B.27}$$

$$p_i = \left(\frac{y}{y_i}\right)^{\nu} \tag{B.28}$$

$$y = \left[\sum_{i=1}^{2} y_i^{1-\nu}\right]^{\frac{1}{1-\nu}} \tag{B.29}$$

$$w_i = \chi \tilde{w}_i \tag{B.30}$$

$$w_1 = (1 + \lambda) w_2 \tag{B.31}$$

$$y_i = h_i^{\alpha} \left(\tilde{h}_i^{\mu} + k_i^{\mu}\right)^{\frac{1-\alpha}{\mu}} \tag{B.32}$$

$$\frac{w_i}{p_i} = \alpha \frac{y_i}{h_i} \tag{B.33}$$

$$\frac{\tilde{w}_i}{p_i} = (1-\alpha)\frac{\tilde{h}_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}}\frac{y_i}{\tilde{h}_i} \tag{B.34}$$

$$\frac{r}{p_i} = (1-\alpha)\frac{k_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}}\frac{y_i}{k_i} \tag{B.35}$$

$$c + \frac{\delta}{q}k = y \tag{B.36}$$

$$h_1 + h_2 + \tilde{h}_1 + \tilde{h}_2 = n \tag{B.37}$$

$$k_1 + k_2 = k \tag{B.38}$$

where $i = 1, 2$.

Equilibrium conditions (B.26) and (B.27) are from the household's problem, (B.28) and (B.29) are from the final goods-producing firms' problem, (B.32) to (B.35) are from the firm's problem, (B.30) and (B.31) are wage rules, and (B.36) through (B.38) are market-clearing conditions. One can easily show that the household budget constraint is redundant (Walras' law).

B.3 Comparison of Predictions from Competitive and Non-Competitive Theories

In the main text, we argued that it is the non-competitive labor market theories that can explain our findings, not the competitive labor market theories. In this section, we show, with a simple static equilibrium model where the wage rate of a worker is equal to her productivity, that the predictions of the competitive theory are not consistent with our empirical findings. In particular, we show that it is the firm that paid the **lowest wage** to its workers that first introduces new capital (or other production factors) to substitute for workers. As a result, the high-wage firm experiences job polarization later than other firms that pay relatively lower wages, which contradicts predictions from the non-competitive labor market theories and our empirical findings.

In this section, we first present predictions from the competitive theory and then present predictions from the non-competitive theory for comparison.

B.3.1 Competitive Theory Suppose that there exist the same numbers (measure 1) of workers and firms in the economy. In the labor market, each firm, which produces the same consumption goods, is matched to one worker. Each worker is assumed to have different productivity as follows.

Assumption B.1 (Worker Heterogeneity)**.** *Let x_n denote the productivity of a worker where $n \in [0, 1]$. Without loss of generality, x_n is assumed to be decreasing in n.*

Production function of a firm is given as follows.

$$y = x_n + x_k k \tag{B.39}$$

where k is the amount of capital a firm buys from the international market at unit price p and x_k is the productivity (efficiency) of the capital measured by the consumption goods.

The production function assumes perfect substitutability between labor and capital. Hence, one implicit assumption here is that workers of this economy are routine workers.[49]; Notice that if there is no capital, $y = x_n$ so that competitive labor market implies $w_n = x_n$. Hence, workers earn labor incomes that are equal to their productivities.

Before we proceed, we first consider the case when either capital is not available to firms or price of capital is too high so that the firms only use labor to produce consumption goods. Then $w_n = x_n$ for worker n and this is the equilibrium for the firm's problem. Hence, the wage differentials across workers is the direct result of productivity differences across workers.

Now, we introduce capital to the economy and consider the cost minimization problem of a firm that initially hired a worker n:

$$\min TC = w + pk$$

[49]The key results are identical even when we non-routine workers in production function. For example, $y = \min\{x_{nr}h, x_r + x_k k\}$ where x_{nr} is the productivity of the non-routine worker and h is the number of non-routine workers that are employed by the firm.

subject to

$$y = x_n + x_k k$$

Suppose that a firm that initially hired worker n produces 1 unit of consumption goods. Then, the total cost of producing 1 unit of consumption goods is equal to $1/x_n$ when it uses only labor while it is equal to p/x_k when it uses only capital. This implies the threshold condition of the firm for production: a firm chooses to use labor (resp. capital) in the production if $x_k/p < x_n$ (resp. $x_k/p > x_n$). Suppose that initially the price of capital was too high so that $x_k/p < \min\{x_n\}$. That is, no firm used capital.

Now the price of capital decreases over time due to the "routine-replacing technology changes". Then the following proposition holds.

Proposition B.1 (Prediction of Competitive Model)**.** *Suppose that p satisfied $x_k/p < \min\{x_n\}$ hence no firm used capital. As p decreases, the (relatively) lowest-wage firm adopts capital at first. In other words, the occurrence of job polarization, i.e., the replacement of workers with capital (other production factors) is first observed in the low-wage firms.*

Proof. Obvious from the threshold condition. □

Therefore, the prediction of the competitive labor market theory is exactly opposite to our empirical findings. This comes from the fact that the total cost of producing goods is higher in low-wage firms; because they hire workers with relatively low productivity, they pay higher production costs. As a result, the new technology is adopted faster in these firms.

B.3.2 Non-competitive Theory Now we consider the simplified version of the non-competitive model. We assume $x_n = x$ for all n; productivity is identical across workers. In this alternative model, wage differentials come from some exogenous factors. Let λ_n reflect the differences across firms. With production function $y = x$ without capital, a fraction of profit of the firm is distributed to the worker as $w = \lambda x$ and another fraction of the profit is received by the firm's owner as $\pi = (1 - \lambda)x$. Thus higher negotiation power of the worker implies higher wage. Formally,

Assumption B.2 (Firm Heterogeneity)**.** *Let λ_n denote the degree of labor market friction that is faced by firm n where $n \in [0, 1]$. It can be any factors that are not controlled by the firm. For instance, heterogenous λ reflects (1) differences in the power of labor union, (2) differences in the disutility of workers from working in different firms, or (3) different technology to detect shirking workers across industries.*

Similarly to the firm's problem in the previous section, the total cost of producing 1 unit of consumption goods is equal to λ_n/x when the firm uses only labor and is equal to p/x_k when firm uses only capital. Then the following proposition immediately follows. For simplicity, we normalize $x \equiv 1$.

Proposition B.2 (Prediction of Non-competitive Model)**.** *Suppose that p satisfied $p > x_k \max\{\lambda_n\}$ hence no firm used capital. As p decreases, the (relatively) highest-wage firm adopts capital at first. In other words, the occurrence of job polarization, i.e., the replacement of workers with capital (other production factors) is first observed in the high-wage firms.*

Hence, this is the simplified version of Proposition 3.1 in Section 3: job polarization is more evident in high-wage industries because they have larger incentives to replace workers with other production factors and this is consistent with data.

B.4 Additional Tables

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: 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 (5.4). We normalize the industry wage premium.

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