Interindustry Wage Differentials, Technology Adoption, and Job Polarization*

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Abstract

Based on observations that high-wage industries in 1980 experienced more evident job polarization between 1980 and 2009, we hypothesize that the persistent structure of interindustry wage differentials leads to heterogeneity in job polarization across industries; as the relative price of ICT capital declines, firms respond to exogenous wage differentials by replacing routine workers with capital. Our empirical analysis shows that, during the last three decades, the annualized growth rate of ICT capital per worker increased by 0.34 percent and that of routine employment decreased by 0.41 percent in the U.S. industries that paid 10 percent higher wages in 1980.

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

Keywords: Job Polarization, Interindustry Wage Differentials, Endogenous Technology Adoption

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1 Introduction

The structure of the labor market in the United States has changed dramatically over the past 30 years. One of the most notable changes 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 routine occupations that can be easily replaced by machines.[1] In the U.S., routine occupations accounted for around 60 percent of total employment in 1980, 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); Jaimovich and Siu (2014); and Cortes (2016)), 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, using the U.S. Census data. 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. One potential explanation for the different degrees of changes in employment share over time is that the production function is heterogenous across industries; industries value routine and non-routine workers differently, which results in heterogeneous aspects of job polarization across industries (Autor, Levy, and Murnane (2003)).

[1]As emphasized by Goos, Manning, and Salomons (2009), Autor (2010), Michaels, Natraj, and Reenen (2014), and Coelli and Borland (2016), job polarization is not restricted to the U.S.; several European countries and Australia have experienced job polarization as well.

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

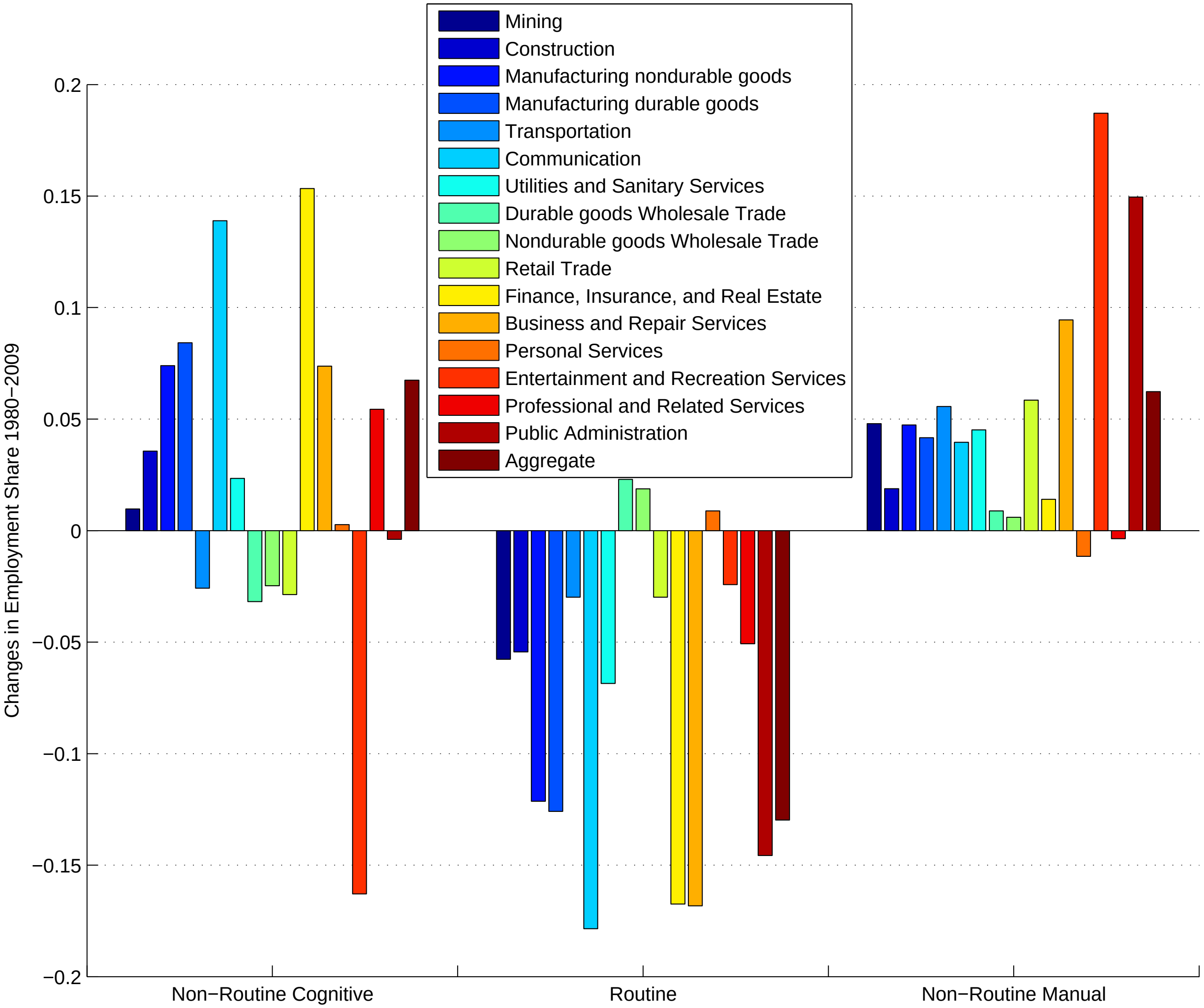

Figure 1.1: Changes in Employment Share by Industry between 1980 and 2009

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 and American Community Survey (ACS).

This paper takes an alternative, new, approach to understand heterogeneity in job polarization across industries, instead of relying on the assumption of differential production process. In particular, we argue that "interindustry wage differentials," the phenomenon that observationally equivalent workers earn differently when employed in different industries, are closely related to the heterogeneous job polarization across industries. In order to explain the link between job polarization and interindustry wage differentials, we hypothesize that the persistent structure of interindustry wage differentials (Dickens and Katz (1987)), which may arise from exogenous factors that are beyond firm's control, pushes high-wage firms to seek alternative ways for reducing production costs instead of lowering wages. The firm's response to the industry wage premium would thus change employment toward other production factors as in Borjas and Ramey (2000). Firm's adjustment of its employment, however, is not even across workers; routine workers are more easily replaced by information and communication technology (ICT, henceforth) capital than non-routine workers. As the price of ICT capital has substantially declined since the 1980s, firms in a high-wage industry are more likely to substitute ICT capital for routine workers than firms in a low-wage industry, which results in different degrees of job polarization across industries.

The empirical analysis with the U.S. data supports our hypothesis. First, the annualized growth rate of routine employment between 1980 and 2009 decreased by 0.41 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 between 1980 and 2009 was more apparent in the high-wage industries in 1980. Second, the annualized growth rate of ICT capital per worker between 1980 and 2007 increased by 0.34 percent when the initial industry wage premium in 1980 increased by 10 percent. In contrast, the annualized growth rate of non-ICT capital per worker was not associated with the initial industry wage premium. We also examine whether the relative price of routine to non-routine workers, initial share of routine workers, or capital-labor ratio can predict our results, and confirm that these hypotheses are not supported by data.

This paper has two major contributions. First, our study contributes to the literature on job polarization by aiding understanding of heterogeneity in job polarization across industries. In particular, we provide the first evidence that polarized employment is connected with interindustry wage differentials. In the literature, industry differences in the degree of job polarization have so far been explained as a result of the different task mix of industries and derived demand effects (see Goos, Manning, and Salomons (2014), for instance). This paper provides an additional, novel, explanation for these industrial differences, namely as an outcome resulting from firms responding to interindustry wage differentials. Second, this paper provides additional evidence to the literature on firms' optimal responses to the labor market structure (see Caballero and Hammour (1998); and Acemoglu (2002)). Our empirical findings can be explained as firms' endogenous responses to interindustry wage differentials (labor market structure): firms that paid high industry wage premia coped with the wage pressure by substituting ICT capital for routine workers, with the falling cost of automating routine, codifiable job tasks.

We note with caution that our finding does not rule out the theory of industry wage premia based on unobserved worker heterogeneity; it might still be an important factor. What our analysis reveals is that factors that are not directly connected to unmeasured worker heterogeneity and out-of-control from the perspective of firms can also play a crucial role in generating interindustry wage differentials.

The paper is organized as follows. Section 2 introduces two key concepts, interindustry wage differentials and job polarization, with reviews of related literature. We introduce a simple theory that provides testable implications in Section 3. Section 4 describes the data, and Section 5 presents our main empirical analysis. Section 6 concludes.

2 Interindustry Wage differentials and Job Polarization

In this section, we introduce key concepts that are important to understand our paper and discuss the related literature.

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 puzzling from the perspective of the 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 of a competitive labor market, however, is not supported by data; for instance, a worker employed in the petroleum-refining industry earned about 40 percent more than a worker in the leather-tanning and finishing industry in 1984 even after controlling for possible 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 shows 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. This is also consistent with Borjas and Ramey (2000)'s finding that wages exhibit little mean convergence between 1960 and 1990. Further, Blackburn and Neumark (1992) show that their measure of unobserved ability (test scores) accounts for only about one-tenth of the variation in interindustry wage differentials. Based on these observations, we focus on the non-competitive view throughout this paper that wage differentials originate from exogenous factors (for a rent-sharing model, see Nickell and Wadhwani (1990); and Montgomery (1991), and for an efficiency wage model, see Walsh (1999); and Alexopoulos (2006)).[3] We also find, as Dickens and Katz (1987) show, that an industry variable has been a consistently significant factor in explaining wage differentials.[4]

Our paper is unique in this literature in the sense that we study how interindustry wage differentials can be associated with structural changes in the aggregate labor market such as job polarization. In this regard, to our best knowledge, Borjas and Ramey (2000) is the only paper related to our study. 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. Our paper is distinctive from their paper in several dimensions. First, while they focus on the "average" effect of interindustry wage differentials on workers, our findings emphasize the importance of considering heterogeneity across occupations in studies of the labor market. Second, we use a theoretical framework with "exogenously" determined interindustry wage differentials

[3]Furthermore, as discussed in Online Appendix B.1, assuming worker heterogeneity does not explain our findings.

[4]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.1. In particular, 4 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 time, which implies that industry should be considered as an important factor in explaining wages.

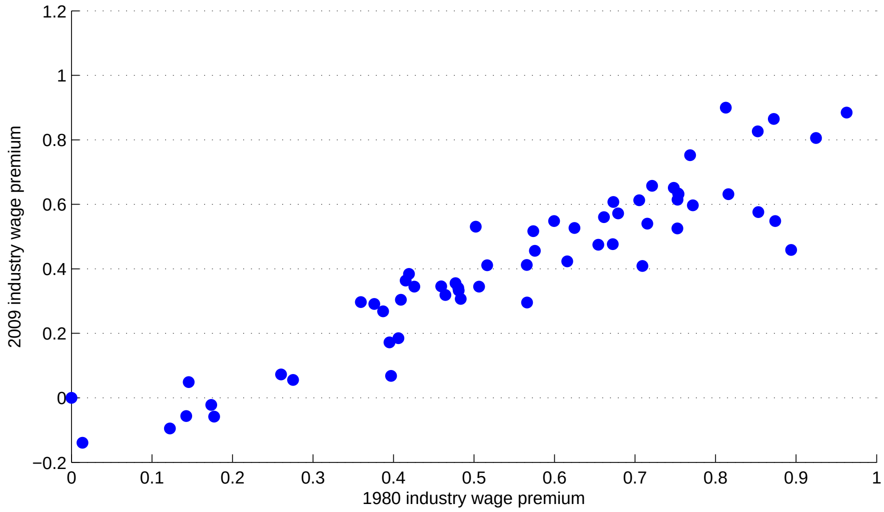

Figure 2.1: Persistency of Interindustry Wage Differentials: Comparison between 1980 and 2009

Note: We omit the industry of "hotels and lodging places," which 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 in 1980.
Source: The U.S. Census and American Community Survey (ACS).

that provides testable predictions while they do not.

2.2 Job Polarization

Polarized employment can be observed by classifying occupations into three groups as follows, which is consistent with the job polarization literature including Autor (2010), Acemoglu and Autor (2011), and Cortes (2016):

- 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 and building and grounds cleaning; and Personal care and personal services

Then we can find that the employment share of routine occupations has decreased, while that of non-routine cognitive (henceforth, cognitive) and non-routine manual (henceforth, manual) occupations has grown over time (Figure 1.1).

One intuitive reason behind job polarization is that the skill content (task) 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. Meanwhile, cognitive and manual occupations are not easily substituted. For instance, managers (cognitive occupations) are hard to be replaced by technology; introduction of new 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 great portion of the tasks that a bank clerk performs can be 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.[5] 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 the 1970s.[6]

A few papers have studied the possibility of heterogeneous job polarization across industries.[7] Acemoglu and Autor (2011) show 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 polarization may be more pronounced in the construction and manufacturing industries. Autor, Levy, and Murnane (2003), Goos, Manning, and Salomons (2014), and Michaels, Natraj, and Reenen (2014) also consider possible differences in job polarization across industries; their analyses are based on the assumptions that production technology is different across industries. Our paper is distinctive from the previous literature by showing that different degrees of job polarization across industries might come from firms' responses to wage differentials across industries, which yields contrasting effects on different types of workers within an industry.[8] In addition, our finding is complement to Michaels, Natraj, and Reenen (2014): They find that job polarization is faster in industries with a faster growth rate of ICT capital. Our analysis provides a rationale why the growth of ICT capital was different across industries, on which they are silent.

[5] "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.

[6] The period in which the growth rate of investment-specific technological changes increased does not perfectly match the occurrence of job polarization, which is usually said to be after 1980. Consistently with this timing problem, we find that job polarization also occurred before 1980, while the magnitude was smaller than that after 1980.

[7] Some recent papers, including Mazzolari and Ragusa (2013), Autor, Dorn, and Hanson (2013), and Autor, Dorn, and Hanson (2015), analyze job polarization at the local labor market level.

[8] We thank an anonymous referee for pointing this out.

3 A Simple Framework and Predictions

In this section, we introduce a simple framework and derive several testable predictions on the link between interindustry wage differentials and heterogeneity in the degree of job polarization across industries; it is the firm's optimal response to the existing interindustry wage differentials, which arise from exogenous factors that cannot be controlled by firms. In order to exogenously generate the industry wage premia, we assume that labor unions in different sectors have different market powers.[9] We note that while our model is abstract from possible worker heterogeneity, this does not necessarily mean that unobserved heterogeneity among workers does not have a role in generating interindustry wage differentials. Rather, our model shows that it is also important to consider exogenous factors, that are industry-specific and cannot be controlled by firms, when studying industry wage premia.

The theoretical implications in the following section are preserved even when we consider the general equilibrium model. In particular, the supply side of the labor market is introduced in Appendix B.3, where the labor supply in each sector is positive.

3.1 Setup

We assume that the goods market is perfectly competitive so that a firm's profit is zero in equilibrium. Each firm produces an output by utilizing two types of workers and capital.[10] 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

[9] Industry wage premia derived in equation (3.4) can be also obtained in different ways: 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). Introduction of compensating wage differentials (hedonic approach) is another way. In this sense, the labor market environment used in our model parsimoniously generates wage differentials across industries with exogenous factors. One might worry that labor is supplied only in the high-wage sector, which is resolved under a labor market environment discussed in Appendix B.3.

[10] 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. The same strategy is used by Beaudry, Green, and Sand (2013) and Jaimovich and Siu (2014).

supplied to industry i and w_{it} (resp. $\tilde{w}_{it}$) is the corresponding wage rate. We assume that labor is infinitely supplied by workers as firms would like to hire and capital is rented at the competitive international market at rate r, which can 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 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 in Autor and Dorn (2013), capital is a *relative substitute* for routine workers and a *relative complement* to non-routine workers. Hence, capital in our model can be interpreted as ICT capital rather than general-purpose capital whose elasticity of substitution is the same between routine and non-routine workers.

A final remark on the firm's problem is that the implications of our model are preserved even when we assume heterogeneous production functions (different α and μ) across industries.[11] Hence, we will maintain the assumption that production functions are the same across industries in this paper.

Among different ways to introduce an exogenous industry wage premium in our framework, we particularly consider the labor market environment usually used in the New Keynesian literature, as in Smets and Wouters (2007) and Erceg, Henderson, and Levin (2000): a firm is assumed to buy labor only through a labor union.

The labor market is organized as follows. Firstly, the labor market (broker) supplies workers to the labor union of each industry at W_t and $\tilde{W}_t$; the wage rate is not industry-specific in order to ensure positive employment in each sector. Any profit of the labor union coming from its market power is assumed to be distributed back to workers in a lump-sum manner. The labor union unpacks the labor into different varieties, $h_{it}(l)$ and $\tilde{h}_{it}(l)$, $l \in [0, 1]$, and sells them at wage rates, $w_{it}(l)$ and $\tilde{w}_{it}(l)$, respectively. In so doing, the union acts as a monopolist for each single variety. The different labor varieties are purchased by perfectly competitive intermediaries, called labor packers. They produce aggregate labor for each task according to the CES (Dixit-Stiglitz) production function:

[11] For the high-wage industry to experience more pronounced job polarization, the industry wage premium should exceed some threshold level. Detailed results are available upon request.

$$h_{it} = \left[\int_0^1 (h_{it}(l))^{\frac{1}{1+\lambda^i}}\, dl\right]^{1+\lambda^i} \tag{3.2}$$

$$\tilde{h}_{it} = \left[\int_0^1 \left(\tilde{h}_{it}(l)\right)^{\frac{1}{1+\lambda^i}}\, dl\right]^{1+\lambda^i}, \tag{3.3}$$

where λ^i, the wage markup in industry i, measures the market power of the union. We assume that the wage markup is the same across different occupations (tasks) so that it measures the average industry wage premium.[12] Notice that if $\lambda^i = 0$, the labor union does not have any market power, so that wage rates will be determined at the competitive rate.

In a symmetric equilibrium, $w_{it}(l) = w_{it}$ and $\tilde{w}_{it}(l) = \tilde{w}_{it}$ for all l, the following relationship can be derived[13]:

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

where we assume $\lambda \equiv \lambda^1 > \lambda^2 = 0$, and hence the labor union in industry 2 does not have any market power. That is, the wage in industry 1 is higher than that in industry 2 by a factor λ.

Demand for goods is given by $y_t = \left[y_{1t}^{1-\nu} + y_{2t}^{1-\nu}\right]^{\frac{1}{1-\nu}}$ where $\nu > 0$ so that the individual inverse demand function can be derived as $p_{it} = \left(\frac{y_t}{y_{it}}\right)^{\nu}$.

3.2 Testable Implications

We particularly focus on the fact that the relative price of (ICT) capital over wage of routine workers has declined over time (an increase in $\tilde{w}/r$ in our model); one can think of the steady-state economy as the U.S. economy in 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 $s_i \equiv \frac{h_i}{\tilde{h}_i}$, which 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 $\kappa_i \equiv \frac{k_i}{\tilde{h}_i}$, which is the capital-routine worker ratio. While we only consider two industries (firms), the analysis can be extended easily to $n > 2$ industries. We use the wage of routine workers in the low-wage industry ($\tilde{w}_2$) as a numéraire.

Prediction (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:*

[12] In Online Appendix B.2, we allow occupation-specific industry wage premia, which does not change the implications of the model.

[13] See Appendix A.1 for derivation.

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,*

$$\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} = (1+\lambda)^{\frac{1}{1-\mu}} \frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} > 0, \tag{3.5}$$

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

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

$$\frac{ds_i}{d\frac{\tilde{w}_2}{r}} = \frac{\alpha}{\chi(1-\alpha)} \frac{d\kappa_i^\mu}{d\frac{\tilde{w}_2}{r}} > 0, \tag{3.6}$$

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

$$\frac{ds_1}{d\frac{\tilde{w}_2}{r}} = (1+\lambda)^{\frac{\mu}{1-\mu}} \frac{ds_2}{d\frac{\tilde{w}_2}{r}}. \tag{3.7}$$

Proof. See Appendix A.2. □

First of all, it is a natural consequence of the model that industries 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. Moreover, the fact that $\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}}$ increases in λ, the parameter that governs the industry wage premium, implies that the higher the wage an industry pays to workers, the higher its incentive to utilize capital. Hence, the first prediction is the key channel through which job polarization can be heterogenous across industries; the high-wage industry has more incentive to replace routine workers with ICT capital than the low-wage industry. That is, the availability of capital as a substitute for routine labor leads to the demand for routine labor being more elastic than that for non-routine labor, and thus the industry wage premium reduces the demand for routine labor more than it reduces the demand for non-routine labor.

The second prediction shows that, consistent with previous models on job polarization, including Autor, Levy, and Murnane (2003), Autor and Dorn (2013), and Cortes (2016), a decline in the relative price of capital over routine workers is one of the crucial factors in job polarization. The last prediction is another key implication of our hypothesis: 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 industry that faces higher labor costs. 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.

In sum, two key implications of our hypothesis, tested in Section 5, are the positive correlation between (1) the degree of job polarization and the initial industry wage premium (third prediction) and (2) the subsequent growth rate of ICT capital per worker and the initial industry wage premium (first prediction).

3.3 Theory to Empirics

We now discuss how the predictions of the model are tested with data in the next sections.

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. ICT capital per worker provides, however, the same information as the prediction in the following sense: the capital-(total) labor ratio is $k_i/(h_i + \tilde{h}_i)$ and it 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 $\tilde{w}_i/r$ 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 regress the growth rate of employment for each occupation group on the initial industry wage premium and compare the coefficients of the regression to evaluate the last prediction of the model. 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[14] and (2) the EU KLEMS data. Following 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.[15] We drop farmers (and related industries) and the armed forces.[16] Age is restricted to 16−64 years and we only consider persons employed in wage-and-salary sectors. We follow Dorn (2009) to overcome the inconsistency problem of occupation codes due to the frequent changes in the Census occupation coding scheme and to construct consistent occupation series. Table B.1 in Supplementary Online Appendix B describes the industry classification used in the analysis.

The second data set, EU KLEMS, has information on value added, labor, and capital for various industries in many developed countries. 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. 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 (NAICS). Since the industry classification of EU KLEMS is different from the Census data, we reclassify industries to be consistent between the Census and the EU KLEMS data. Table B.3 in Supplementary Online Appendix B describes the industry classification of EU KLEMS used in the analysis.

5 Empirical Analysis

This section presents our empirical findings. We first estimate industry wage premia for each Census year as follows.

[14] 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)).

[15] In determining the sample size, 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.

[16] Farmers are excluded because the substantial share of them are undocumented workers and so their employment and wage information might be inaccurate (Autor (2010)).

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

where w_{hit} is the wage rate of worker h in industry i in Census year t; X_{hit}, a vector of socioeconomic characteristics, includes the worker's age (five age groups: 16−24, 25−34, 35−44, 45−54, or 55−64 years), educational attainment (five educational groups: less than 9 years, 9 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, occupation, and region of residence (indicating in which of the nine Census regions the worker lives). Our findings are not sensitive to controlling for state dummies, detailed occupation dummies, and various interaction terms of age, gender, race, and education in the wage regression. ω_{it}, an industry fixed effect, measures the industry wage premium.[17]

The result of equation (5.1) for the Census year 1980 is reported in Table A.2.[18] After obtaining the estimated coefficients for 60 industry dummies, $\hat{\omega}_{it}$, from equation (5.1), we estimate the second-stage regression as follows:

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

where y_{ijt} is the variable of interest such as employment of occupation group j in industry i in Census year t. $\Delta y_{ijt,t+k}$ is the annualized growth rate of y_{ijt} between periods t and $t+k$ (for the main result, between 1980 and 2009), and $j \in \{cognitive, routine, manual\}$.[19] 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 size 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.[20]

[17] We omit an industry dummy with the lowest wage premium to make all the premia positive. The estimated industry wage premium has an average of 0.57 and a standard deviation of 0.25. See Supplementary Online Appendix Table B.4.

[18] The estimated coefficients are consistent with the usual intuition: (1) wages increase in education, (2) wages also rise in ages until workers reach their prime age, and then decrease slightly, (3) cognitive occupations earn the most, followed by routine occupations, and (4) African-American and females earn less.

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

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

Despite the estimated industry wage premium does not suffer from the generated regressor problem, however, there might be a potential endogeneity problem in equation (5.2) such as omitted variable bias.[21] 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) for the 1980 industry wage premium.[22,23] Due to the persistent structure of industry wage differentials, the instrument is expected to be correlated with the next decade's wage premium. In addition, as the instrument is determined in 1970, that is, a decade prior to the 1980 industry wage premium, it would be uncorrelated with growth rates between 1980 and 2009. The first-stage results indicate that the instrument is highly significant in each estimation. For instance, the first-stage coefficient for the regression of routine occupations is 1.05, which is significant at the 1 percent level, with F-statistic of 405.51.[24]

5.1 Job Polarization and Initial Industry Wage Premia

In this section, we formally test if interindustry wage differentials are related to different degrees of job polarization across industries. If there is no link between industry wage dispersion and job polarization, the coefficients on $\hat{\omega}_{it}$ in equation (5.2) would not differ across occupations; that is, the subsequent employment growth of each occupational group does not react differently to industry wage premia. If they are related, however, we should observe $\theta_r < \theta_c$, θ_m, 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 premium 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 can observe that the slope of the fitted line is negative and the steepest in the case of routine occupations (Figure 5.2), which

[21] For instance, as Autor and Dorn (2013) point out, there might be unobserved demand shocks that potentially affect the initial wage premium and subsequent employment growth. Suppose that a certain manufacturing industry experiences a surge in demand, which attracts routine workers into that industry. This demand shock will then affect both the wage premium and the growth rate of routine employment, biasing OLS estimates in equation (5.2).

[22] For the use of endogenous variables' historical counterparts as an instrument, see Autor and Dorn (2013). To address potential endogeneity problems in the analysis of the growth of low-skill service occupations between 1980 and 2005, Autor and Dorn (2013) instrument initial routine shares with their historical counterparts.

[23] If union power is an exogenous source of industry wage differentials, the previous decade's unionization rate at the industry level might be an instrument for the 1980 industry wage premium. Unfortunately, the information on union membership at the industry level is only available from 1983 (Hirsch and Macpherson (2003)). When we use the 1983 unionization rate as well as the 1970 wage premium as instruments for the 1980 wage premium, the results do not change much. Detailed results are available upon request.

[24] For the first-stage results, see Table A.3.

supports the hypothesis that industries facing high wages reduce their demand for routine workers more than other industries. That is, high-wage industries, such as mining, petroleum and coal products, motor vehicles, railroads, and air transportation, have experienced lower employment growth of routine workers between 1980 and 2009 than low-wage industries, such as hotels and lodging places, retail trade, entertainment and recreation services, and child care and social services. 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 5.2.

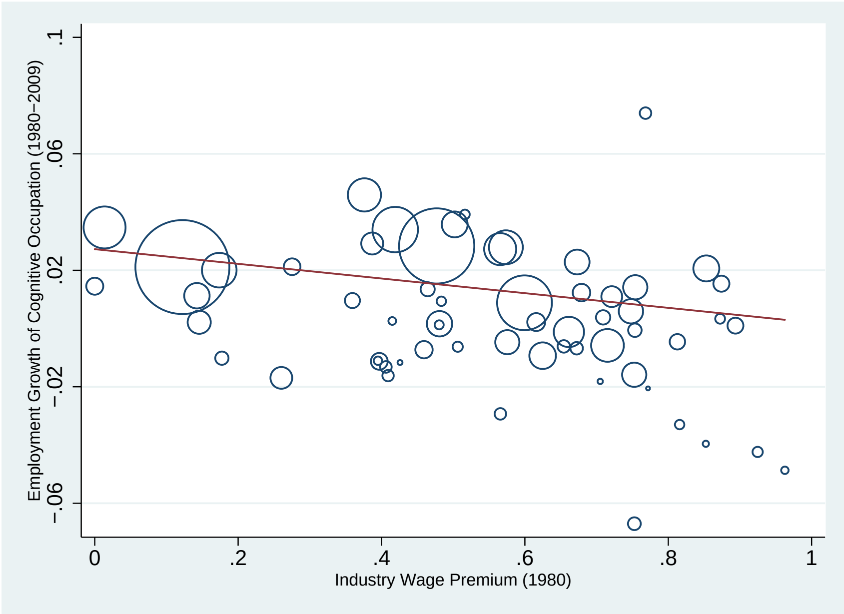

Figure 5.1: Dynamic Responses of Industries to Industry Wage Premia–Cognitive Occupations

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

The main empirical finding based on equation (5.2) is reported in Table 5.1. The dependent variable in the first column is the annualized growth rate of aggregate employment for industry i. 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; they use the Census data between 1960 and 1990.

In the remaining columns, we report the estimates 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. Thus, the results in Table 5.1 reveal how "average" industry wage premia affect different occupational groups in a distinct manner. In Section 5.2, we will show the results using

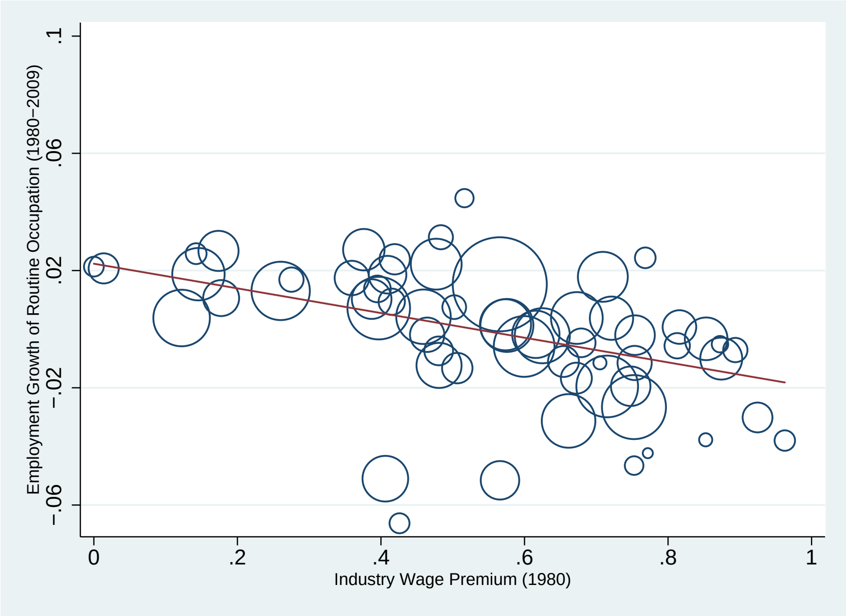

Figure 5.2: Dynamic Responses of Industries to Industry Wage Premia–Routine Occupations

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

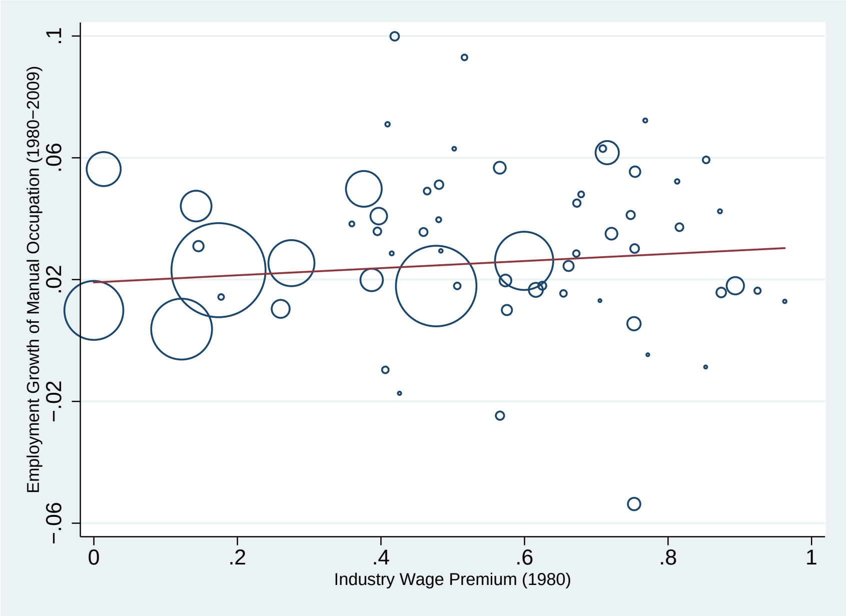

Figure 5.3: Dynamic Responses of Industries to Industry Wage Premia–Manual Occupations

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

"occupation-specific" industry wage premia.

The estimated coefficients reported in the second to fourth columns in Table 5.1 are consistent with

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

	OLS			
	Total	Cognitive	Routine	Manual
Industry Wage Premium in 1980	−0.0359	−0.0240	−0.0409	0.0095
	(0.0066)***	(0.0067)***	(0.0081)***	(0.0118)
R^2	0.25	0.13	0.22	0.02
	IV			
	Total	Cognitive	Routine	Manual
Industry Wage Premium in 1980	−0.0310	−0.0183	−0.0393	0.0174
	(0.0064)***	(0.0065)***	(0.0080)***	(0.0109)
F-Statistic	205.9	582.98	405.51	44.87

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

Figures 5.1 to 5.3. The average growth rate of routine employment between 1980 and 2009 decreased by 0.41 percent when the initial industry wage premium in 1980 increased by 10 percent, while that of cognitive employment decreased by 0.24 percent.[25] The initial industry wage premium has a positive but economically small relationship with the subsequent employment growth of the manual occupation group and the estimate is not significant.[26] The IV estimates with first-stage F-statistic are also reported in Table 5.1. Both the OLS and IV regressions yield similar coefficients, which implies that measurement errors in $\hat{\omega}_{it}$ and the endogeneity problem are not severe.[27] In summary, the employment growth of routine occupations between 1980 and 2009 is negatively affected by the initial industry wage premium.[28,29]

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

[25] Given that the estimated wage premium takes a value between 0 and 1 and the standard deviation is 0.25, a 10 percent increase in the wage premium is less than half a standard deviation change.

[26] 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 occupations.

[27] Reported standard errors for IV estimates are often smaller than those for corresponding OLS estimates. This might be because the previous decade's industry wage premium might be a very strong IV for the 1980 wage premium; or because the IV, by construction, might have large variation than the potential endogenous variable.

[28] The result using only two groups of workers as in the model shows that the relative employment of non-routine workers to routine workers has increased in industries with high initial wage premia. The result is reported at Online Appendix B.4 (Table B.2).

[29] Interindustry wage differentials had been observed even prior to 1980; for instance, the estimation of Borjas and Ramey (2000) is based on the industry wage premium in 1960. The magnitude of the responsiveness is, however, much lower than that of the latter period and the explanatory power drops by half. This suggests that the heterogeneous aspect of job polarization across industries became more pronounced after 1980.

between 1980 and 2007, which is reported in Table 5.2. The 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.[30] 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 are more likely to have routine occupations. In Table A.4, 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			
	Total	Cognitive	Routine	Manual
Industry Wage Premium in 1980	−0.0377	−0.0246	−0.0395	0.0021
	(0.0079)***	(0.0078)***	(0.0088)***	(0.0131)
R^2	0.22	0.12	0.19	0.00
	IV			
	Total	Cognitive	Routine	Manual
Industry Wage Premium in 1980	−0.0321	−0.0181	−0.0365	0.0074
	(0.0078)***	(0.0074)**	(0.0090)***	(0.0129)
F-Statistic	205.9	582.98	405.51	44.87

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. We test the robustness of our results to the inclusion of various industry-specific factors by estimating the following equation:

$$\Delta y_{ijt,t+k} = \beta_j \chi_{it} + \theta_j \hat{\omega}_{it} + \eta_{ijt}, \tag{5.3}$$

where χ_{it} includes the share of routine workers in industry i in 1980, capital per worker and ICT capital per worker in industry i in 1980,[31] and union membership rate in industry i in 1983.[32] In particular, the initial share of routine workers might be an important factor as the employment share of routine workers

[30] Estimates with a sample period between 1980 and 2006 are also similar to the main results.
[31] Information on capital is only available for 29 industries in EU KLEMS data; thus, we assign the information for those industries to the 60 Census industries by matching industry codes.
[32] Union data at industry level are available only from 1983. See Hirsch and Macpherson (2003) for details.

is positively correlated with the industry wage premium. For instance, the manufacturing industry had a higher share of routine workers than other industries in 1980 and it paid relatively higher wages. Therefore, as the relative price of capital has declined, the high-wage industries would have experienced more replacement of routine workers because they had a higher share of routine workers in 1980; that is, the "level effect" might be a dominant reason why the job polarization was more evident in the high-wage industries.[33]

In addition, the high wage premium might be the consequence of high capital-labor ratio in 1980, which is 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 since they are more efficient in using capital by the intrinsic nature of the industries. As a result, more (routine) workers might have been replaced by (ICT) capital in capital-intensive industries. The estimation results after controlling for these industry-specific factors are reported in Table 5.3.

We find that the inclusion of the various industrial factors does not alter our results in Table 5.1.[34] Rather, it enlarges the differences between the coefficients of routine workers and non-routine workers: both the OLS and IV estimates show that only routine occupations have a negative and significant relationship between initial industry wage premia and subsequent employment growth during 1980-2009. Hence, our main results are robust to the addition of other industry-specific 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 on firms. This might be because routine workers were mostly covered by unions until the 1990s and unions might prevent firms from replacing them with capital.

[33] In the sense that the level effect is the product of heterogeneous production functions across industries, this analysis can be interpreted as the indirect test of the hypothesis based on production functions (see Autor, Katz, and Krueger (1998) for related discussions).

[34] In addition, for the growth rate of routine employment, R^2 does not increase much when those industrial factors are added.

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

	OLS			IV		
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
Industry Wage Premium in 1980	0.0005	−0.0338	0.0063	0.0085	−0.0340	0.0180
	(0.0071)	(0.0115)***	(0.0132)	(0.0078)	(0.0095)***	(0.0130)
Routine Share in 1980	−0.0402	−0.0078	0.0270	−0.0449	−0.0077	0.0200
	(0.0087)***	(0.0129)	(0.0135)*	(0.0079)***	(0.0109)	(0.0138)
Capital per Worker in 1980	0.0002	0.0001	0.0001	0.0002	0.0001	0.0001
	(0.0001)**	(0.0001)**	(0.0001)	(0.0001)**	(0.0001)**	(0.0001)
ICT Capital per Worker in 1980	0.0052	0.0026	0.0114	0.0047	0.0026	0.0102
	(0.0012)***	(0.0011)**	(0.0048)**	(0.0012)***	(0.0013)**	(0.0039)***
Union Membership in 1983	−0.0419	−0.0179	−0.0572	−0.0429	−0.0178	−0.0641
	(0.0112)***	(0.0142)	(0.0144)***	(0.0114)***	(0.0120)	(0.0116)***
R^2	0.52	0.28	0.29			
F-Statistic				411.96	332.8	41.94

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

As the last robustness check, we estimate the same second-stage regression with a different dependent variable–the change in employment share of occupation groups between 1980 and 2009. 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. Table 5.4 summarizes the results of the alternative estimation.[35]

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

	OLS		
	Cognitive	Routine	Manual
Industry Wage Premium in 1980	0.0126	−0.1749	0.1187
	(0.0766)	(0.0528)***	(0.0886)
R^2	0.00	0.19	0.12
	IV		
	Cognitive	Routine	Manual
Industry Wage Premium in 1980	0.0216	−0.2243	0.1590
	(0.0772)	(0.0543)***	(0.0767)**
F-Statistic	582.98	405.51	44.87

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

First, the employment share of routine occupations decreases more in industries with a high initial wage premium, which is consistent with the previous results. Second, the coefficient for manual occupations is much greater than zero in both the OLS and IV regressions, while the coefficient for cognitive occupations is estimated to be almost zero. This is because (1) the negative responsiveness of the employment growth of cognitive occupations to the initial industry wage premium is not large compared to that of routine occupations and (2) there is weak correlation between the subsequent employment growth of manual occupations and the initial industry wage premium.

[35] Controlling for the various industrial factors increases the degree of job polarization as in Table 5.3.

5.2 Task Content vs. Relative Price explanations So far, the analysis has shown how "average" industry wage premia affect different occupations. In principle, 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 were paid more than other groups, firms would decrease their relative demand for the routine occupation group since this group was actually the most expensive production factor (although the property of tasks required by routine occupations may enhance the firms' 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 h denotes the worker, 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 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 in other industries, and this also allows for within-industry comparisons of the wage premia.[36]

Figure 5.4 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 and investment. All values are estimated in 1980. Figure 5.4 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.[37]

[36] For the estimation result, see Supplementary Online Appendix Table B.4.

[37] One interesting finding is that the slope of the line in Figure 5.4 is steeper for routine occupations than for cognitive

Figure 5.4 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 employment growth of the manual occupations is not negative in Table 5.1; 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 5.4) paid manual workers less than quite a few other industries (on the left) 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.

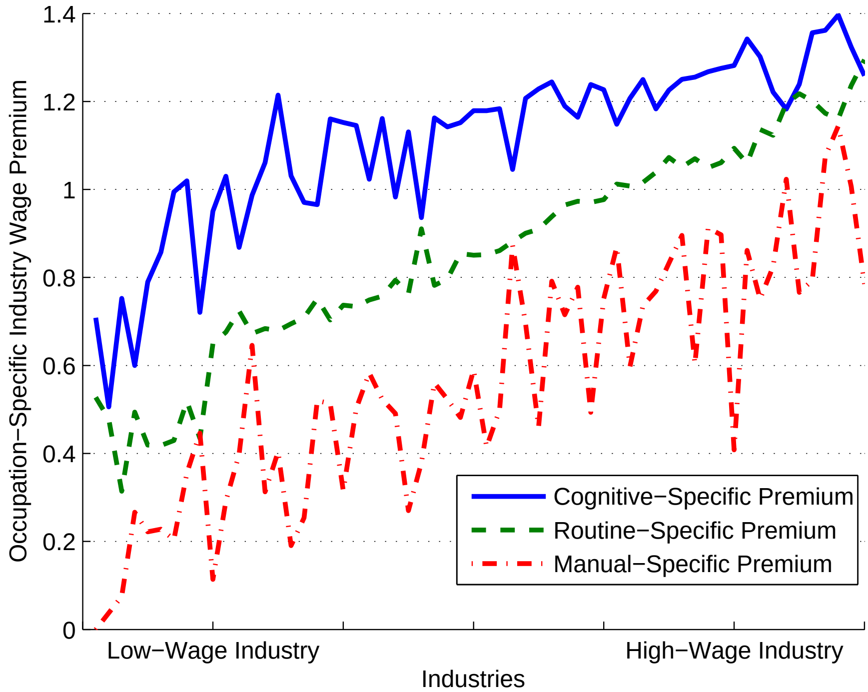

Figure 5.4: Occupation-Specific Industry Wage Premium

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

occupations. In the end, the gap between the cognitive occupation-specific industry wage premium and the routine occupation-specific industry premium becomes almost zero. This fact implies that while cognitive occupations are paid more than routine occupations, high-wage industries are likely to pay relatively more to routine occupations than are 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.

Table 5.5 shows estimates where the dependent variable is the average growth rate of employment for occupation j in industry i between 1980 and 2009 and the main regressor is the initial occupation-specific industry wage premium ($\omega_{ij,1980}$). Both the OLS and IV estimates show that industry's cognitive and manual wage premia do not affect employment growth of those occupations. In contrast, the average growth rate of routine employment decreased by 0.3 percent when the initial routine-specific wage premium increased by 10 percent, suggesting that our main result is robust to using occupation-specific industry wage premium.

Table 5.5: Estimates of Employment Growth by Occupation Groups (1980−2009) using Occupation-Specific Wage Premium

	OLS			IV		
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
Cognitive-Specific in 1980	−0.0023			−0.0019		
	(0.0085)			(0.0099)		
Routine-Specific in 1980		−0.0305			−0.0308	
		(0.0112)***			(0.0094)***	
Manual-Specific in 1980			0.0072			0.0112
			(0.0083)			(0.0073)
Industry specific factors	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.52	0.27	0.30			
F-Statistic				161.28	433.47	33.95

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
4. Industry specific factors include routine share, capital per worker, ICT capital per worker in 1980, and union membership in 1983.

5.3 ICT Capital per Worker and Initial Industry Wage Premia In this section, we test if the growth rate of ICT capital per worker since 1980 is related to the initial industry wage premium, which is the channel through which the heterogeneity in job polarization is connected with wage dispersion across industries. In addition, we also analyze how the growth of non-ICT capital per worker responds to initial industry wage premia. If non-ICT capital is general-purpose capital, the coefficient for non-ICT capital per worker would be lower in magnitude than that for ICT capital per worker.

For the analysis, we use the EU KLEMS data. Since they provide information on employment and capital for 29 industries, we recompute the initial industry wage premium in 1980 by reclassifying the Census 60 industries into 29 industries.[38] Each capital series (aggregate capital, ICT capital, and non-ICT capital) is real fixed capital stock based on 1995 prices. In order to obtain capital per worker series, we divide capital by employment for each industry.

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

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

We first show graphical evidence of our argument. Figure 5.5 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 5.6, however, suggests that the change in non-ICT capital per worker between 1980 and 2007 may not be precisely related to interindustry wage differentials.

[38]Details on the classification can be found in Supplementary Online Appendix Table B.3.

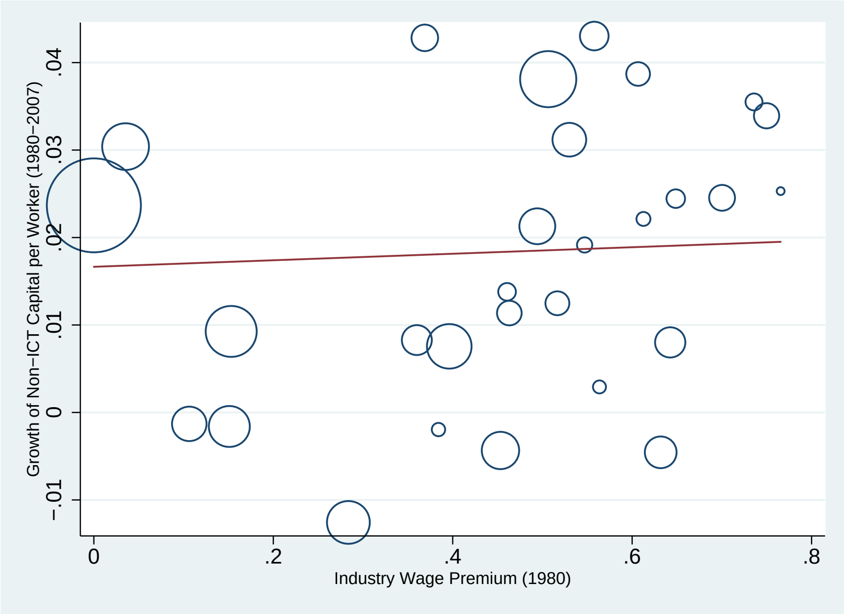

Figure 5.6: Non-ICT Capital per Worker to Initial Industry Wage Premium (1980−2007)

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

For the complete analysis, we estimate equation (5.5).

$$\Delta y_{it,t+k} = \theta \hat{\omega}_{it} + \eta_{it}, \tag{5.5}$$

where y_{it} is capital per worker, output, or employment in industry i at time t. The OLS and IV results, which are quite similar, are reported in Table 5.6. Before we discuss the main result, we focus on the estimates when the dependent variable is the average growth rate of aggregate employment for industry i. The OLS and IV estimates using the EU KLEMS data are similar to the coefficients obtained from the Census data (see Table 5.1), which confirms the robustness of our findings.

The relevant coefficients for different types of capital per worker are presented in the first row. As the initial industry wage premium increased by 10 percent, the annualized growth rates of aggregate capital per worker, ICT capital per worker, and non-ICT capital per worker between 1980 and 2007 increased by 0.14 percent, 0.34 percent, and 0.03 percent, respectively. That is, $\theta_{ICT} > \theta_{Aggregate} > \theta_{non-ICT}$. Furthermore, only θ_{ICT} is statistically significant. This finding is consistent with our hypothesis that a high-wage industry tends to adopt more ICT capital to replace routine workers.

This finding provides supporting evidence of "directed technology changes" suggested by Acemoglu

Table 5.6: Estimates of Capital, Productivity, and Employment Growth (1980−2007)

	OLS		
	Capital/Worker	ICT Capital/Worker	Non-ICT Capital/Worker
Industry Wage Premium in 1980	0.0135	0.0342	0.0033
	(0.0126)	(0.0184)*	(0.0129)
	Output	Labor Productivity	Employment
	−0.0061	0.0273	−0.0334
	(0.086)	(0.0088)***	(0.0073)***
	IV		
	Capital/Worker	ICT Capital/Worker	Non-ICT Capital/Worker
Industry Wage Premium in 1980	0.0136	0.0397	0.0034
	(0.0133)	(0.0171)**	(0.0139)
	Output	Labor Productivity	Employment
	−0.057	0.0255	−0.0313
	(0.0084)	(0.0086)***	(0.0071)***

Note: 1. 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.

(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 them 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 three decades. Our findings suggest that an environment of interindustry wage differentials has generated industry differences in the degree of job polarization.

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 toward both cognitive and manual occupations. In this paper, we show that the degree of job polarization is different across industries and the heterogeneity in job polarization is connected with wide dispersion in wages across industries, which is different from the literature assuming heterogeneity in production functions. The empirical analysis finds that industries with initially high industry wage premia experienced greater reductions in routine employment and increases in ICT capital intensity during the last three decades. This finding can be explained by considering high-wage firms' strong incentive to automate routine tasks as price of ICT capital declines.

Therefore, the heterogeneous aspect of job polarization across industries can be the result of optimal responses of industries to the existing wage structure.

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A Appendix

A.1 Derivation of Equation (3.4) For convenience, we only consider the non-routine workers in this appendix since the problem is symmetric between the routine and non-routine workers; one can replace variables without tilde with variables with tilde for routine workers.

The cost minimization of labor packers yields the following labor demand equation:

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

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

Now we consider the labor union's problem:

$$\max_{w_{it}(l)} d_{it}(l) = (w_{it}(l) - W_t)\, h_{it},$$

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

$$\begin{aligned} h_{it}(l) - \frac{1+\lambda^i}{\lambda^i_w} (w_{it}(l) - W_t)\, \frac{h_{it}(l)}{w_{it}(l)} &= 0 \\ \Leftrightarrow \lambda^i w_{it}(l) &= \left(1+\lambda^i\right)(w_{it}(l) - W_t) \end{aligned} \tag{A.2}$$

Hence,

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

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

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

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

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

$$w_{1t} = (1 + \lambda)\, w_{2t}. \tag{A.4}$$

Hence, the equation (3.4) is endogenously determined without changing equilibrium outcomes.

A.2 Proof of Prediction We first list the equilibrium conditions for the firm's problem in the steady state.

$$w_1 = (1+\lambda) w_2 \text{ and } \tilde{w}_1 = (1+\lambda)\tilde{w}_2. \tag{A.5}$$

$$y_i = h_i^{\alpha} \left(\tilde{h}_i^{\mu} + k_i^{\mu}\right)^{\frac{1-\alpha}{\mu}}. \tag{A.6}$$

$$\frac{w_i}{p_i} = \alpha \frac{y_i}{h_i}. \tag{A.7}$$

$$\frac{\tilde{w}_i}{p_i} = (1-\alpha) \frac{\tilde{h}_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}} \frac{y_i}{\tilde{h}_i}. \tag{A.8}$$

$$\frac{r}{p_i} = (1-\alpha) \frac{k_i^{\mu}}{\tilde{h}_i^{\mu} + k_i^{\mu}} \frac{y_i}{k_i}. \tag{A.9}$$

We obtain the following equations by dividing equation (A.7) (equations (A.8) and (A.9)) for industry 1 by equation (A.7) (equations (A.8) and (A.9)) for industry 2 and apply the wage structure given in equation (A.5):

$$1 + \lambda = \frac{p_1}{p_2} \frac{y_1}{y_2} \frac{h_2}{h_1}. \tag{A.10}$$

$$1 + \lambda = \frac{p_1}{p_2} \frac{y_1}{y_2} \frac{\tilde{h}_2^{1-\mu}}{\tilde{h}_1^{1-\mu}} \frac{\tilde{h}_2^{\mu} + k_2^{\mu}}{\tilde{h}_1^{\mu} + k_1^{\mu}}. \tag{A.11}$$

$$\frac{p_1}{p_2} \frac{y_1}{y_2} = \frac{k_1^{1-\mu}}{k_2^{1-\mu}} \frac{\tilde{h}_1^{\mu} + k_1^{\mu}}{\tilde{h}_2^{\mu} + k_2^{\mu}}. \tag{A.12}$$

Combining equations (A.11) and (A.12), we obtain the following relationship:

$$\frac{k_1}{\tilde{h}_1} = \phi \frac{k_2}{\tilde{h}_2}, \tag{A.13}$$

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.8) and (A.9) to get the following equation:

$$\frac{\tilde{w}_i}{r} = \kappa_i^{1-\mu}. \tag{A.14}$$

We differentiate equation (A.14) with respect to $\frac{\tilde{w}_i}{r}$:

$$\frac{d\kappa_i}{d\frac{\tilde{w}_i}{r}} = \frac{\kappa_i^{\mu}}{1-\mu} > 0. \tag{A.15}$$

Hence,

$$\begin{aligned} \frac{d\kappa_1}{d\frac{\tilde{w}_1}{r}} &= \frac{\kappa_1^{\mu}}{1-\mu} = \frac{(\phi\kappa_2)^{\mu}}{1-\mu} = \phi^{\mu} \frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} \\ \Leftrightarrow \frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} &= \phi \frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}}. \end{aligned} \tag{A.16}$$

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 decrease in the relative price of capital provides an incentive for the high-wage industry to replace routine workers with capital.

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. An increase in s_i 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.7) and (A.8):

$$\frac{1}{\chi} = \frac{1-\alpha}{\alpha}\frac{s_i}{1+\kappa_i^{\mu}}. \tag{A.17}$$

Here, we use the fact that $\frac{\tilde{w}_i}{w_i}$ is the same across industries due to (A.5) 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, $\frac{ds_i}{d\frac{\tilde{w}_i}{r}} > 0$. Formally,

$$\frac{ds_i}{d\frac{\tilde{w}_i}{r}} = \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_i^{\mu-1}\frac{d\kappa_i}{d\frac{\tilde{w}_i}{r}} = \frac{\alpha}{\chi(1-\alpha)}\frac{d\kappa_i^{\mu}}{d\frac{\tilde{w}_i}{r}} > 0. \tag{A.18}$$

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.18), the relationship $\kappa_1 = \phi\kappa_2$, and $\tilde{w}_1 = (1+\lambda)\tilde{w}_2$:

$$\begin{aligned}\frac{ds_1}{d\frac{\tilde{w}_2}{r}} &= \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_1^{\mu-1}\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} \\ &= \frac{\alpha}{\chi(1-\alpha)}\mu\phi^{\mu-1}\kappa_2^{\mu-1}\phi\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} = \phi^{\mu}\frac{ds_2}{d\frac{\tilde{w}_2}{r}}.\end{aligned} \tag{A.19}$$

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 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.

A.3 Additional Tables

Table A.1: Source of Wage Variation (R^2)

	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 (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.2: OLS Estimates of the Wage Regression in 1980

Variable	Coefficient	Variable	Coefficient
Female	−0.535(0.001)***	Cognitive Occupation	0.485(0.002)***
Age1	−0.857(0.002)***	Routine Occupation	0.226(0.002)***
Age2	−0.275(0.001)***	Region1	−0.011(0.002)***
Age3	−0.077(0.001)***	Region2	−0.031(0.001)***
Age4	0.008(0.001)***	Region3	−0.001(0.001)***
Edu1	−0.586(0.002)***	Region4	−0.092(0.002)***
Edu2	−0.614(0.002)***	Region5	−0.066(0.001)***
Edu3	−0.261(0.001)***	Region6	−0.121(0.002)***
Edu4	−0.227(0.001)***	Region7	−0.064(0.002)***
African-American	−0.068(0.001)***	Region8	−0.068(0.002)***
Constant	9.185(0.005)***		
R^2	0.39	Observations	4,307,598

Note: 1. Robust standard errors are reported in parentheses.
2. 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, and Mountain Division, and Pacific Division, respectively.
3. Age1 to Age5 correspond to 18−24, 25−34, 35−44, 45−54, and 55−64, respectively.
4. Edu1 to Edu5 correspond to workers with fewer than 9 years, 9 to 11 years, 12 years, 13 to 15 years, and at least 16 years of schooling, respectively.

Table A.3: First-Stage Results

	1980 Wage Premium			
	Total	Cognitive	Routine	Manual
1970 Wage Premium	1.0446	1.1177	1.0533	0.8676
	(0.0728)***	(0.0463)***	(0.0523)***	(0.1295)***
R^2	0.92	0.95	0.91	0.88

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: OLS Estimates of Employment Growth by Occupation Groups, Full-Time Workers Only (1980−2009)

	OLS			
	Total	Cognitive	Routine	Manual
Industry Wage Premium (1980)	−0.0398	−0.0248	−0.0435	0.0081
	(0.0071)***	(0.0064)***	(0.0087)***	(0.0110)
R^2	0.26	0.14	0.21	0.02
	IV			
	Total	Cognitive	Routine	Manual
Industry Wage Premium (1980)	−0.0337	−0.0184	−0.0403	0.0164
	(0.0070)***	(0.0066)**	(0.0084)***	(0.0098)*
F-Statistic	245.45	577.4	421.52	51.12

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 Prediction with Worker Heterogeneity This section examines if the competitive view of the labor market on interindustry wage differentials can explain our findings. One of the main arguments for industry wage dispersion is that workers' productivities are actually different (due to unobserved heterogeneity). This also nests the case where a worker is paid more because she is more productive in using capital.

Suppose that there exist the same numbers (measure 1) of workers and firms in the economy. In the labor market, each firm that produces the same consumption goods is matched to one worker. Each worker n is assumed to have different productivity, and x_n denotes the productivity of a worker where $n \in [0, 1]$. Without loss of generality, x_n is assumed to be decreasing in n. The production function of a firm is given as $y = x_n + x_k k$, 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. For simplicity, the production function assumes perfect substitutability between labor and capital. Thus, one implicit assumption here is that the workers in this economy are routine workers.[39] Note that if there is no capital, $y = x_n$ such that the competitive labor market implies $w_n = x_n$. Hence, the wage differentials among workers are the direct result of their productivity difference.

We now introduce capital into the economy, and the firm minimizes $TC = w + pk$ subject to the production function. Suppose that a firm that initially hired worker n produces x_n unit of consumption goods. Then, the total cost of producing consumption goods is equal to x_n when the firm employs only labor, and $p\frac{x_n}{x_k}$ when it uses only capital to produce the same amount of goods. This implies the threshold condition of the firm for production: a firm chooses to use labor (resp. capital) in the production if $x_k/p < 1$ (resp. $x_k/p > 1$). Suppose that the price of capital was initially so high that $x_k/p < 1$, and hence, no firm used capital.

The price of capital decreases owing to the "routine-replacing technology changes." Then, the following prediction holds, which is a natural consequence of the model above.

Prediction (Job Polarization when Workers are Heterogeneous)**.** *Suppose that $x_k/p < 1$; hence, no firm used capital. As p decreases, the adoption of new technology to use capital occurs in every firm at*

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

the same time. In other words, the occurrence of job polarization, that is, the replacement of workers with capital (other production factors), is not apparent in the high-wage firms.

Therefore, the prediction of the model that assumes only ex-ante heterogeneous workers is not consistent with our empirical findings.

B.2 Introduction of Occupation-Specific Industry Wage Premium into Model In this appendix, we show that predictions drawn from the benchmark model are robust to the introduction of occupation-specific industry wage premia. Alternatively to equation (3.4), we now assume that the industry wage premium is different across occupations as follows:

$$w_1 = (1 + \lambda_{nr})w_2 \text{ and } \tilde{w}_1 = (1 + \lambda_r)\tilde{w}_2, \tag{B.1}$$

where subscripts nr and r represent non-routine and routine, respectively. We now allow $\lambda_{nr} \neq \lambda_r$.

Following the same steps, we can obtain

$$\kappa_1 \equiv \frac{k_1}{\tilde{h}_1} = \phi\kappa_2, \tag{B.2}$$

where $\kappa_i \equiv \frac{k_i}{\tilde{h}_i}$ and $\phi = (1 + \lambda_r)^{\frac{1}{1-\mu}} > 1$, which corresponds to equation (A.13).

Combining equations (A.8) and (A.9), we obtain

$$\frac{\tilde{w}_i}{r} = \kappa_i^{1-\mu}. \tag{B.3}$$

Hence, except the expression for ϕ is a function of λ_r, equation (A.15) is identical, implying that the first prediction is equivalent to the model without the occupation-specific industry wage premium.

We now turn our focus to the second and the third predictions. We first combine equations (A.8) and (A.9) and obtain

$$\frac{\tilde{w}_i}{w_i} = \frac{1-\alpha}{\alpha}\frac{s_i}{1+\kappa_i^{\mu}}. \tag{B.4}$$

We note that $\frac{\tilde{w}_1}{w_1} = \lambda\frac{\tilde{w}_2}{w_2} \equiv \frac{\lambda}{\chi}$, where $\frac{\tilde{w}_2}{w_2}$ is defined as $\frac{1}{\chi}$ and $\frac{1+\lambda_r}{1+\lambda_{nr}} \equiv \lambda$. Taking the same steps to obtain the following relationships:

$$\frac{ds_2}{d\frac{\tilde{w}_2}{r}} = \frac{\alpha}{\chi(1-\alpha)}\mu\kappa_2^{\mu-1}\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} > 0, \tag{B.5}$$

and

$$\begin{aligned}\frac{ds_1}{d\frac{\tilde{w}_2}{r}} &= \frac{\alpha\lambda}{\chi(1-\alpha)}\mu\kappa_1^{\mu-1}\frac{d\kappa_1}{d\frac{\tilde{w}_2}{r}} \\ &= \frac{\alpha\lambda}{\chi(1-\alpha)}\mu\phi^{\mu-1}\kappa_2^{\mu-1}\phi\frac{d\kappa_2}{d\frac{\tilde{w}_2}{r}} = \lambda\phi^{\mu}\frac{ds_2}{d\frac{\tilde{w}_2}{r}}.\end{aligned} \tag{B.6}$$

Hence, as long as $\lambda\phi^{\mu} > 1$ holds, i.e., $\lambda_r > \lambda_{nr}(1-\mu)$ so that the non-routine occupation-specific wage premium is not too much higher than the routine occupation-specific wage premium, the predictions are identical to those from the benchmark model.

B.3 Supply Side of Labor Market

B.3.1 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.[40]

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

$$\max_{\{c_t,k_{t+1},x_t,n_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty}\beta^t\left[\log c_t + \theta(\bar{n}-n_t)\right], \tag{B.7}$$

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 to generate investment goods, x_t, with the technology q. Hence, higher q means that the technology to generate investment

[40]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.

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. Detailed discussions on wage rates are provided in the next section.[41]

The key optimality condition for the household problem is given as follows:[42]

$$\frac{c_{t+1}}{c_t} = \beta \left[q r_{t+1} + (1 - \delta) \right]. \tag{B.8}$$

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.

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{q}. \tag{B.9}$$

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.3.2 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.[43] 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.

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

[41] 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.

[42] 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.

[43] 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.

$$w_{1t} = (1+\lambda)w_{2t} \text{ and } \tilde{w}_{1t} = (1+\lambda)\tilde{w}_{2t}. \tag{B.10}$$

As non-routine occupations[44] require more complex skills of a worker, the broker sets the following wage rule to compensate the skill difference across occupations:[45]

$$w_{it} = \chi \tilde{w}_{it}. \tag{B.11}$$

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.[46] 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 for the hours supplied to industry 1 is rebated to the household as a lump-sum transfer:

$$\pi_t = \tilde{w}_{2t}(\lambda\chi h_{1t} + \chi h_{2t} + \lambda \tilde{h}_{1t}). \tag{B.12}$$

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

[44] Here, we focus on cognitive occupations.

[45] 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.

[46] 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.

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: Estimates of Employment Share of Non-Routine over Routine (s_i) (1980−2009)

	OLS		IV
Industry Wage Premium	1.0564		1.3429
	(0.3876)***		(0.3940)***
R^2	0.15	F-Statistic	205.9

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

Table B.3: EU KLEMS Industry Classification

Industry	IND1990 Code
Mining and quarrying	40 – 50
Total manufacturing	
Food, beverages, and tobacco	100 – 130
Textiles, textile, leather, and footwear	132 – 152, 220 – 222
Wood and of wood and cork	230 – 242
Pulp, paper, printing, and publishing	160 – 172
Chemical, rubber, plastics, and fuel	
Coke, refined petroleum, and nuclear fuel	200 – 201
Chemicals and chemical products	180 – 192
Rubber and plastics	210 – 212
Other non-metallic mineral	262
Basic metals and fabricated metal	270 – 301
Machinery, NEC	310 – 332
Electrical and optical equipment	340 – 350
Transport equipment	351 – 370
Manufacturing NEC; Recycling	371 – 392
Electricity, gas, and water supply	450 – 472
Construction	60
Wholesale and retail trade	
Sale, maintenance and repair of motor vehicles and motorcycles; Retail sale of fuel	500, 612 – 622, 672, 751
Wholesale trade and commission trade, except of motor vehicles and motorcycles	501 – 571
Retail trade, except of motor vehicles and motorcycles; Repair of household goods	580 – 611, 623 – 671, 681 – 691
Hotels and restaurants	762 – 770
Transport and storage and communication	
Transport and storage	400 – 432
Post and telecommunications	440 – 442
Finance, insurance, real estate, and business services	
Financial intermediation	700 – 711
Real estate, renting, and business activities	712 – 760
Community, social, and personal services	761 – 810
Public administration and defence; Compulsory social security	900 – 932
Education	842 – 861
Health and social work	812 – 840, 841
Other community, social, and personal services	862 – 893

Table B.4: Occupation-Specific Industry Wage Premia in 1980

Industry	Average	Cognitive	Routine	Manual
Metal mining	0.882(0.010)	1.210(0.018)	1.240(0.011)	1.067(0.066)
Coal mining	0.999(0.007)	1.293(0.018)	1.345(0.008)	0.823(0.084)
Oil and gas extraction	0.841(0.006)	1.322(0.009)	1.183(0.008)	0.779(0.054)
Nonmetallic mining and quarrying, except fuels	0.742(0.010)	1.174(0.025)	1.065(0.011)	0.905(0.061)
Construction	0.596(0.005)	1.172(0.007)	0.900(0.005)	0.501(0.030)
Food and kindred products	0.644(0.005)	1.226(0.008)	0.943(0.006)	0.718(0.016)
Tobacco manufactures	0.796(0.012)	1.357(0.023)	1.097(0.014)	0.914(0.067)
Textile mill products	0.599(0.005)	1.200(0.011)	0.898(0.006)	0.619(0.024)
Apparel and other finished textile products	0.440(0.005)	1.234(0.013)	0.726(0.006)	0.406(0.032)
Paper and allied products	0.782(0.006)	1.284(0.010)	1.093(0.006)	0.954(0.027)
Printing, publishing, and allied industries	0.481(0.005)	0.999(0.008)	0.802(0.006)	0.497(0.033)
Chemicals and allied products	0.773(0.005)	1.290(0.007)	1.095(0.006)	0.930(0.018)
Petroleum and coal products	0.889(0.007)	1.372(0.012)	1.232(0.009)	0.829(0.053)
Rubber and miscellaneous plastics products	0.686(0.006)	1.262(0.010)	0.985(0.007)	0.821(0.030)
Leather and leather products	0.464(0.008)	1.183(0.025)	0.755(0.009)	0.535(0.053)
Lumber and woods products, except furniture	0.541(0.006)	1.181(0.014)	0.832(0.007)	0.584(0.035)
Furniture and fixtures	0.515(0.006)	1.181(0.014)	0.807(0.007)	0.542(0.047)
Stone, clay, glass, and concrete products	0.703(0.006)	1.182(0.011)	1.019(0.007)	0.816(0.036)
Metal industries	0.784(0.005)	1.266(0.007)	1.097(0.005)	0.934(0.015)
Machinery and computing equipments	0.741(0.005)	1.266(0.006)	1.058(0.005)	0.758(0.019)
Electrical machinery, equipment, and supplies	0.686(0.005)	1.207(0.006)	1.005(0.006)	0.753(0.021)
Motor vehicles and motor vehicle equipment	0.903(0.005)	1.377(0.008)	1.216(0.006)	1.111(0.018)
Other transportation equipment	0.770(0.005)	1.239(0.006)	1.113(0.006)	0.870(0.025)
Professional and photographic equipment and watches	0.700(0.006)	1.244(0.008)	1.014(0.007)	0.775(0.034)
Miscellaneous manufacturing industries, toys, amusement, and sporting goods	0.493(0.006)	1.166(0.011)	0.777(0.007)	0.518(0.035)
Railroads	0.947(0.006)	1.344(0.010)	1.272(0.006)	1.041(0.029)
Bus service and urban transit / Taxicab service	0.418(0.007)	1.013(0.016)	0.708(0.008)	0.676(0.030)
Trucking service / Warehousing and storage	0.742(0.005)	1.227(0.011)	1.055(0.006)	0.596(0.037)
U.S. postal service	0.822(0.005)	1.228(0.012)	1.141(0.006)	0.852(0.026)
Water transportation	0.779(0.010)	1.274(0.017)	1.111(0.011)	0.645(0.054)
Air transportation	0.902(0.006)	1.406(0.010)	1.180(0.007)	1.165(0.013)
Pipe lines, except natural gas, services incidental to transportation	0.526(0.009)	1.155(0.016)	0.818(0.011)	0.539(0.050)

Communications	0.860(0.005)	1.250(0.007)	1.237(0.006)	0.788(0.034)
Utilities and sanitary services	0.739(0.005)	1.198(0.007)	1.071(0.006)	0.803(0.017)
Durable goods	0.642(0.005)	1.246(0.007)	0.942(0.006)	0.454(0.031)
Nondurable goods	0.592(0.005)	1.201(0.007)	0.891(0.006)	0.509(0.024)
Lumber and building material retailing	0.497(0.007)	1.154(0.014)	0.790(0.008)	0.246(0.083)
General merchandiser	0.244(0.005)	1.043(0.008)	0.509(0.006)	0.341(0.013)
Food retail	0.348(0.005)	1.090(0.010)	0.644(0.006)	0.227(0.016)
Motor vehicle and gas retail	0.461(0.005)	1.174(0.009)	0.751(0.006)	0.269(0.030)
Apparel and shoe	0.147(0.006)	1.021(0.012)	0.403(0.007)	0.174(0.044)
Furniture and appliance	0.365(0.006)	0.970(0.012)	0.666(0.007)	0.082(0.055)
Eating and drinking	0.101(0.005)	0.888(0.007)	0.349(0.007)	0.144(0.006)
Miscellaneous retail	0.137(0.006)	0.809(0.009)	0.417(0.006)	0.209(0.026)
Banking and credit	0.585(0.005)	1.193(0.006)	0.877(0.006)	0.436(0.019)
Security, commodity brokerage, and investment companies	0.779(0.008)	1.297(0.014)	1.115(0.009)	0.448(0.058)
Insurance	0.682(0.005)	1.253(0.007)	0.990(0.006)	0.504(0.031)
Real estate, including real estate-insurance offices	0.393(0.006)	0.887(0.010)	0.735(0.007)	0.425(0.011)
Business services	0.389(0.005)	1.047(0.007)	0.697(0.007)	0.318(0.009)
Automotive services	0.431(0.006)	1.064(0.014)	0.730(0.007)	0.090(0.06)
Miscellaneous repair services	0.435(0.009)	0.992(0.022)	0.743(0.009)	0.245(0.086)
Hotels and lodging places	(Omitted)	0.731(0.012)	0.550(0.010)	(Omitted)
Personal services	0.293(0.006)	0.740(0.013)	0.448(0.009)	0.477(0.008)
Entertainment and recreation services	0.109(0.007)	0.611(0.010)	0.459(0.011)	0.212(0.010)
Health care	0.486(0.004)	1.036(0.005)	0.765(0.006)	0.601(0.006)
Legal services	0.508(0.007)	0.952(0.011)	0.923(0.008)	0.347(0.073)
Education services	0.129(0.004)	0.764(0.005)	0.326(0.006)	0.097(0.006)
Miscellaneous services	0.012(0.005)	0.517(0.007)	0.484(0.008)	0.026(0.009)
Professional services	0.428(0.005)	0.984(0.006)	0.763(0.008)	0.536(0.028)
Public administration	0.613(0.004)	1.056(0.005)	0.897(0.006)	0.892(0.006)

Note: 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).