Industry Heterogeneity and Wage Inequality

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Introduction

- Wage Inequality has risen since the 1980s.
- The distribution of wages inside firms does not follow the same trend as the entire economy.
- Song, Price, Guvenen, Bloom, and Von Wachter (2019), show that a substantial part of the rise in dispersion has occurred between firms instead of within firms.
- At the same time there has been an increase in occupational and educational, segregation of employees.

Introduction

- I want to focus on two trends and their relationship:
  - the change in the composition of the workforce, the Labor Input Ratio of skilled to unskilled workers.
  - The change on the premium paid to skilled workers.

Introduction

- To analyze the relationship between those trends I will use the model proposed by Krusell, Ohanian, Ríos-Rull, and Violante (2000) (KORV).
- This model allows to isolate two effects influencing the growth of the skill premium:
  - the effect of the relative input of skilled vs. unskilled workers.
  - the effect of skill-biased technological change. (Capital-skill complementarity hypothesis)
- I will analyze these effects have evolved industry level.

Objectives

This work has two primary objectives:

- Extend the analysis from KORV beyond the original period.
- Evaluate the capital-skill complementarity hypothesis at the industry level.

Motivation

- In a recent work Haltiwanger, Hyatt, and Spletzer (2022), show that the rise in wage inequality is concentrated in a small number of industries (about 10%).
  - They analyze industries at the 4-digit NAICS level.
  - Due to data availability limitations I work at a higher level of aggregation.
- As in Haltiwanger, Hyatt, and Spletzer (2022), Industries in my sample exhibit a positive correlation between mean wage and wage inequality.

Industry Level Trends

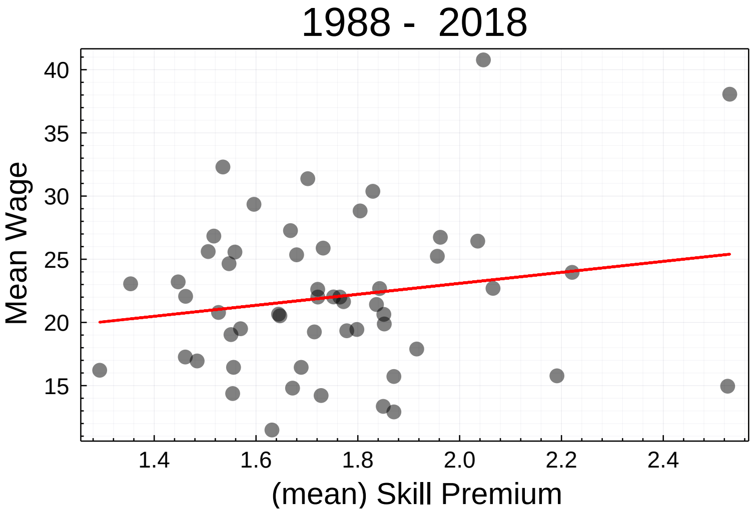

Figure: Relationship between skill premium and mean wage.

Data

- Following the methodology of Ohanian, Orak, and Shen (2021), I built data series for wages, labor input, and capital input from 1963 to 2018.
  - The original data from KORV covers the period from 1963 to 1992.
- I then Re-create the same series for 56 industry groups for the period from 1998 to 2018.

Capital Data

- I obtained investment series in equipment (I_e) and structures (I_s) from NIPA.
- Equipment (K_e) and structure (K_s) capital series were constructed using the perpetual inventory method:

$$K_{i_{t+1}} = (1 - \delta_{i_t})K_{i_t} + I_{i_t} \qquad i \in \{e, s\}$$

- To obtain capital series at the industry level I used the BEA Fixed Assets dataset.
- This dataset contains 76, industry groups.

Labor Shares

- To construct series of the labor share of income by industry, I used the BEA-BLS Integrated Industry-level Production Accounts (KLEMS),
- KLEMS data consists of 56 industry groups some of which are aggregations of industries on the BEA dataset.

Labor Data

- Labor input and wages are estimated using the march supplement of the Current Population Survey (CPS).
- Again, I follow the methodology of Ohanian, Orak, and Shen (2021) to clean and aggregate the data.
- To obtain industry-level data I partitioned the CPS dataset into the 56 industry groups for which capital data is available and then aggregate repeating the same procedure as before.
- The classification of a worker being a skilled or an unskilled worker is based on the latest year of education completed, a worker with 4 years or more of college education is considered skilled.

Industry Groups

- I used the crosswalk between the KLEMS, BEA, and CPS industry codes provided by Acemoglu, and Restrepo (2020) to map the industry codes.
- KLEMS codes are often the combination of the several BEA and CPS codes:

Industry Groups

- I used the crosswalk between the KLEMS, BEA, and CPS industry codes provided by Acemoglu, and Restrepo (2020) to map the industry codes.
- KLEMS codes are often the combination of the several BEA and CPS codes:
  - Oil and gas extraction: KLEMS-*211*, BEA-*2110*, CPS-*42*
  - Hospitals and nursing and residential care facilities: KLEMS-*622HO*, BEA-*622h, 6230*, CPS-*831,832 and 870*.
  - The largest KLEMS code (Retail trade) consists of 131 CPS codes.

Industry Level Trends

- To check the relationship between the trends of labor input ratio and the skill premium, I computed the slope of each series in the period:

Industry Level Trends

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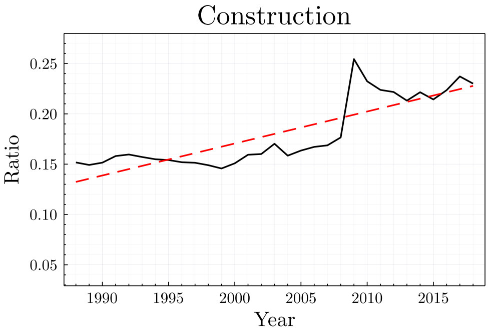
(a) Labor Input Ratio



(b) Skill Premium

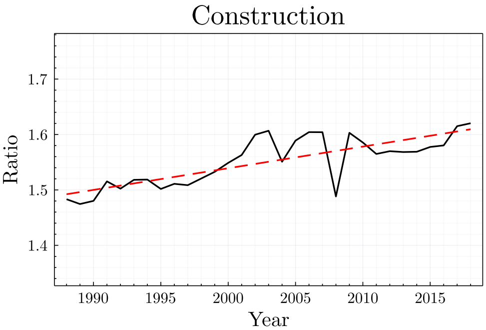


Figure: Trends for the 1988 – 2018 period.

Industry Level Trends

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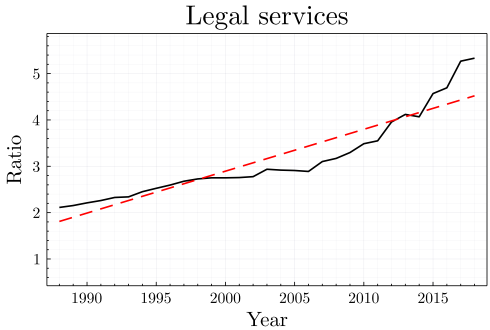
(a) Labor Input Ratio



(b) Skill Premium

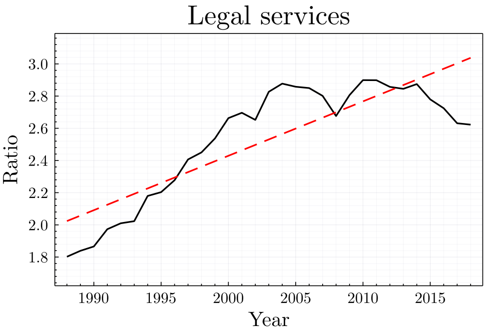


Figure: Trends for the 1988 – 2018 period.

Industry Level Trends

- To check the relationship between the trends of labor input ratio and the skill premium, I computed the slope of each series in the period:

- For 49 industries (87.5%) the skill premium increased in the period the input ratio showed the same pattern for 52 (92.8%) industries.

Industry Level Trends

▸ Back

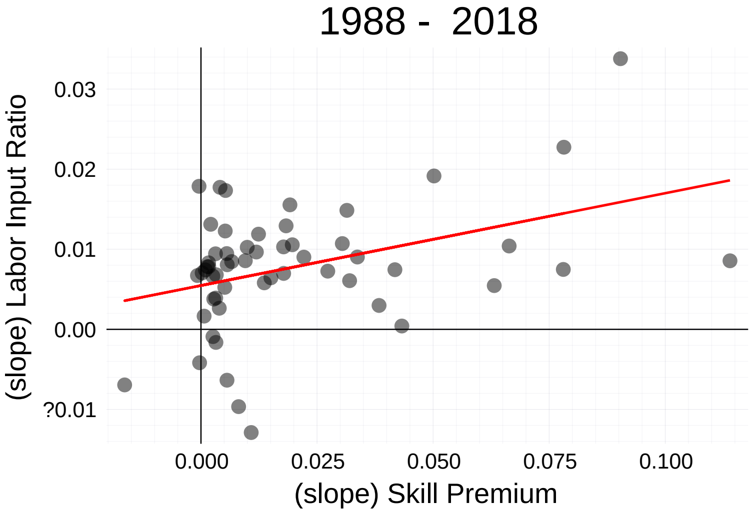


Figure: Realtionship between the trends of Labor Input and Skill Premium. For 84% both trends are increasing.

Model

- In the next slides I will present the model and show how it can be employed to decompose the growth of the skill premium.
- Then I will briefly explain the estimation procedure.

KORV

- Two types of capital
  - k_s, structures.
    - Buildings.
  - k_e, equipment, with a relative price equal to $1/q$
    - Machines, computers, intellectual property.

- Two types of labor
  - u low-skilled labor.
    - $u = \psi^u h_u$ where h_u is hours (observed) and ψ^u is the quality of low-skilled labor (unobserved).
  - s high-skilled labor.
    - $s = \psi^S h_s$ where h_s is hours (observed) and ψ^s is the quality of high-skilled labor (unobserved).

KORV

- There are three final goods:
  - Consumption c
  - Structure investment i_s
  - Equipment investment i_e.
- Aggregate production:

$$c_t + i_{e_t} + i_{s_t} = Y_t = A_t G(k_{s_t}, k_{e_t}, u_t, s_t) \tag{1}$$

Production function

- The production function is:

$$G(k_{s_t}, k_{e_t}, u_t, s_t) = k_{s_t}^{\alpha} \left(\mu u_t^{\sigma} + (1-\mu) \left(\lambda k_{s_t}^{\rho} (1-\lambda) s_t^{\rho} \right)^{\frac{\sigma}{\rho}} \right)^{\frac{1-\alpha}{\sigma}} \tag{2}$$

- $\sigma_H = 1/(1-\rho)$ is the elasticity of substitution between equipment and high-skilled.

- $\sigma_L = 1/(1-\sigma)$ is the elasticity of substitution between low-skilled and equipment + high-skilled.

- Firms solve the following profit maximization problem

$$\max_{k_{s_t}, k_{e_t}, u_t, s_t} G(k_{s_t}, k_{e_t}, u_t, s_t) - r_{s_t} k_{s_t} - r_{e_t} k_{e_t} - w_{u_t} h_{u_t} - w_{s_t} h_{s_t} \tag{3}$$

Production Function

- My objective is to use this model to test whether the change in the wage premium for skilled labor in different industries can be explained using the capital-skill complementarity hypothesis.

- Next, I show how we can obtain the growth rate of the skill premium from optimality conditions of the Firm.

Skill Premium in the Model

- Assuming competitive markets, workers are paid their marginal products per unit, of work:

$$\omega_t = \frac{w_{s_t}}{w_{u_t}} = \frac{G_{h_s}(k_{s_t}, k_{e_t}, u_t, s_t)}{G_{h_u}(k_{s_t}, k_{e_t}, u_t, s_t)}$$

- We can obtain the following (log-linearized) expression for ω_t:

$$\ln \omega_t \simeq \lambda \frac{\sigma - \rho}{\rho} \left(\frac{k_{e_t}}{s_t} \right)^{\rho} + (1 - \sigma) \ln \left(\frac{h_{u_t}}{h_{s_t}} \right) + \sigma \ln \left(\frac{\psi_t^s}{\psi_t^u} \right) \tag{4}$$

- Which in turn can be written in terms of growth rates (g_x):

$$\begin{aligned} g_{\omega t} \simeq & (1 - \sigma) \left(g_{h_{u_t}} - g_{h_{s_t}} \right) + \sigma \left(g_{\psi_t^s} - g_{\psi_t^u} \right) \\ & + (\sigma - \rho) \lambda \left(\frac{k_{e_t}}{s_t} \right)^{\rho} \left(g_{k_{e_t}} - g_{h_{s_t}} - g_{\psi_t^s} \right) \end{aligned} \tag{5}$$

Skill Premnium Decomposition

We have decomposed the skill premium into three parts:

- $(1-\sigma)(g_{h_{u_t}} - g_{h_{s_t}})$ depends on the difference of the growth rates of skilled and unskilled and labor.
  - If both types of labor are substitutes i.e $\sigma_u < 0 \implies (1-\sigma) < 0$
  - If skilled labor grows at a faster rate than unskilled labor, then the skill premium decreases. Data

Skill Premnium Decomposition

We have decomposed the skill premium into three parts:

- $\sigma\left(g_{\psi_t^s} - g_{\psi_t^u}\right)$ depends on the growth rate of the productivity of skilled and unskilled and labor.
  - I follow KORV in making the following stochastic assumptions about labor productivity:

$$\psi_t^i = \psi_0^i + \epsilon \qquad \epsilon \sim N(0, \eta_\omega^2) \qquad i \in \{s, u\} \tag{6}$$

  - On average $\sigma(g_{\psi_t^s} - g_{\psi_t^u})$ is constant over time and does not affect the growth rate of the skill premium.

Skill Premnium Decomposition

We have decomposed the skill premium into three parts:

- $(\sigma-\rho)\lambda\left(\frac{k_{e_t}}{s_t}\right)^{\rho}\left(g_{k_{e_t}}-(g_{h_{s_t}}+g_{\psi_{s_t}})\right)$. This component depends on two factors:

  1. The growth rate of equipment relative to the growth rates of skilled labor input.

     - Characterize the capital-skill complementarity hypothesis as $\sigma > \rho$.
     - If equipment capital grows faster than skilled labor, the skill-premium will increase.

  2. The ratio of capital equipment to skilled labor

     - The effect will get larger (smaller) over time if $\rho > 0$ $(\rho < 0)$.

Estimation

- I follow the same methodology as KORV to estimate the model parameters.
- To simplify notation :

$$\begin{aligned} \psi_t &= \{\psi_t^u, \psi_t^s\} \\ X_t &= \{k_{s_t}, k_{e_t}, h_{s_t}, h_{u_t}\} \\ \Phi &= \{\alpha, \sigma, \rho, \mu, \lambda, \psi_0^u, \psi_0^s, \eta_\omega\} \end{aligned}$$

- Any of $\{\mu, \lambda, \psi_0^u, \psi_0^s\}$ act as scaling parameters thus, one can be fixed.
- There are 7 parameters to be estimated.

Estimation

- The parameters are estimated using the following structural equations:

$$\frac{w_{s_t}h_{s_t} + w_{u_t}h_{u_t}}{Y_t} = lsh(X_t, \psi_t \mid \Phi)$$

$$\frac{w_{s_t}h_{s_t}}{w_{u_t}h_{u_t}} = wbr(X_t, \psi_t \mid \Phi)$$

$$A_{t+1}G_{k_s}(X_{t+1}, \psi_{t+1} \mid \Phi) = q_t A_{t+1} G_{k_s}(X_{t+1}, \psi_{t+1} \mid \Phi) + (1-\delta_e)\left(\frac{q_t}{q_{t+1}}\right) + \nu_t$$

Estimation

- The estimation method is a two-stage simulated pseudo-maximum likelihood estimation (SPMLE).

- In the first stage labor input is considered to be endogenous and is instrumented using: both capital series, lagged capital series, lagged prices, and indicators of the business cycle.

- In the second stage:
  - Taking the variance η_ω as given, for each date t, generate S realizations of the model.
  - For each date t calculate the mean and covariance matrix.
  - Minimize the distance between the first moments of the model and the data, using the second moment as a weighting matrix.

Results

- First, I will show the results of the replication of the model using updated data.
- Second, I will show the results of applying the model to each industry.

KORV Replication

	KORV Estimation 1963 – 1992	**Replication** 1963 – 1992	**Updated Data** 1963 – 2018	**Updated Data** 1988 – 2018
α	0.117	0.113	0.118	0.08
σ	0.401	0.464	0.503	0.313
ρ	-0.495	-0.56	-0.343	-0.154
η_ω	0.043	0.043	0.083	0.043

Table: Parameter estimates KORV model.

KORV Replication

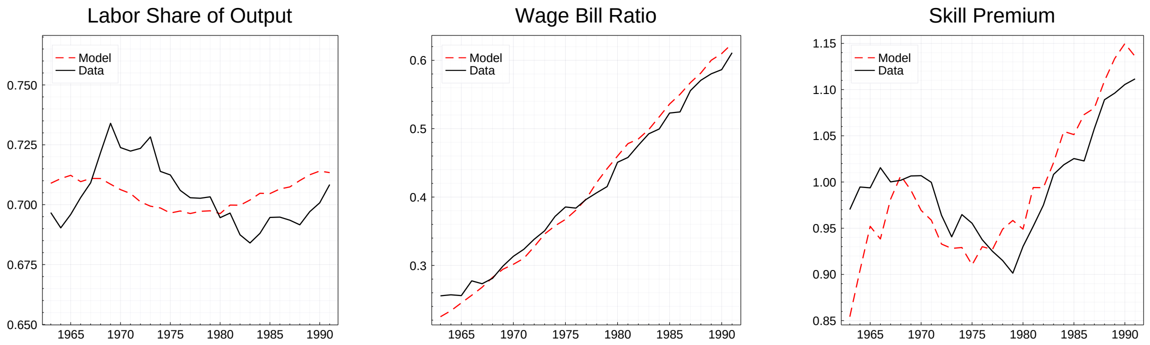


Figure: Fit for the 1963 - 1992 period with KORV Data.

KORV Replication

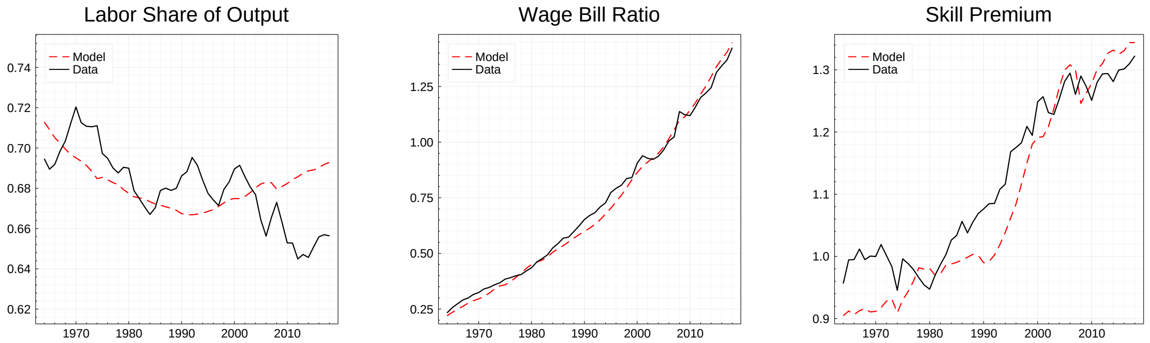


Figure: Fit for the 1963 - 2018 period with Updated Data.

KORV Replication

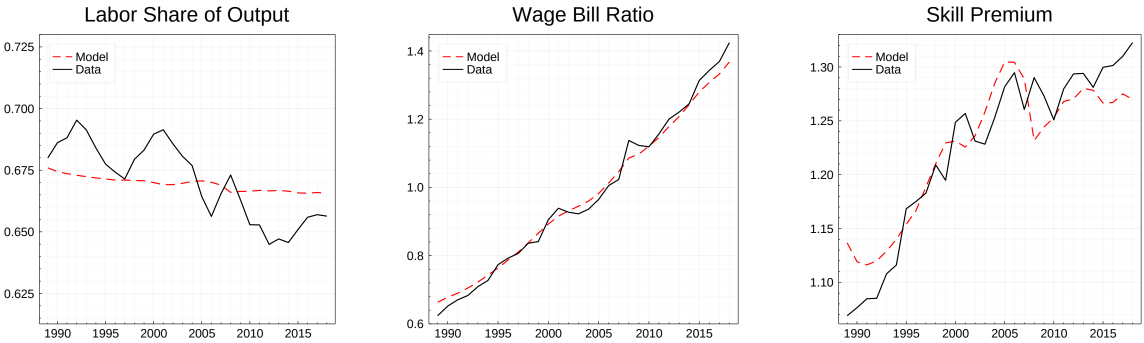


Figure: Fit for the 1988 - 2018 period with Updated Data.

Caveats

- Convergence is highly sensitive to the initial conditions.
    - Not a problem when estimating KORV.
    - But when estimating the model for each industry, the initial conditions are not well defined.
- Initially I tried to sweep the parameter space to find the best initial conditions, I tried 10 values for each parameter (total of 700 points), but it took me more than a day to run the code.
- I settled on 10 initial conditions.

Industry Level Results

	Updated Data 1988 - 2018	**Industry Level** (mean)	**Industry Level** (std)
α	0.08	0.241	0.206
σ	0.313	0.483	0.710
ρ	-0.154	-0.289	0.816
η_ω	0.043	0.131	0.195

Table: Industry Level Estimates.

Industry Level Results

- On average the Capital-skill complementarity hypothesis $(\sigma > \rho)$ is held at the industry level.

- Specifically, the hypothesis holds for 44 of 56 (78.8%) industries.

Future Work

- Improve the estimation using an altertive methodology, e.g.
  - Polgreen, and Silos(2008) discuss the sentitivity of KORV to variations in the data and propose a methodology to estimate the parameters that avoid the instabilities that can arise in maximizing a multidimensional function numerically
- Incorporate alternative sources of data. Specifically, Quarterly Workforce Indicators (QWI, published as part of the Longitudinal Employer-Household Dynamics. This will allow me to avoid having to segment the CPS data to estimate the labor input and wage series at the industry level.

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