Decomposing Wage Polarization

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Wage Polarization

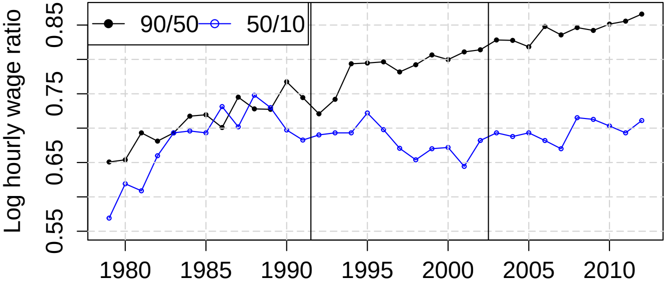

Figure : Wage Ratios - All Population

The vertical lines are changes in occupational coding.
Data resource: CPS - ORG

Preview of Results

This project has two parts

1. Methodological
   - Introduce skewness decomposition
   - Method to decompose wage polarization
   - Simpler and more robust
   - Discuss other potential applications

Preview of Results

2. Empirical
   - First direct evidence that wage polarization is related to routine occupations
   - Driven by a decrease in inequality within low-paying, routine occupations
   - Wages drop mostly for higher-paid routine workers
   - Not due to a decrease of wages in middle-skill occupations as we thought
   - Not a result of solely compositional changes
   - Stops around 2000

Outline

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Polarization

- Wage polarization
  - Late 80's - Early 00's
  - Relative decline in middle wages in the U.S. (Autor et al., 2006, 2008)

  ▸ Show More

- Job polarization
  - Simultaneously there is a decline at employment levels for middle-skill jobs (Goos and Manning, 2007; Autor et al., 2006, 2008)
  - Occurs in almost all developed countries (Goos et al., 2009)
  - Accelerates in last decade Autor (2014)
- Inequality increased in high paying occupations and decreased in low paying occupations (Firpo et al., 2013)

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Potential Explanations

- Routine Biased Technological Change (Autor et al., 2008)
  - Computers are substitutional to workers in routine tasks.
  - Routine tasks are usually done by middle-skill workers.
  - Decrease in demand for workers in middle-skill occupations.
  - Works very well with employment trends (“job polarization”)
  - Drop in routine task prices creates wage polarization (Acemoglu and Autor, 2011)
- Changes in returns to skill (Firpo et al., 2013)
- Minimum wage
- Economic boom

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Motivation

- A basic tool for inequality research is Variance Decomposition
- We can write log wages (Y) as the sum of group averages and residual

$$Y = E\left[Y|X\right] + \varepsilon$$

for $\varepsilon = Y - E\left[Y|X\right]$

- Groups (X) can be occupations, industry, skill group etc.
- Taking the variance we get

$$Var\left[Y\right] = Var\left(E\left[Y|X\right]\right) + E\left[\varepsilon^2\right] = \underbrace{Var\left(E\left[Y|X\right]\right)}_{Between} + \underbrace{E\left[Var\left(Y|X\right)\right]}_{Within}$$

  - Enables to decompose to between-group inequality and within-group inequality.

Motivation

- Need a single index for wage polarization
  - We used a set of wage quantiles ratios.
- Also, quantile measures of inequality do not have a straightforward decomposition.
- Therefore people usually use decomposition methods that build an entire counterfactual distribution (Juhn et al., 1993; DiNardo et al., 1996; Autor et al., 2005)

Limitations of Counterfactual Distribution Methods

- Decompose by composition, between group prices, within group prices.
  - No component for interaction of between and within group.
- Decompose into marginal components (not independent)
  - Order matters
  - Not only technical
- Depend on base year
- Cannot accommodate changes in categories coding.
- Skewness decomposition addresses all these issues.

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Wage Polarization Is Wage Skewness

- So far we described polarization with a set of quantile ratios.
- The skewness of log hourly wages captures what we want in a single number.
- Third standardized moment, and calculated with the following formula:

$$S(Y) = E\left[\left(\frac{Y - E[Y]}{\sigma}\right)^3\right]$$

- It increases when upper tail inequality rises and lower tail inequality drops.

Skewness of Log-Wages

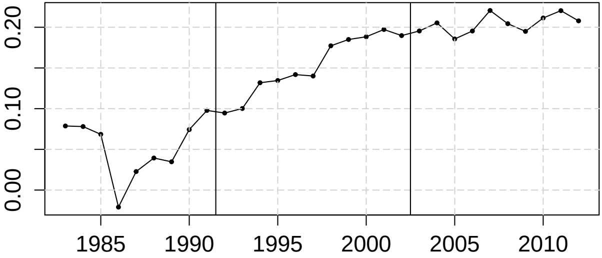

Figure : Skewness of Log-Hourly Wage

The vertical lines are changes in occupational coding.Wages at the top and bottom 5% were dropped.
Data resource: CPS - ORG

Skewness Decomposition

- If Y is standardized log wage, skewness is $E\left[Y^3\right]$
- So skewness decomposition is simply $E\left[Y^3\right] = E\left[\left(E\left[Y|X\right] + \varepsilon\right)^3\right] =$

$$E\left[\varepsilon^3\right] + E\left[E\left[Y|X\right]^3\right] + 3E\left[E\left[Y|X\right]\varepsilon^2\right]$$

- Which can also be written as

$$\underbrace{E\left[\mu_3\left(Y|X\right)\right]}_{Within} + \underbrace{\mu_3\left(E\left[Y|X\right]\right)}_{Between} + \underbrace{3COV\left(E\left[Y|X\right], V\left[Y|X\right]\right)}_{Covariance}$$

  - μ_3 is the third centralized moment

Advantages of Skewness Decomposition

- Decompose into independent (and not marginal) components.
- Does not depend on base year.
- The covariance component is first introduced (and turns out to be important).
- Does not assume any model
- Can accommodate changes in X encoding

Other Potential Applications

Skewness decomposition can be applied to other cases where we are interested in the skewness of the distribution.
Here are few examples:

- Top end inequality (the 1%)
- Firm productivity (TFP)
- Capital distribution
- Wage distribution without logs
- Life expectancy

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Skewness Decomposition by Occupation

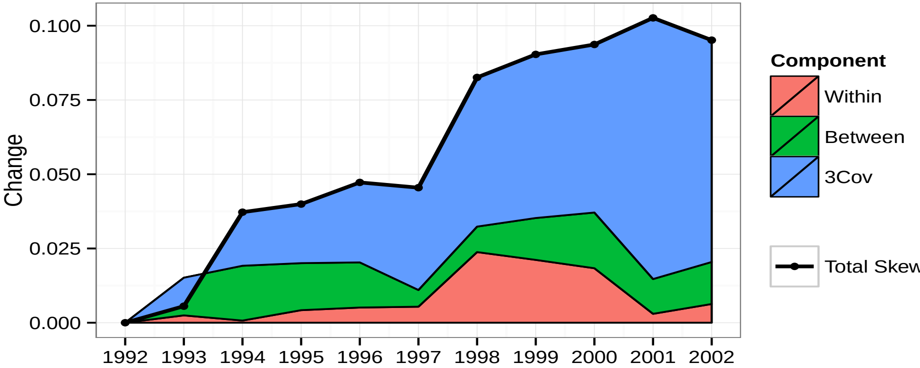

Figure : Skewness Decomposition Changes 1992-2002

Data resource: CPS-ORG

Skewness Decomposition by Occupation

- The within component is "residual" and it is small.
  - Suggests that the trend is related to occupations.
  - This will not be the case when decomposing by other groups. ▸ Show
- The between component is negligible.
  - Opposite of what we would predict from a model of decreasing demand for middle-wage occupations.
- Most of the increase is due to increase in correlation between Expectation and Variance
  - High paying occupations have larger inequality.
  - Low paying occupations have smaller inequality.
  - Documented before by Firpo et al. (2013)
- Very similar results for Israeli data.

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The Importance of Occupations

- Other categories yield much larger residual (within) component
- The trend in the covariance is unique for occupations
- When compared directly, occupations clearly seem to explain most of the increase in skewness
- For industries - using the linear model Skew Dec in Linear Models

$$\ln w_i = occ_i + ind_i + \varepsilon_i$$

- All the increase is in

$$COV\left(occ_i, \varepsilon_i^2\right)$$

  and nothing in

$$COV\left(ind_i, \varepsilon_i^2\right)$$

- The only other important component is $\mu_3\left(occ\right)$ (between occupations)

Occupations and Industries

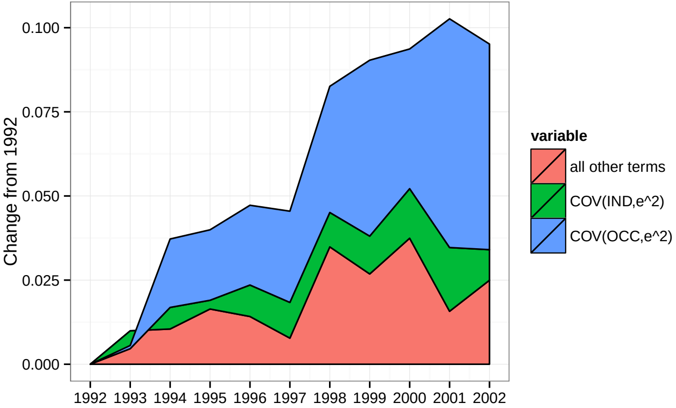

Figure : Skewness Decomposition by Occupation and Industry

Data resource: CPS-ORG

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Changes in Variance 1992-2002

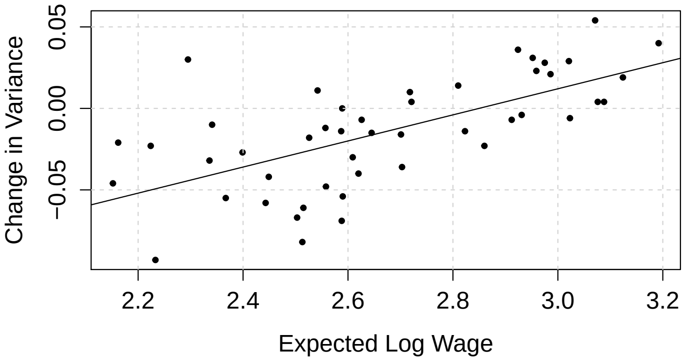

Figure : Change in $V[\ln w|occ]$ by $E[\ln w|occ]$ 1992-2002

Data resource: CPS-ORG

Variance Trends in Other Decades

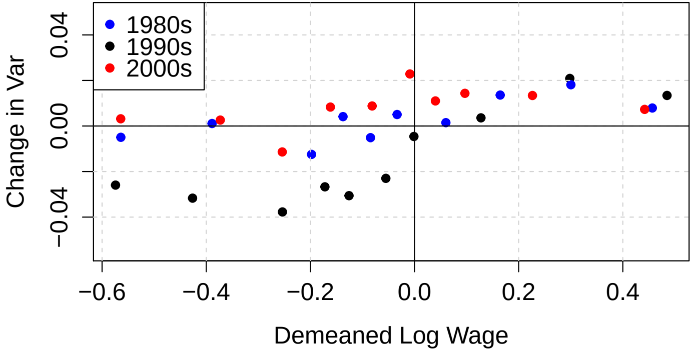

Figure : Change in $V[\ln w|occ]$ by $E[\ln w|occ]$ - Binned Scatter Plot

Data resource: CPS-ORG

Trends Summary

- Asymmetric trends in occupational inequality in the 1990s:
  - High-paying occupations experienced an increase in inequality
  - Low-paying experienced a decrease
  - The drop in variance is more significant in absolute terms
- Variance trend alone can explain the increase in covariance ▸ Show
  - And so is responsible for most of "wage polarization"
- The increase in variance for high-paying occupations is steady across 3 decades
- The 90s are unique for the drop in inequality within occupations at the bottom

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Characterizing Occupations with Drop in Inequality

- Showed inequality dropped in low paying occupations in the 1990s
- Now I'll show that this happens mostly in routine occupations
- Wages relatively drop for higher paid workers in routine jobs
- I'll show this in two ways
  - Using O*NET data that measure level of routine tasks
  - Running analysis separately on routine and non routine jobs
    - Routine defined as administrative workers, operators and producers

O*NET Data

- In addition to CPS, I'll also use O*NET data:
  - Description of occupation characteristics
  - Very wide data (more variables than occupations)
- Use standard indices from the literature:
  - Analytic, Routine Cognitive, Routine Manual, Non-routine Manual, Offshorability (from Acemoglu and Autor, 2011)
  - Social (from Deming, 2015)

O*NET Results

Dep Variable	ΔV		$\Delta P \times 10^3$	
log-wage	.055***		5.71***	
	(.011)		(2.17)	
NR Analytic	.001	.012***	1.92**	3.10***
	(.004)	(.003)	(.79)	(.66)
Routine Cognitive	-.000	.001	-1.70***	-1.51***
	(.002)	(.002)	(.46)	(.45)
Routine Manual	-.009***	-.009***	-.10	-.12
	(.003)	(.003)	(.68)	(.69)
NR Manual	-.001	-.001	.20	.60
	(.003)	(.003)	(.66)	(.65)
Offshorability	-.002	-.000	.14	.32
	(.002)	(.002)	(.51)	(.51)
Social	-.003	.002	-.02	.57
	(.003)	(.003)	(.70)	(.67)

Variance Trend in Routine/Non-routine Occupations

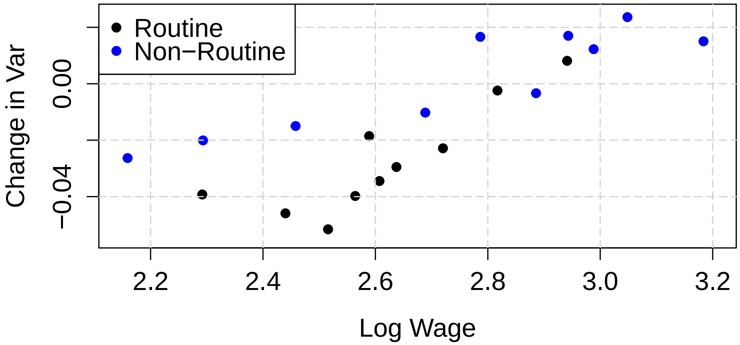

Figure : Change in $V[\ln w|occ]$ by $E[\ln w|occ]$ 1992-2002

Data resource: CPS-ORG. Routine occupations are administrators, producers and operators. Categories are divided

Variance Trend in Routine/Non-routine Occupations

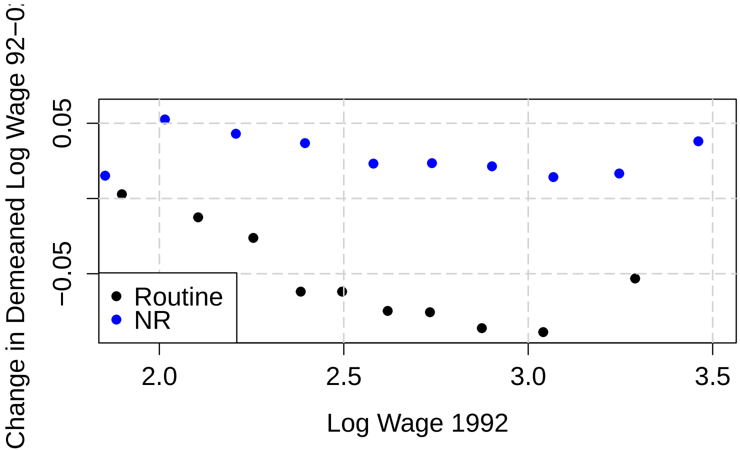

Figure : Change in Relative Wages 1992-2002, Routine and Non-Routine Occupations

Routine Results Summary

- Inequality is dropping mostly in low income routine occupations
  - Drop is much less significant in non-routine low income occupations (such as services)
- In non routine occupations there is no wage polarization
- But relative wages do not drop for all routine workers
  - Only the higher paid ones
- Higher paid routine workers are concentrated at the middle of the distribution
  - Relative drop in their wage leads to drop in middle wages in total

Compositional Changes?

- We know that there are huge compositional changes that also take place ("job polarization")
- It is possible that drop in inequality is driven by compositional changes
  - Example: more high paid routine workers are leaving to non-routine jobs
- I use PSID data, to exam the change in the distribution of "stayers"
  - These are workers who stayed in routine occupations between 1992-2001
  - Inequality is also dropping in this sample.

Convergence Among Stayers

Figure : Binned Scatter of Change in log w - Stayers

Data : PSID

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Job Polarization by Year

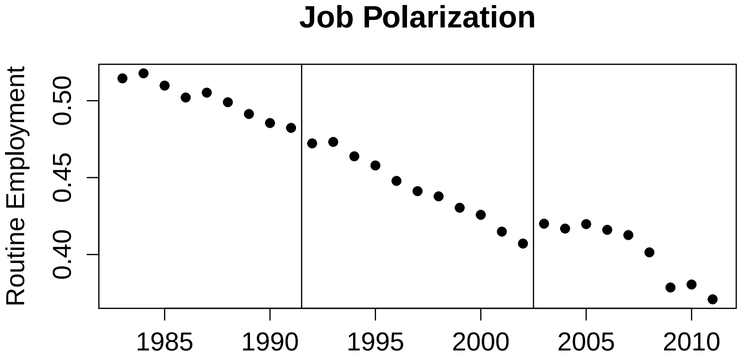

Figure : Share of Working Hours in Routine Occupations

Data resource: CPS-ORG

Demand Drop?

- Seem to have a steady drop in demand for routine tasks
  - A bit slower in early 2000s but accelerates rapidly during the recession
- Simple hypothesis: the market adjusts to the drop in demand through both employment and wage levels.
- Look at total share of labor income that goes to routine workers s_R
- This equals relative wages in routine workers $\times$ Share of workers in routine occupations
- In logs

$$\log s_R = \log \frac{w_R}{w_T} + \log \frac{L_R}{L_T}$$

Share of Labor Income from Routine Workers

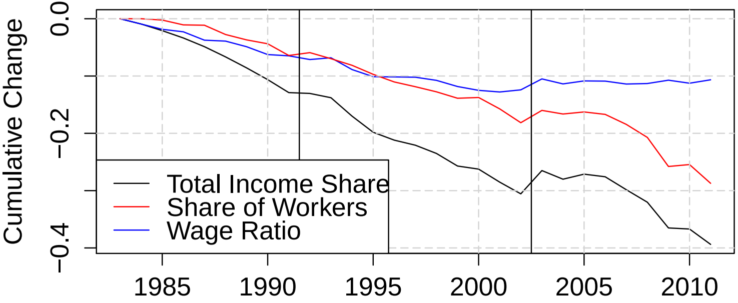

Figure : Decomposition of Income Share by Routine Workers

Data resource: CPS-ORG

Inequality in Routine Occupations by Year

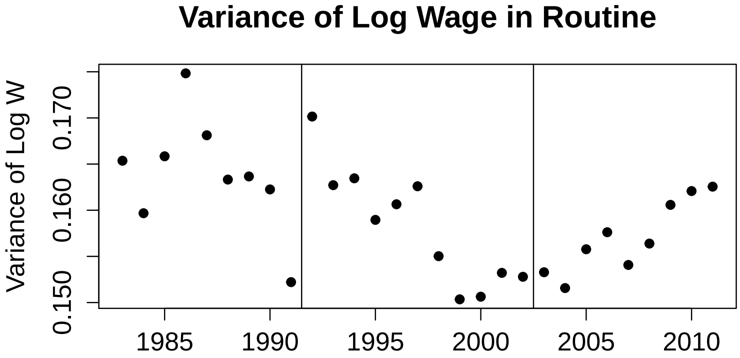

Figure : $V[\log w]$ for Workers in Routine Jobs

Data resource: CPS-ORG

Summary of Results

- Job Polarization trend is almost linear
- Wage Polarization stops around 2000
    - Wage ratio stabilizes
    - Inequality stops decreasing and starts even increasing back

Main Puzzles

- I showed some supporting evidence for why wage polarization seems to be also related to the drop in demand for routine workers.
- There are two main questions that are left unanswered:

1. Why do wages drop mostly for the higher paid routine workers?
2. Why did wage trends stopped around 2000, while employment trends continue?

- I will now review potential explanations and work in progress on them

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Real Wage Growth in 1990s

- Rapid real wage growth in the 1990s
- Stops around year 2000
- When wages grow in other occupations, relative wages in routine jobs become lower
- Since 2000, wages in non routine jobs has stagnated as well, so ratio doesn't change

Wage Growth and Inequality

- But why should wage drop mostly for higher paid routine workers?
- Minimum wage?
    - Minimum wages increased during 1990s
    - Maybe this prevented low wages in routine jobs to drop further
    - Similar timing in Israel
- Outside option?
    - High paid workers in routine jobs may have skills that are hard to transfer to other jobs
    - Less skilled workers may have higher elasticity of substitution between jobs
    - Should predict that job polarization would be more significant for low-wage workers
    - No evidence for that

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Technological Change Starts from Top?

- There are adjustment costs for automation that replaces workers
- If this cost is orthogonal to wages
- Expect firms to first replace the more expensive workers
- Once again, this predicts that job polarization should be more significant among low-wage workers
- No empirical evidence for that

Summary

- New method to quantify the contribution of independent factors to the decline in middle wages
  - Skewness decomposition
- Direct evidence that the decline in middle wages is related to occupations
- Driven by a decrease in inequality within low-paying routine occupations
  - Wages relatively fall for higher paid workers in routine occupations
  - Not due to a decrease of wages in middle-skill occupations
  - Occurs only during 1990s

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Support for Minimum Wage Hypothesis

- Timing: during the 90's there is an increase of the minimum wage (Autor et al., 2015)
- Should reduce inequality in low paying occupations
- Why is it mostly seen in occupations?
    - Occupations might be a good predictor of being close to the minimum wage (more than education or industry)

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Other Predictors of Closeness to Minimum Wage

- Within low paying occupations, race and gender should also be good predictors of being close to minimum wage.
- Minimum wage mostly affect female workers (Autor et al., 2015)
- However, trends in variance are similar for both genders (even stronger for males)
- Decomposing by occupations, gender and race

$$\ln w_i = occ_i + occ_i \times gender_i + occ_i \times race_i + \varepsilon_i$$

shows all the increase is in

$$COV\left(E\left[\ln w | occ_i\right], \varepsilon_i^2\right)$$

Decomposition by Occupation Gender and Race

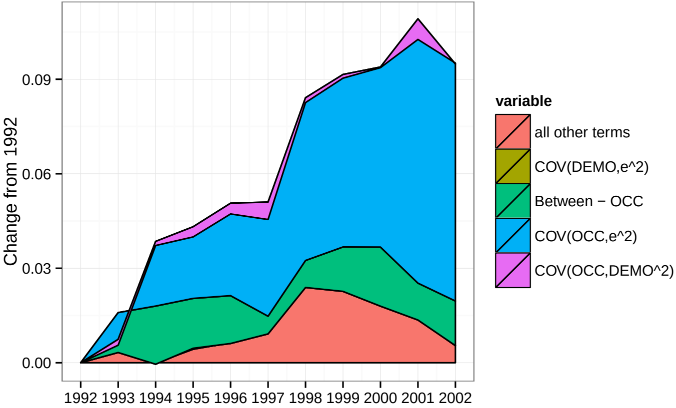

Figure : Skewness Decomposition by Occupation Gender and Race

Data resource: CPS-ORG

Changes in Variance 1992-2002

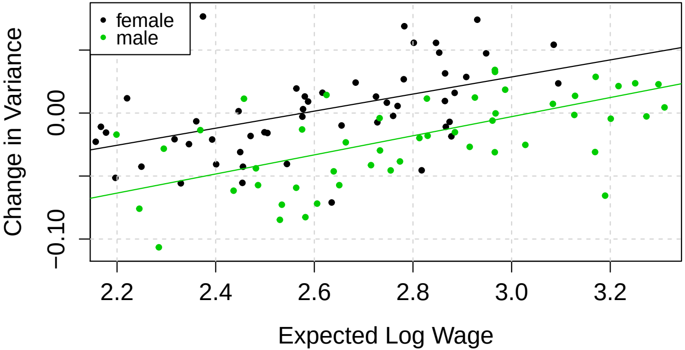

Figure : Change in Variance of Log wages by Expected Log Wage - By Gender

Data resource: CPS-ORG

Correlation With Share Affected by Minimum Wage

- Minimum wage should affect workers at the very bottom much more
- At max, less than 9% are being paid the minimum wage or below (Autor et al., 2015)
- Less than 6% in the 90s
- I look at the correlation of $\Delta V\left(\ln w|occ_i\right)$ between 1992-2002, with share of workers with wages below the 10th percentile in 1992

	(1)	(2)
$P\left(w_{92} < F^{-1}(0.1)\,\vert occ_i\right)$	-0.104	0.054
	(0.014)***	(0.025)**
$E\left[\log w\vert occ_i\right]$		0.088
		(0.011)***

Table : Correlation With Change in Occupational Variance 1992-2002

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Compositional Changes

- If the distribution of s at a certain occupation changes, the variance of $\log w$ will change

$$\ln w_i = \ln p_j + \ln f_j\left(s\right) + \varepsilon_i$$

- Changes in p_j are expected to influence $V\left(\ln f_j\left(s\right)\right)$
    - Increase in demand $\left(p_j\right)$ should attract more workers, and increase the span of $\ln f_j\left(s\right)$, hence

$$\frac{\partial V\left(\ln f_j\left(s\right)\right)}{\partial p_j} > 0$$

- But demand for low-wage occupation only seem to increase at the 90s.

Compositional Changes

- Could also cancel out some other trends
    - If p_j and $E\left[\ln f_j(s)\right]$ move in opposite direction
    - Effect of p_j on between occupations skewness would be attenuated
- I try to use PSID data to address this
- Results seem to suggest that compositional changes have only minor effect
    - But sample size is too small to determine
- Show More

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Decomposition by Occupation - All Data

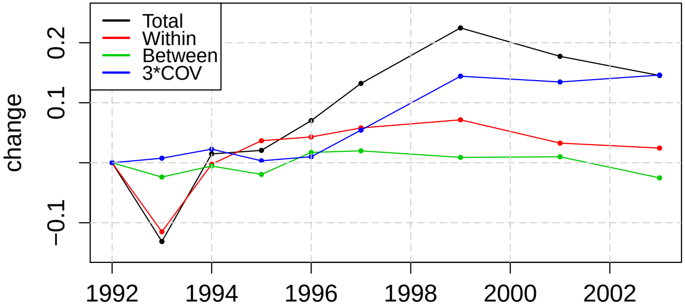


Figure : Skewness Decomposition by Occupation - PSID Data

Variance Trends - PSID

- Looking only at people who stayed at their occupation in the 90s

Dependent Variable: Variance Trend	All (1)	Stayers (2)
$E[\ln(w) \mid occ]$	0.022	0.018
	(0.005)***	(0.011)*

Table : Correlation of $E[\ln(w) \mid occ]$ on trend in $Var[\ln(w) \mid occ]$

Using Skewness Decomposition

- Originally we decomposed by the terms

$$\ln w_{it} = E\left[\ln w_{it} | occ\right] + \xi_{it}$$

- Both terms could be influenced by compositional effects

Occupation Premium

- $E\left[\ln w_{it} | occ\right]$ could also be influenced by composition
- I want to distinguish between compositional part and occupation premium
- Using PSID, I estimate a fixed effect model

$$\ln w_{it} = occ_{it} + \beta_t X_{it} + \eta_i + \varepsilon_i$$

- I then decompose into occupation premium, occupation mean skill and residual

Occupation Premium

$$\ln w_{it} = \underbrace{occ_{it}}_{premium} + \underbrace{E\left[\beta_t X_{it} + \eta_i | occ_{it}\right]}_{mean\ skill}$$
$$+ \underbrace{\beta_t X_{it} + \eta_i + \varepsilon_i - E\left[\beta_t X_{it} + \eta_i | occ_{it}\right]}_{residual}$$

- Occupation premium + mean skill are exactly occupation mean log wage
- Residual is $\xi_{it} = \ln w - E\left[\ln w | occ_{it}\right]$
  - The within component identical to decomposing just by occupations
- The between and covariance component can be further decomposed

Between Component

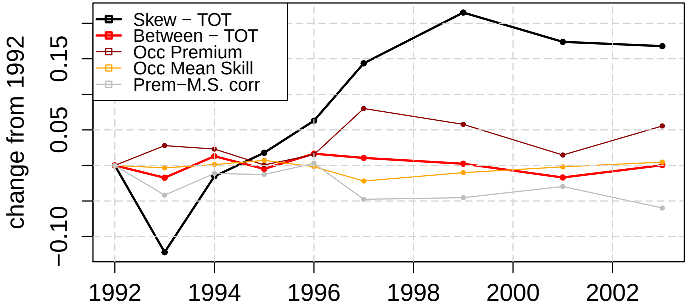


Figure : Change in Variance of Log wages

Data resource: PSID

Covariance Component

Figure : Change in Variance of Log wages

Data resource: PSID

Using Skewness Decomposition

- The variance of ξ could change with the composition
- I try to address that and distinguish between returns to observable skills (education and experience) and residual

$$\xi_{it} = \beta_{occ,t} X_{it} + \varepsilon_{it}$$

- Most (but not all) of the increase in covariance is with ε

$$COV\left(E\left[\ln w_{it} | occ\right], \varepsilon^2\right)$$

Decomposing Occupation Residual

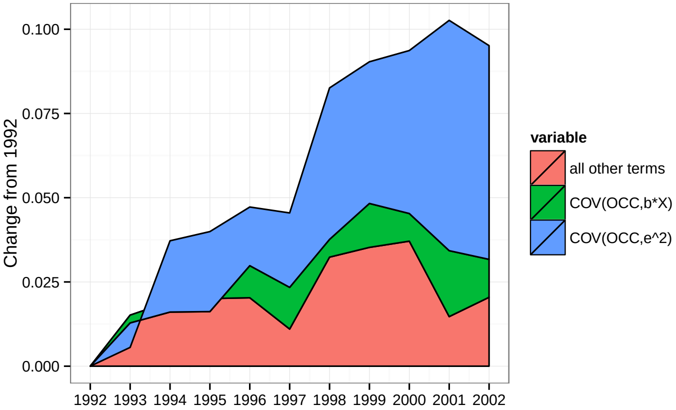
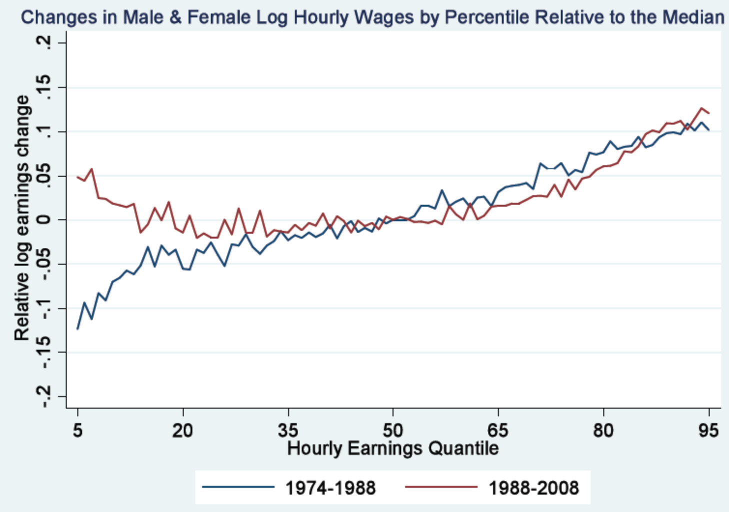


Figure : Skewness Decomposition with Occupational Mincer Equation

Data resource: CPS-ORG

Relative Change at Different Percentiles



From: Acemoglu and Autor (2011) ▸ return

In Linear Models

- More generally - if we are willing to assume some linear model (i.e. Mincer equation)

$$Y = \sum_i X_i$$

- We can use that to decompose the skewness of Y to a sum of skewness, and covariances of the linear components

$$E\left(Y^3\right) = \sum_i E\left(X_i^3\right) + 3\sum_i \sum_{j \neq i} COV\left(X_i^2, X_j\right)$$

$$+6 \sum_i \sum_{j \neq i} \sum_{k \neq i,j} E\left[X_i X_j X_k\right]$$

- This will be useful when we want to decompose by more than one category ▸ return

Proof

$$\mu_3(Y) = E\left[(Y - E[Y])^3\right] =$$

$$E\left[E\left[(Y - E[Y|X] + E[Y|X] - E[Y])^3 |X\right]\right] =$$

$$= E\left[E\left[(Y - E[Y|X])^3 |X\right]\right] + E\left[(E[Y|X] - E[Y])^3\right] +$$

$$+3E[E[(Y - E[Y|X])(E[Y|X] - E[Y])(Y - E[Y])|X]] =$$

$$= E[\mu_3(Y|X)] + \mu_3(E[Y|X]) +$$

$$+3E[(E[Y|X] - E[Y])E[(Y - E[Y|X])(Y - E[Y])|X]] =$$

$$= E[\mu_3(Y|X)] + \mu_3(E[Y|X]) + 3COV(E[Y|X], V[Y|X])$$

return

[label=Full]Full Distribution

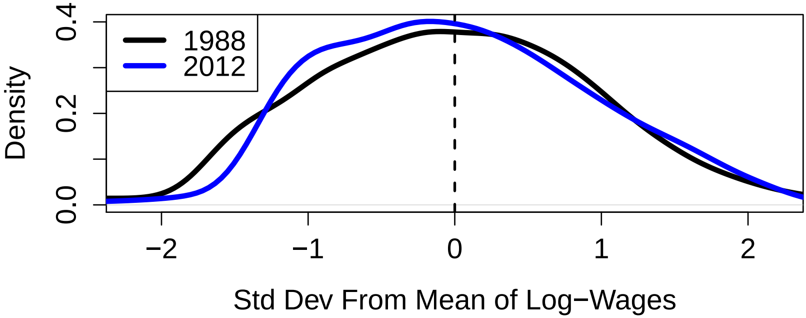


Figure : Standardized Log of Hourly Wages

Kernel density estimation with bandwidth = 0.2.

Skewness Decomposition by Industry

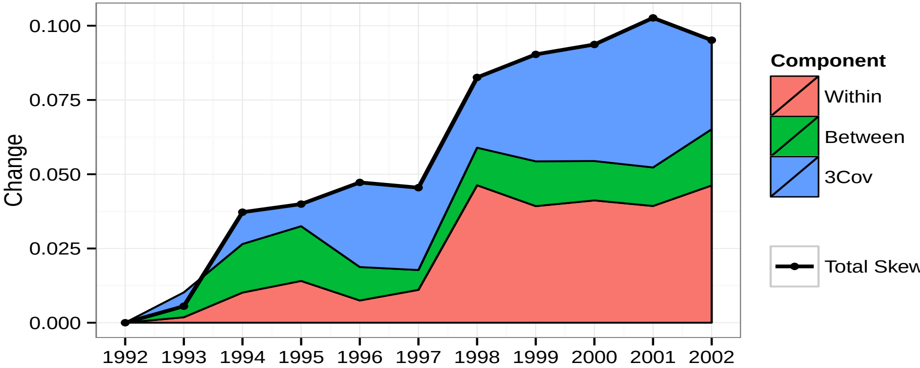


Figure : Skewness Decomposition Changes 1992-2002

Data resource: CPS-ORG

Skewness Decomposition by School × Experience

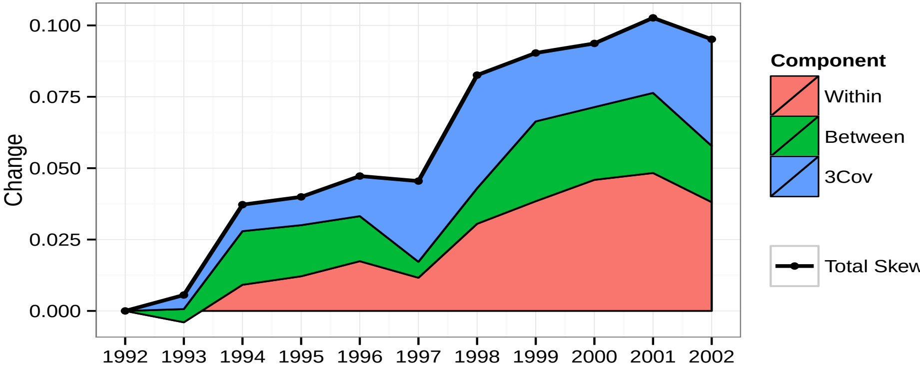


Figure : Skewness Decomposition Changes 1992-2002

Occupations With Largest Increase in Variance

Occupation	$\overline{\Pr}$	$\overline{E}$	ΔV
Financial Managers	0.006	3.071	0.054
Computer system analysts	0.006	3.192	0.04
Sales reps	0.013	2.924	0.036
Electricians	0.007	2.952	0.031
Sales workers, other comm.	0.009	2.295	0.03
Managers and administrators n.e.c.	0.047	3.021	0.029

Table : Occupations With Largest Increase in Variance of Log Wages 1992-2002

Data resource: CPS-ORG. Only occupations with at least 0.5% of total working hours. return

Occupations With Largest Decrease in Variance

Occupation	$\overline{\text{Pr}}$	$\overline{E}$	ΔV
Grinding, buffing machine operators	.001	2.58	-.113
Supervisors - food preparation	.003	2.33	-.101
Butchers and meat cutters	.003	2.48	-.093
Punching and stamp machine operators	.001	2.56	-.093
Stock handlers and baggers	.008	2.33	-.093
Bus drivers	.004	2.60	-.091

Table : Occupations With Largest Decrease in Variance of Log Wages 1992-2002

Data resource: CPS-ORG. Only occupations with at least 0.1% of total working hours. Largest Increase

Broad Categories

Occupation	$\overline{\text{Pr}}$	$\overline{E}$	ΔV
Managers & Professional	.28	2.97	.010
Technicians	.30	2.62	-.005
Production	.12	2.79	-.013
Service	.12	2.38	-.022
Operators/Laborers	.17	2.54	-.046

Table : Summary Statistics of Broad Occupational Categories

Data resource: CPS-ORG.

Change in Inequality Within Occupation

- By definition $COV\left(E\left[Y|X\right], V\left[Y|X\right]\right) =$

$$\sum_x \underbrace{\Pr\left(X = x\right)}_{Composition}\underbrace{\left(E\left[Y|X = x\right] - E\left[Y\right]\right)}_{Mean}\underbrace{V\left(Y|X = x\right)}_{Inequality}$$

- Increase in correlation between occupational wage level and inequality can be the result of:
  - Composition effect
  - Changes in wage levels
  - Changes in inequality
- I will show that this is the result of changes in inequality $\Delta V\left(Y|X = x\right)$

Counterfactual Covariance

- Fix composition and wage levels to their average throughout the entire period.
- Let only the inequality (variance) change each year.
- In formula:

$$\widetilde{COV_t} = \sum_x \overline{\Pr(X = x)} \cdot \overline{(E[Y|X = x] - E[Y])} \cdot V(Y_t|X = x)$$

- We will get that

$$\widetilde{COV_t} \approx COV_t$$

Counterfactual Covariance

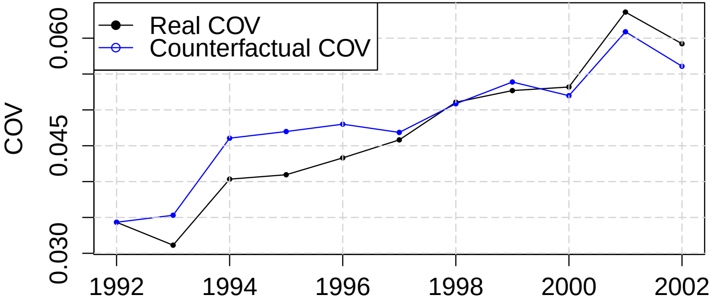


Figure : Covariance of Expectation and Variance of Log-Wage

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