Rising Between Firm Inequality and Declining Labor Market Fluidity: Implications for Economic Mobility?

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Recent studies (e.g., Abowd et. al. (2018), Barth et. al. (2016), Song et. al. (2019), and Haltiwanger and Spletzer (2019)) have documented from administrative data that much of the rise in earnings inequality is accounted for by a rise in between firm inequality. These studies find that more than 70 percent of overall earnings inequality is from a rise in between firm inequality. Using the LEHD data, Haltiwanger and Spletzer (2019) emphasize, using high quality firm-level industry codes from BLS/Census, that a large fraction of this rise in between firm inequality is a rise in between industry inequality (about 75 percent). They also show that this rise in between industry inequality is closely related to changing returns to occupations as in Acemoglu and Autor (2011).

A distinct but potentially important related finding is that there has been a decline in indicators of labor market fluidity (see, e.g., Davis and Haltiwanger (2015), Hyatt and Spletzer (2013), and Molloy et. al. (2016)). Such indicators include a decline in the pace of worker reallocation (hires + separations), job reallocation (job creation + destruction), and job-to-job flows. The findings on declining labor market fluidity are drawn from studies that use administrative data such as the LEHD, business survey data such as the JOLTS, and individual survey data such as the CPS. The LEHD data are the most comprehensive, including the characteristics of the firms and workers engaged in labor market transitions.

In this paper, we will explore the potential connection between rising between firm and between industry inequality and declining labor market fluidity, with a focus on implications for economic mobility. We begin by decomposing total hires (and separations) from the LEHD firm-level data into hires from (separations to) nonemployment, hires from (separations to) the same industry, and hires from (and separations to) other industries. This will allow us to analyze how the decades-long trend in between firm inequality growth relates to the decades-long trend in declining fluidity. Our analysis will specifically look for evidence of declining economic mobility, which we define here as increasing barriers to transitions between firms with increasing large earnings disparities. Given the dominant role of between industry increases in inequality, these increasing barriers could come from between or within industry decline in hires from nonemployment or a decline in hires from industries with low earnings. We will document these changes in patterns of economic mobility by person characteristics such as age, race and ethnicity, gender, and education and explore the role of occupation in this context.

Our analysis of the relationship between declining fluidity and its implications for changes in economic mobility builds upon the job ladder analysis of Haltiwanger, Hyatt, Kahn, and McEntarfer (2018) and Haltiwanger, Hyatt and McEntarfer (2018). Our innovation is to pay special attention to how declining fluidity might motivate an increasing dispersion in between firm and between industry earnings.

To address these questions, our core data infrastructure begins with the LEHD data covering the time period 1996-2015 (see Abowd et al (2009)). Following Haltiwanger and Spletzer (2019), we integrate the LEHD with a rich set of additional databases to provide more contextual information including, for example, the Occupational Establishment Survey (OES) data.

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Supplemental Material for NBER/CRIW Submission:

Between Firm Changes in Earnings Inequality: The Role of Industry and Occupation Effects

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Disclaimer

Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau.

All results have been reviewed to ensure that no confidential information is disclosed.

Overview

- Recent findings emphasize that much of rise in earnings inequality is accounted for by between firm effects
  - Song et. al. (QJE, 2018), Barth et. al. (JOLE, 2016). Follows earlier literature (e.g., Davis and Haltiwanger (1992)).
    - Song et. al.: Between firm effects are accounted for by changes in sorting and segregation of workers across firms **within industry**.
- We confirm dominant role of between firm but find **most of rise is accounted for by between industry effects**
  - Using BLS/Census industry codes:
    - 75% of rise in between firm inequality due to between industry effects
    - Mostly due to changes in returns to working in industries, not change in composition of industries.
    - 50% of rise in between firm inequality due to between industry effects after controlling for differences across firms in worker mix, firm size, firm age and productivity.
  - Why difference? One possibility is that SSA industry measures are more likely to be missing and are of inferior quality to Census/BLS industry codes.

What Accounts for these large rising inter-industry earnings differentials?

- Interaction of differences in occupation distribution across industries and large changes in earnings differentials to occupations.
  - We account for 90+% of rising inter-industry earnings differentials
- Substantial role for rising earnings differentials for management, professional, and technical (STEM) occupations.
- Broadly consistent with Acemoglu and Autor (2011) findings on:
  - Rising role of occupations in accounting for rising inequality post 1990.
  - They also find large role for rising returns management, professional and technical occupations.
- Our contribution: The rising occupational differentials and changing occupation distribution has important implications for rising between firm and inter-industry earnings differentials.

LEHD Data

- Longitudinal Employer-Household Dynamics
  - -- Longitudinally linked employer-employee microdata
  - -- Created at the U.S. Census Bureau
  - -- Microdata from the State UI administrative systems
    wage records and QCEW establishment data
  - -- Enhanced with worker observables (age, gender, education)
  - -- Enhanced with firm information (age, size, labor productivity)

- Different states have joined the LEHD at different times, and have provided different amounts of historical data
  - -- We use 20 states with data from 1996:Q1 to 2015:Q4
  - -- These 20 states account for 46% of national employment

LEHD Earnings

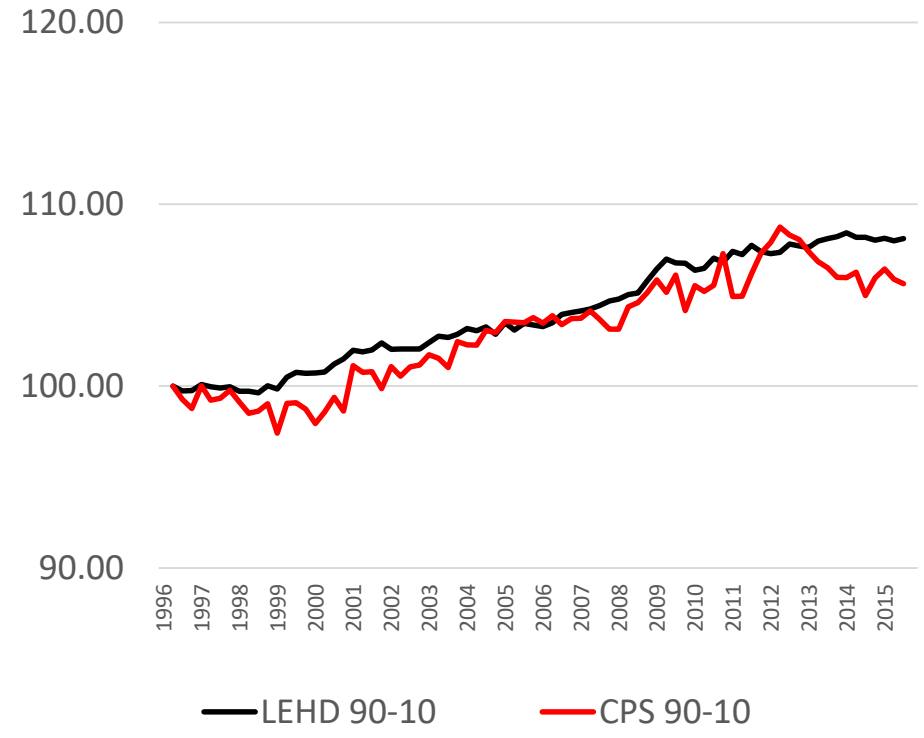
- Our 20-state LEHD data
  - -- 4.9 billion jobs, 1996:Q2 – 2015:Q3
- Earnings at all jobs or at "full quarter" jobs?
  - -- Full quarter jobs are the middle quarter of 3 consecutive quarters at an employer (similar to full time or full year workers in the CPS)
  - -- 3.3 billion full-quarter jobs 1996:Q2 – 2015:Q3
    approximately 42.7 million FQ jobs each quarter (78 quarters)
- Only 2 manipulations to LEHD full-quarter earnings data
  - -- Winsorize earnings at the 99.5 % of state-year-quarter distribution
  - -- Convert to real (2015:Q3 CPI-U-RS) natural-log earnings
- UI earnings include bonuses and exercised stock options (not top coded).
- Results robust to using annual earnings approach of Song et. al. (2018) using minimum earnings threshold

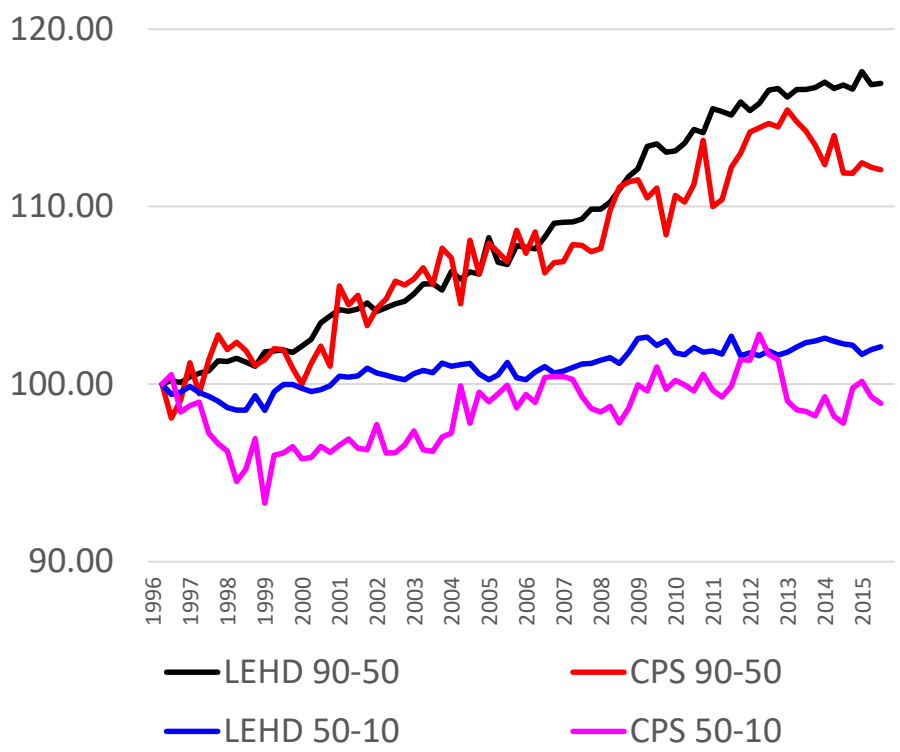
Industry Codes

- LEHD industry codes from BLS QCEW program
- Census industry codes from Census Business Register.
  - Census obtains industry codes from SSA, IRS, BLS and from Economic Census.
  - SSA codes are from SS-4 (Application for New EIN) write-in information.
  - Industry quality hierarchy at Census:
    - Economic Census $\geq$ BLS >> SSA/IRS codes (see Walker (1997)).
    - Census and BLS have strong incentives for high quality detailed industry codes for key indicators: output, employment, prices.
- For a subsample of our data, we have the SSA codes (firms less than 14 years old in 2013).

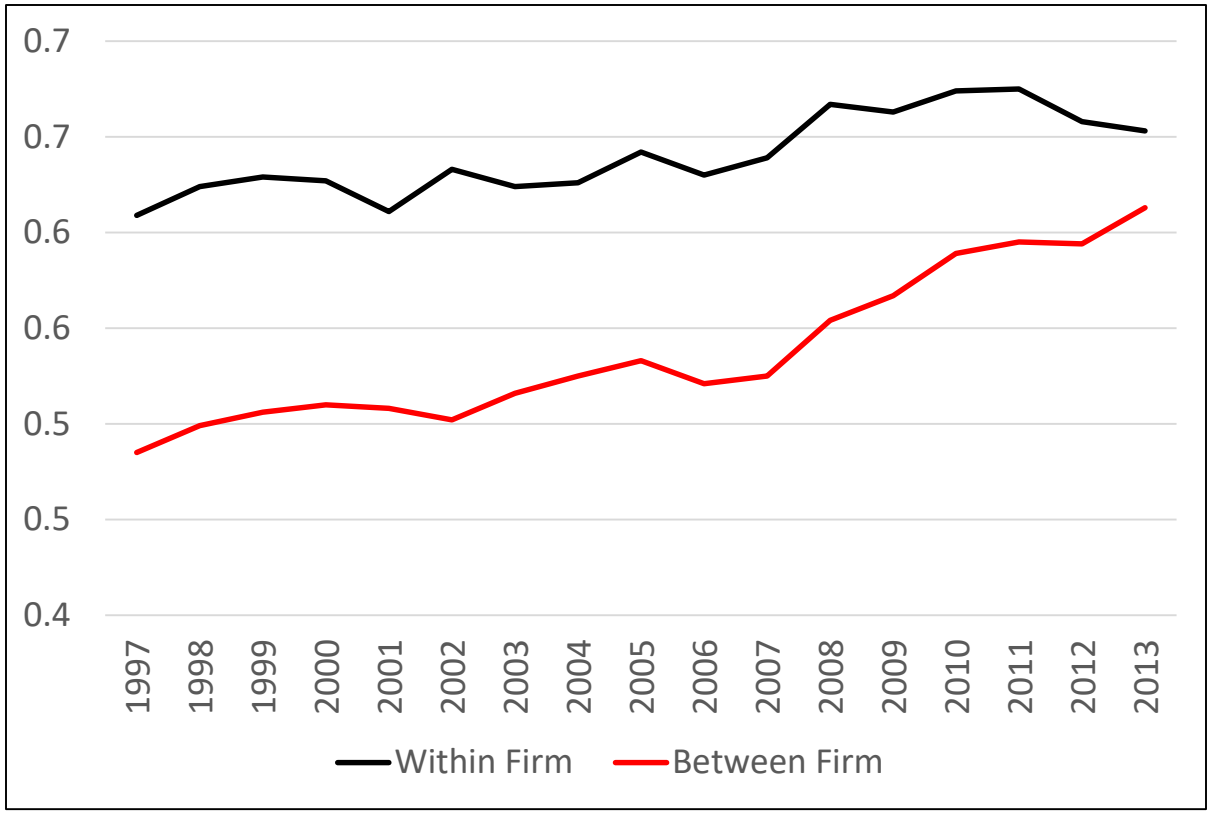
LEHD Earnings mimics Published CPS

CPS-ORG and LEHD FQ, real 2015:Q3 $, quarterly SA

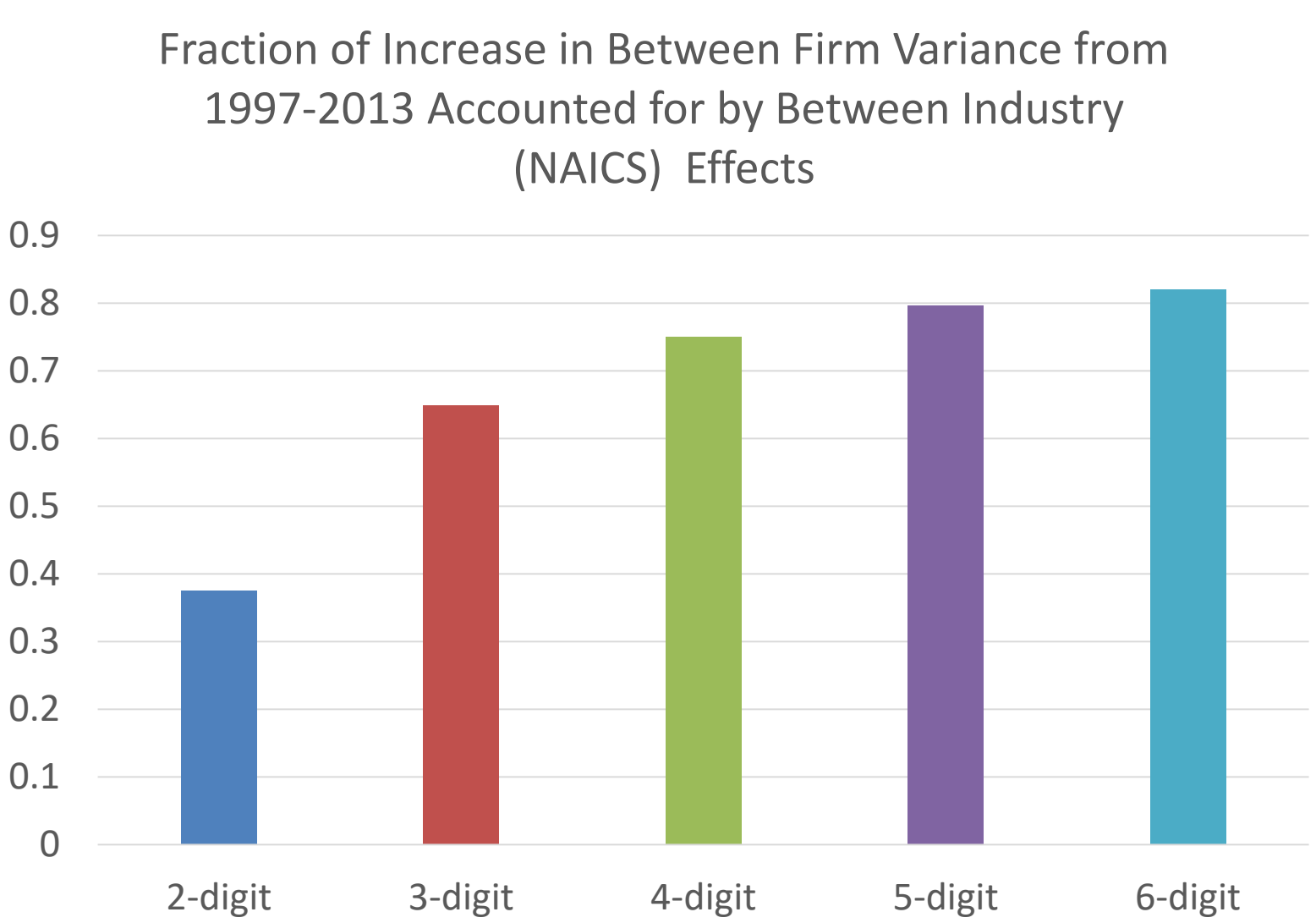




Focus is on Firms Defined at National Enterprise Level (results robust to using SEINs)



74% of variance growth is due to rise in between firm dispersion



Using establishment-level data from LBD for 1997-2007, Barth et. al. find that about 50% of increase from between industry (4-digit SIC). Song et. al. (2018) find a very small role for industry.

Our Methodology for Understanding Industry Effect

1) Employment weighted firm-level regressions

$$\$_{ft} = \alpha + LP_{ft}\gamma + X_{ft}\beta + Ind_{ft}\delta + \varepsilon_{ft}$$

$$\$_{ft} = \alpha_t + LP_{ft}\gamma_t + X_{ft}\beta_t + Ind_{ft}\delta_t + \varepsilon'_{ft}$$

2) Juhn, Murphy, Pierce (JMP) decomposition of increasing variance of between-firm earnings, var($\$_{ft}$), due to
   a) Changing "quantities"

      i.e., changing firm-level characteristics $\{LP_{ft}, X_{ft}, Ind_{ft}\}$
   b) Changing "prices" $\{\gamma_t, \beta_t, \delta_t\}$
   c) Residuals

Employment Weighted Regressions

$$\$_{ft} = \alpha + LP_{ft}\gamma + X_{ft}\beta + Ind_{ft}\delta + \varepsilon_{ft}$$

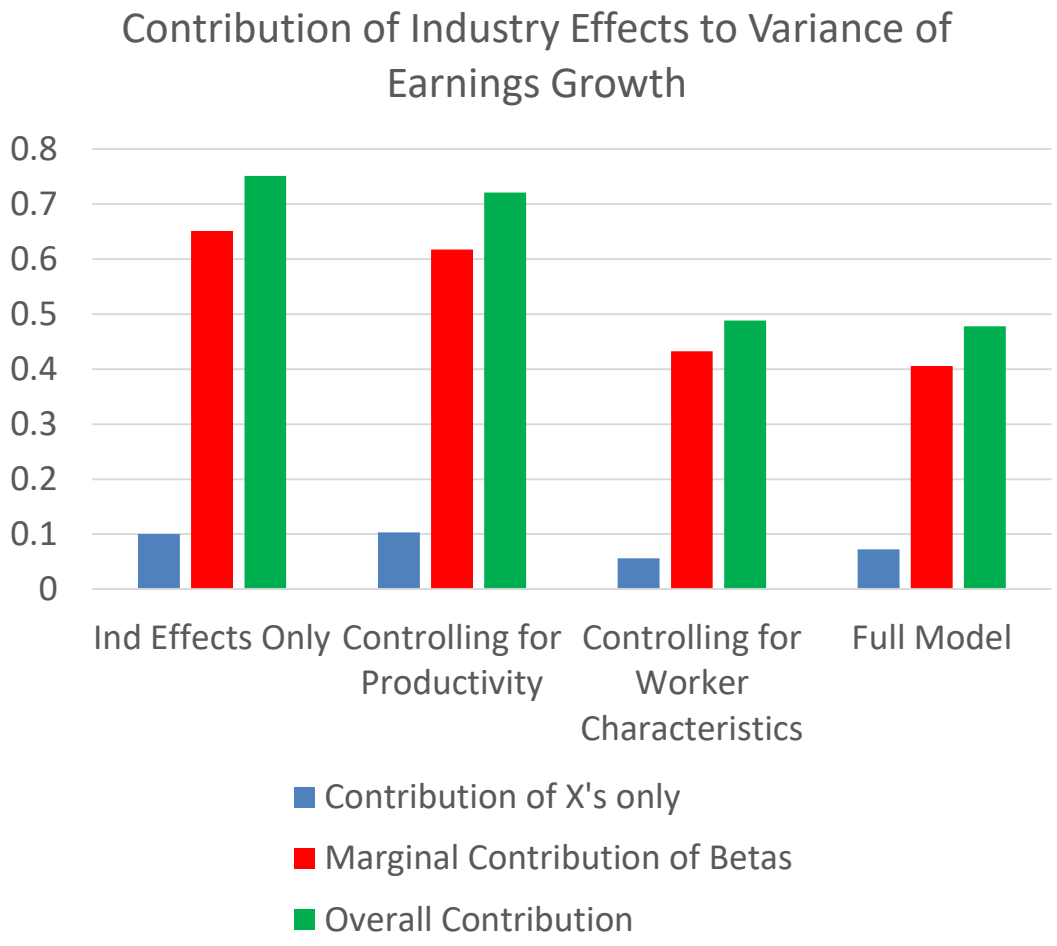
	(1)	(2)	(3)	(4)	(5)
Labor Productivity		.1729			.1015
LN(1 + Firm Age)			.0416		.0365
LN(1 + Firm Size)			.0467		.0353
% Workers in Firm:					
Age < 16				-1.381	-.8916
Age 16-24				-1.291	-1.207
Age 25-34				.0902	.0545
Age 45-54				-.0715	-.0866
Age 55-64				-.2986	-.2662
Age > 65				-1.407	-1.111
Female				-.6407	-.5674
Education < 12				.0110	.0082
Education 13-15				.5233	.4344
Education 16+				1.382	1.182
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	.5429	.5910	.5779	.6765	.7141

Variance growth of between-firm earnings

	(1)	(2)	(3)	(4)	(5)
Labor Productivity		Yes			Yes
Firm age & size			Yes		Yes
Worker demographics				Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
JMP contributions;					
Changing X	10.1%	25.8%	12.0%	-16.2%	-3.4%
Changing β	65.1%	44.9%	63.7%	87.2%	76.6%
Residual	24.9%	29.3%	24.3%	29.0%	26.8%

- Our controls include observable worker characteristics and labor productivity.
- These factors should capture sorting, segregation and rent sharing effects correlated with these observables.
- We focus on models (1) and (5). How much of the 75% due to industry effects from model 1 remains after all controls in model 5?

Understanding the industry effect

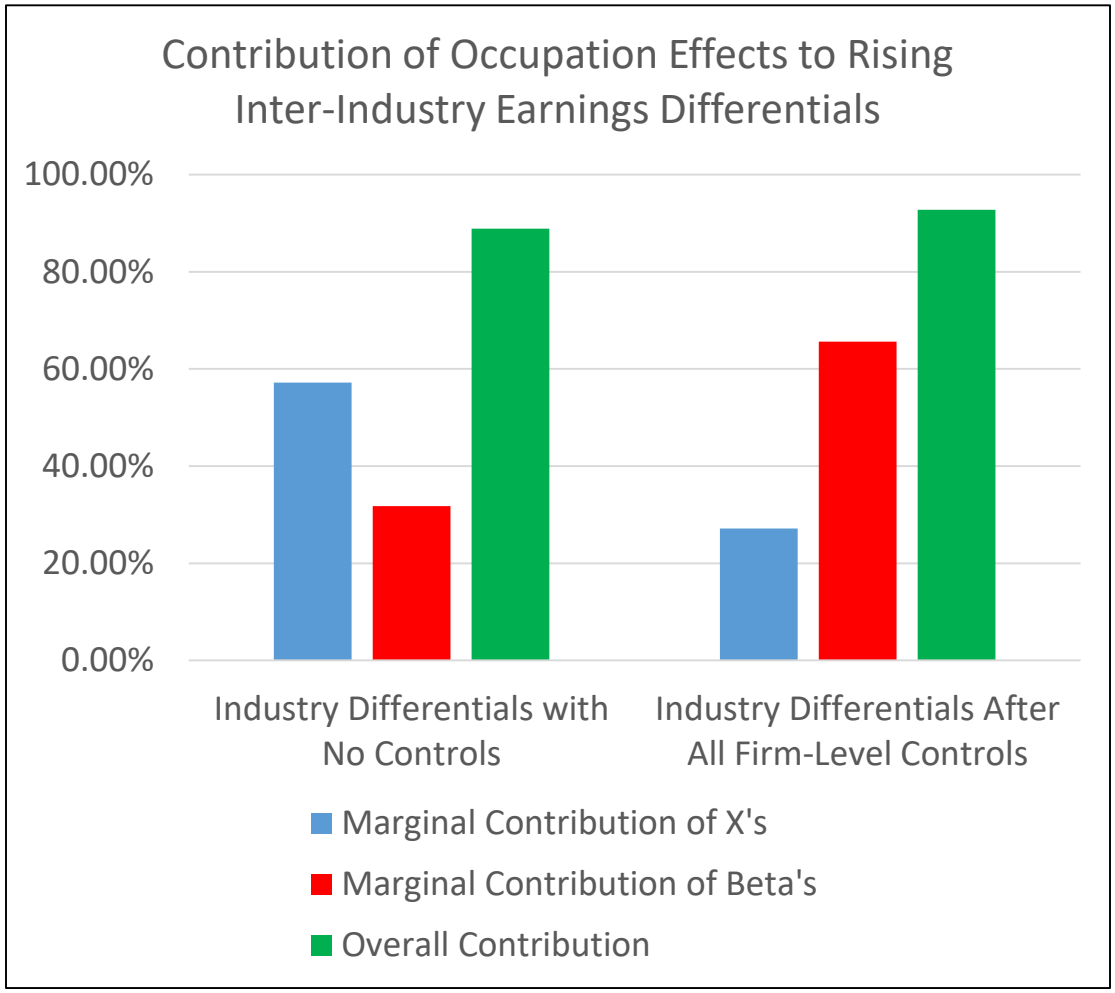


- JMP exercises above report var(LPγ + Xβ + Indδ). This bar chart reports var(Indδ).
- In a model with no covariates, industry effects explain 75%. In the full model, industry effects explain 48%.
- Most of the reduction in industry effects comes from "price" effects of the worker characteristics
- Even in full model, substantial (and unexplained) industry "price" effects

Understanding the industry effect

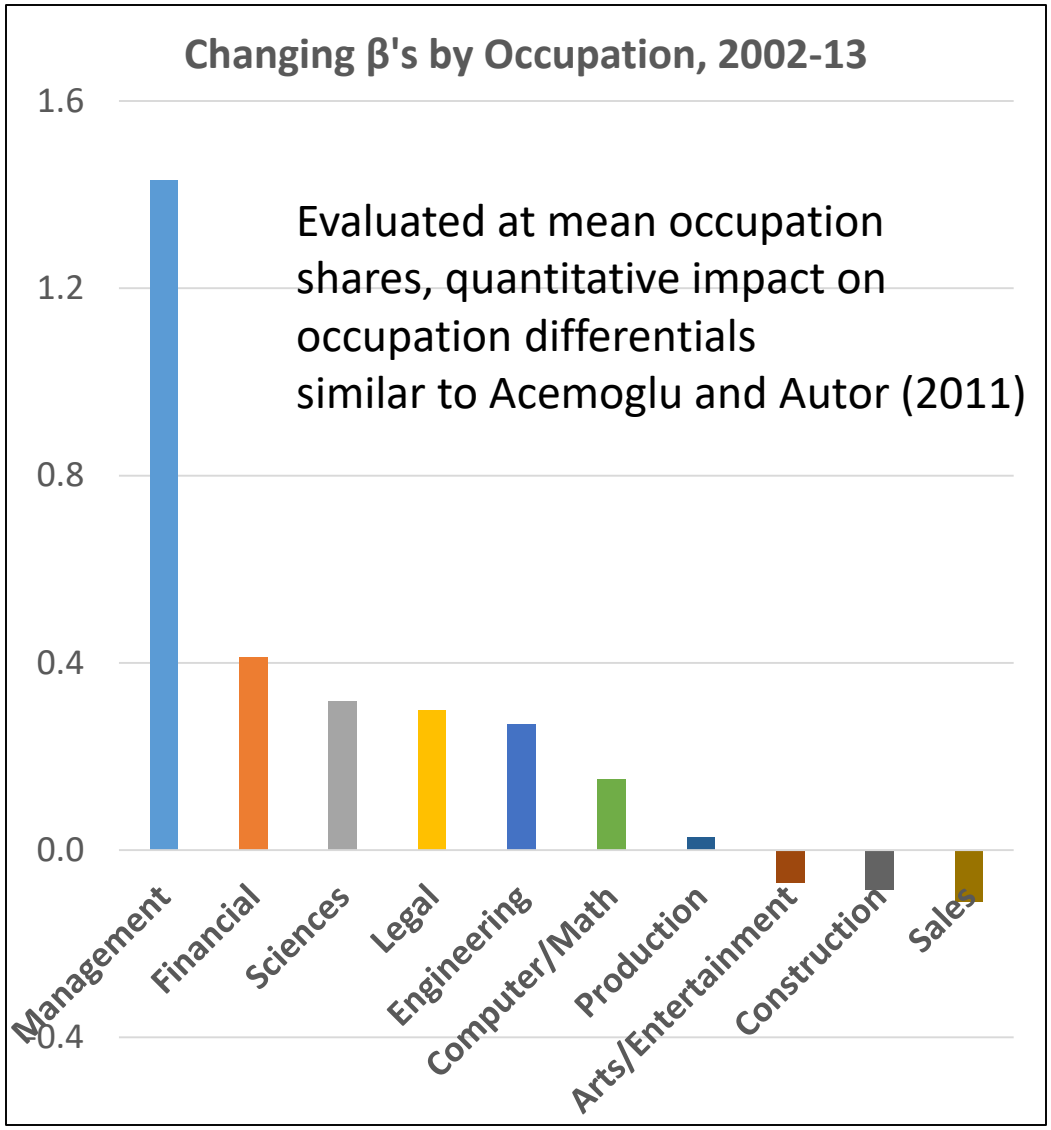
- Merge OES Occupation by Industry Data (from 2002-13)
  - 4-digit industry by 2-digit Occupations (about 20)
- Sample size is 3135 (4-digit industry by year observations)
- Use JMP analysis of between industry earnings differentials using occupation distribution.
  - Dependent Variable: Earnings differential by industry and year
  - Explanatory Variables: Occupation by industry by year shares of employment.
  - Analysis captures contribution of changing occupation distribution by industries (X's) and changing earnings differentials by occupation ($\beta's$).
- Objective: Do the differences in occupation mix across industries with changing $\beta's$ or the changing distribution of occupations across industries help account for the rising inter-industry wage differentials?

Understanding the industry effect



- Almost 90% of the "raw" rise in inter-industry wage differentials accounted for by occupation effects. Changing X's (changing occupation distribution across industries) accounts for 57%, Changing $\beta's$ 32%.
- 93% of residual inter-industry wage differentials accounted for by occupation effects. Changing X's account for 27%, changing $\beta's$ 66%.

Understanding the industry effect

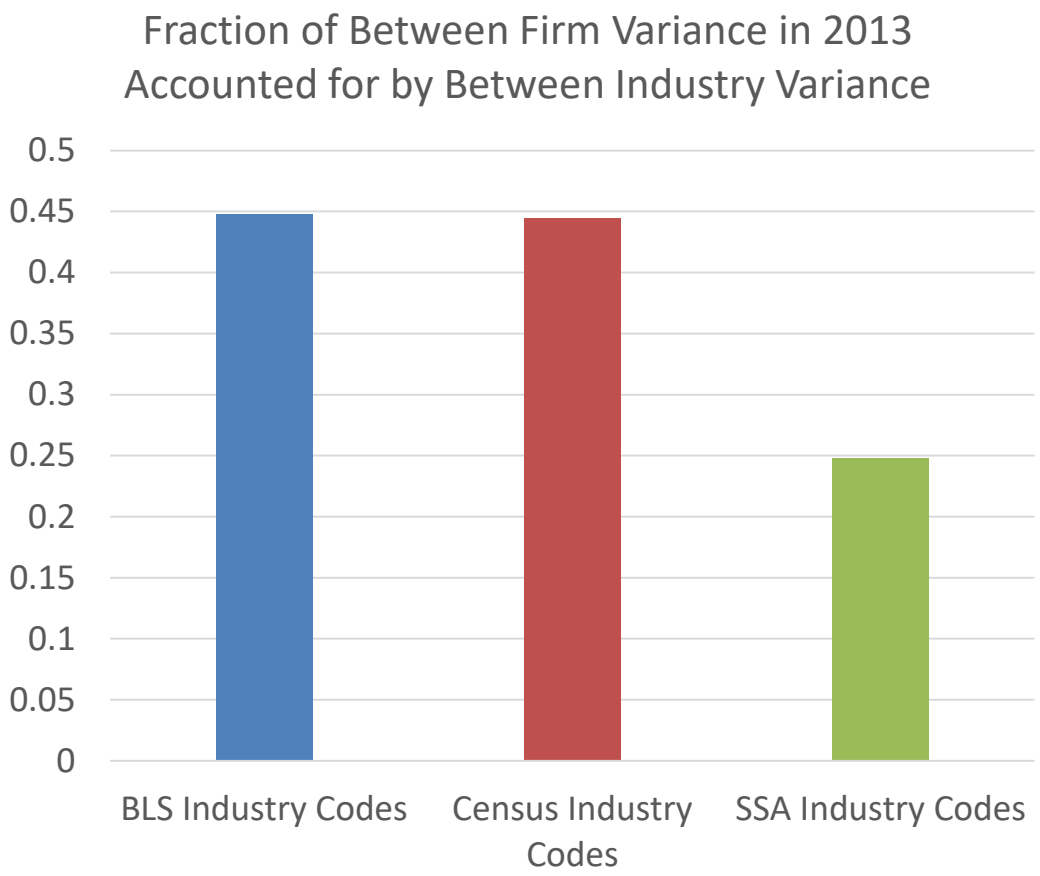


- Changing occupation differentials only relevant in this context if occupational mix differs between industries.
- Setting changing management differentials to zero, decreases contribution of changing $\beta's$ from 66% to 36%.

The Rise of the Importance of Occupations?

- Patterns we obtain are broadly similar to those of Acemoglu and Autor (2011):
  - They find that rising occupation differentials account for more of the rise in earnings inequality in the post 1990 period than rising education differential.
  - Rising occupation differentials especially large for management, professional and technical occupations.
  - For example, from 1989 to 2007 the occupation differential for management rises by more than 20 log points.
- Our contribution: Rising occupation differentials and changing distribution of occupations has important consequences for rising inter-industry wage differentials.
  - To capture this need HIGH QUALITY and DETAILED industry codes with HIGH QUALITY occupation distribution within detailed industries.
  - Such codes are available at Census and BLS.

Revisiting Industry Quality



- In 2013, for firms that are less than 14 years old, industry codes available from BLS, Census and SSA
- Between industry variance accounts for much higher fraction with BLS and Census industry codes compared to SSA.
- For all firms in 2013, BLS and Census codes account for about same fraction.
- Findings consistent with more limited role for SSA based industry.
- Open question: why does SSA data show almost no role for rising inter-industry wage differentials?

Summary of results

(1) Shifting industry earnings differentials account for a substantial amount of the increasing variance growth of between-firm earnings (75% in a simple model, 48% with all firm-level controls)

(2) Larger role for between industry relative to studies using SSA datam matched employer-employee data. Why? One possibility is more complete (less missing) and better measured industry.

(3) More than 90% of residual industry variation accounted for by occupation effects.

   (1) Most of the contribution of occupation due to changing occupation differentials, not changing distribution of occupations across industries.

   (2) Changing distribution of occupations across industries is a major factor in accounting for raw rising inter-industry wage differentials.

   (3) Rising earnings differentials for management, professional and technical occupations plays a substantial role.

Reconciling Results

- In principle our findings could be consistent with rising sorting and segregation of skills:
  - Our results suggest more of it must reflect sorting and segregation of skills across industries and reflect changing returns to skills.
  - Song et. al. (2018) note that their sorting and segregation could be driven by rising skill prices.
    - But using some counterfactuals with their rolling AKM analysis they find that only about 9% of sorting and 35% of segregation is due to rising skill prices.
- How to reconcile sorting/segregation with changing occupation differentials and changing occupation distribution that is apparently quite different across industries?