Predicting Patterns of Early Twentieth Century Wage Inequality

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April 2008

The body of literature seeking to explain the widening wage distribution observed in the United States over the past 30 years has become extensive. Macroeconomic theorists have had some measure of success modeling this phenomenon, attributing high growth rates of educational attainment and technological change to generating this trend (Acemoglu (2004), Beaudry and Green (2005), Aghion, Howitt and Violante (2002), Galor and Moav (2000)). The rapid expansion of skill levels and technology growth observed at the end of the twentieth century are, however, not unique to history. Previous episodes of expanding skilled labour supply and technology provide us with opportunities to test these theories. Understanding factors that might have influenced the historic trends in wages will contribute to our understanding of the current period, as well as improve our ability to assess the success of these models.

The interwar period was one of growing educational attainment and technological progress. In 1900 78.3% of the U.S. population between the ages of 5-17 was enrolled in some educational institution. This national average enrollment rate had risen to 80.6% in 1914, 87.3% in 1924, and 94.2% in 1940. High school graduation rates remained low until the interwar period. In 1900 only 6.3% of seventeen year old Americans had completed high school. By 1915, 12.8% had completed high school and in 1925 this figure had grown to 24.4%. By 1940 the U.S. high school graduation rate had increased to a historically unprecedented 49.0%.[1] Ohio's experience was representative of the U.S. as a whole during this period. According to Goldin (1998), high school enrollment rates in the north-east census region increased from 24.0% in 1910 to 81.0% in 1940, and high school graduation rates rose from 12.5% to 54%, with female graduation rates consistently exceeding male graduation rates by between 4 - 8%.

[1] U.S. school enrollment and high school graduation rates from Series H419 and H599 in the U.S. Historical Statistics (1975).

Technological progress was rapid in this period as well. Alexander Field (2004) compares total factor productivity growth rates over two periods: the interwar period and the 1990s. He finds that in the period 1919 to 1941 "technology" (in the Solow residual sense) grew faster than at any other time in history. Calculating the compound average annual growth rate of output per worker-hour (private non-farm economy), he finds that TFP grew at an average rate of 2.02% per year between 1919 and 1929, 2.31% per year in the period 1929 to 1941 and only 0.78% per year in the period 1989 to 2000. Additionally, Goldin and Katz (1998) find that technology is biased in favour of skilled workers in the early part of the twentieth century and that the capital-skill complementarity is as large as in the current period.

Changes in the relative distribution of wages in this interwar period have attracted considerable attention in the literature. Goldin and Katz (1995, 1998, 1999) find that the ratio of machinist to labourer wages wage fell between 1890 and 1940 and credits this decline in inequality to the growth in high school graduation rates and the failure of demand to meet in the increasing supply of skilled workers. Williamson and Lindert (1985), on the other hand, find no net wage compression in the period 1910-1929. They determine that while demographic trends were putting downward pressure on the wage structure, "convergence-in-factor-intensity" was exerting upward pressure. In the period 1910-1920 the first effect dominates and in 1920-1929 the second dominates, leaving no net effect over the decade. Using the ratio of clerical to production wages, Goldin & Margot (1992) find inequality growing over the period 1922-1932 and attribute this to changes in work hours which disproportionately disadvantaged production workers.

Given that the interwar period was one of rapidly expanding educational attainment, growth in total factor productivity and movements in the distribution of wages, it seems to be a good starting point for evaluating the predictions of a model of wage inequality. This paper uses a data set collected by the state of Ohio from 1914 to 1937, which reports the weekly wages of over 94% of the Ohio workforce, to test the predictions of a model in which new technology is biased in favour of skilled workers, educational attainment (and occupational choice) decisions are determined as

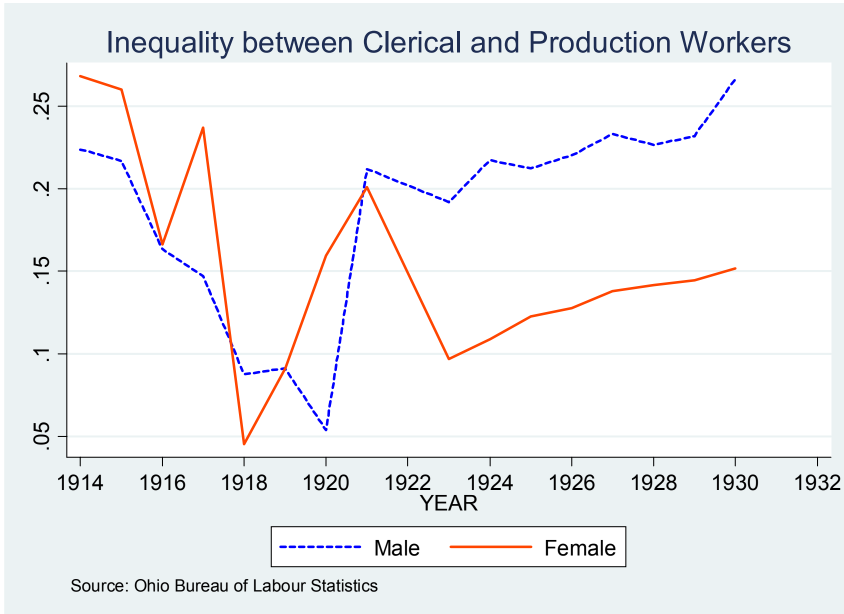


Figure 1: Inequality between clerical and production workers, by gender, for all industries aggregated, where the measure of inequality is the difference in the share of clerical workers in the top of the clerical distribution and production workers in the top of the production distribution.

a function of relative wages and the distribution of wages within, and between, skill groups is a function of the distribution of ability of workers in each group. I compute a novel metric for measuring changes in income inequality that captures changes in the relative distributions of wages rather than merely in the mean wage ratio of skilled and unskilled workers. The predictions of the model are tested with panel data analysis which exploits variations in the wage distributions over industry-year observations.

1 Measuring Inequality

In 1912 the State of Ohio passed a law requiring all firms with five or more workers to report employment and wage figures by occupation type: production ('waged') workers; clerical workers; and salesmen. The results of these surveys were published in the Ohio Division of Labor Statistics' annual report for the years 1914, 1915, and 1923 through to 1937. In total the data set contains

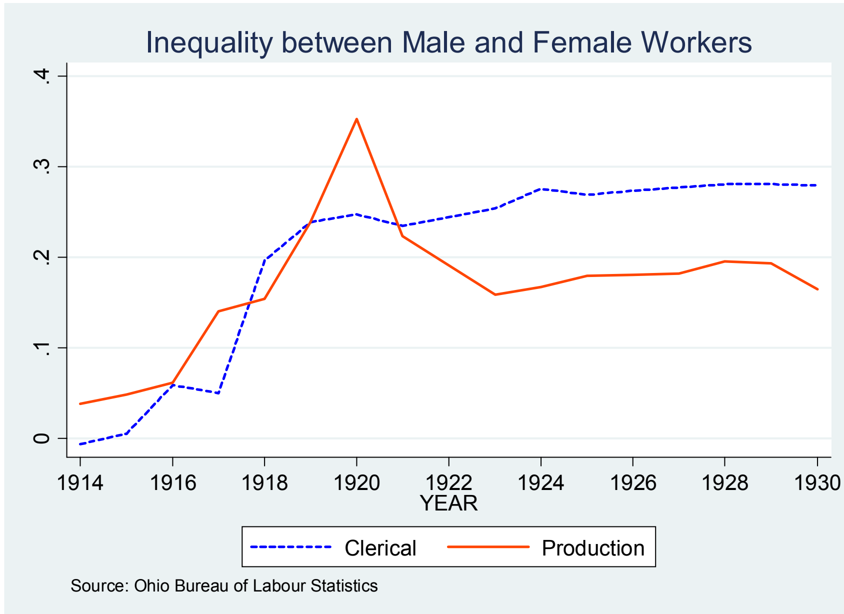


Figure 2: Inequality between male and female workers by occupation,

2,566 industry-year observations, distributed across 14 years of the sample and for approximately 200 industries.[2] The data set reports the distribution of wages for each worker type. For example, the annual report in 1914 reports the number of workers by industry, occupation, age (over and under the age of 18) and gender who earned in each weekly wage category: "Under \$4"; "Over \$4 but Under \$5"; "Over \$5 but Under \$6"; . . . ;"\$25 but under \$35"; and "Over \$35".

The division of workers into rough occupational groups limits the effectiveness of the data in determining relative skill levels by occupation. Production workers may vary from unskilled day labourers to skilled machinists; workers with relatively high levels of occupation-specific on the job training. Clerical workers are somewhat more homogenous in skill levels; those workers require general purpose numeracy and literacy associated with formal education. In an attempt to address this shortcoming, I combine the Ohio data with industry specific statistics compiled from the 1940 Public-Use Microdata Survey. Using the sample for the Midwest census region, I calculate the

[2]With the exception of the years 1924 through 1928 in which only the aggregate industries (the equivalent of the S.I.C. two digit codes) are reported.

share of workers in each industry by occupation and gender who have less than twelve years of education and the median years of education level of each type of worker. In the aggregate, 77% of male production workers had less than a grade twelve education compared to 38% of male clerical workers. This distinction is greater for female workers where 80% of production workers had less than a grade 12 education compared to 30% of clerical workers. The median grade completed for both male and female clerical workers is 12, while male production workers have more education than female clerical workers at median levels of 9 and 8 years.[3]

I develop a measure of relative wage inequality which measures the difference in the share of clerical workers in the top of the clerical wage distribution and the share of production workers in the top of the production wage distribution. If $I_{i,t}$ is inequality in industry i in year t this measure is

$$I_{i,t}^{[f,m]} = \frac{C_{i,t}^{w>\alpha}}{C_{i,t}} - \frac{P_{i,t}^{w>\alpha}}{P_{i,t}}$$

where $C_{i,t}$ is the total number of clerical workers employed in this industry year/pair for either male or female workers and $C_{i,t}^{w>\alpha}$ is the number of (either male or female) clerical workers with a weekly wage greater than some cut-off in the top of the distribution (discussed below). Correspondingly $P_{i,t}$ is the total number of (either male or female) production workers employed in this industry year/pair and $P_{i,t}^{w>\alpha}$ is the number of production workers with a weekly wage greater than the same cut-off. The cut-off in the current exercise is determined by fixing the share of male production workers in the top of the distribution (as closely as possible to 20%) and using that cut-off for male clerical workers. The cut-off for female production workers was fixed in the first period (below that of male production workers) and increased every period by the same dollar value as the male cut-off. For example in the years 1914 and 1915, $\alpha = \$18$ for male workers and $\alpha = \$8$ for female

[3]The share of workers in each industry, by occupation and gender, who have less than a high-school education are calculated from the Census of Population, 1940 (United States): Public- Use Microdata Sample (ICPSR 8236). Clerical Workers are all workers classified as Clerical and Kindred Workers and Production workers are all workers classified as Craftsmen, Foremen, and Kindred Workers and well as Operatives and Kindred Workers. All states are included in the sample and sample line weights are applied. All employed workers between the ages 18 and 39 were included.

workers. For 1923 to 1929, $\alpha = \$40$ for male workers and $\alpha = \$30$ for female workers. Table One provides a statistical summary of the shares for both types of male and female workers for the subset of years used in this analysis.

Figure One plots this inequality measure, $I_{i,t}$, for male and female workers over the period 1914 to 1930, including years for which only aggregate data are available (i.e. 1916-1922 and 1924-1928). The measure indicates that the share of clerical workers in the right tail of the distribution decreased, relative to production workers, in the early part of the sample. This trend is reversed, however, for the latter part of the sample, starting in the early twenties and continuing to the end of the decade. The overall effect for men over the whole period is a small but positive increase in the inequality measure from $I^M_{1914} = 0.225$ to $I^M_{1930} = 0.267$. The evidence for women is similar, a decrease in the inequality measure in the first part of the sample with an increase in the later period: however, the overall effect is a significant decrease in the measure from $I^F_{1914} = 0.268$ to $I^F_{1930} = 0.115$.

Figure Two plots a slightly different measure which captures changes in the male wage distribution relative to the female wage distribution. The measure here is

$$G^{[p,c]}_{i,t} = \frac{M^{w>\alpha}_{i,t}}{M_{i,t}} - \frac{F^{w>\alpha}_{i,t}}{F_{i,t}}$$

where $M_{i,t}$ is the total number of male workers, either clerical or production, employed in this industry year-pair and $M^{w>\alpha}_{i,t}$ is the number of (either clerical or production) male workers with a weekly wage greater than the cut-off in the top of the distribution. Correspondingly $F_{i,t}$ is the total number of (either clerical or production) female workers employed in this industry year/pair and $F^{w>\alpha}_{i,t}$ is the number of female workers with a weekly wage greater than the cut-off. The cut-off α is identical to that used above. The results in Figure Two suggest that, with all industries aggregated, male workers in either type of employment were moving into the top of the wage distribution at a faster rate for the period up to 1920. After this period there is a leveling off for both types of workers, with a small increase in the measure for clerical workers and a small decrease for production workers. Overall the increase is dramatic, from almost complete equality for clerical workers, $G^c_{1914} = -0.01$ to a wide dispersion in the later part of the sample, $G^c_{1930} = 0.279$. While the effect for production workers is small relatively, from $G^p_{1914} = 0.03$ to $G^p_{1930} = 0.16$, the evidence is in favour of a widening gender wage gap for both clerical and production workers.

The empirical results, presented in section three, exploit the industry specific nature of these data and uses a panel data analysis to test the predictions of a theoretical model, presented below.

2 The Model[4]

The model is based on Oded Galor and Omer Moav's model of ability-biased technological change (2000) and draws on the intuition in A.D. Roy's paper on the distribution of earnings (1951). In the model, the productivity of an individual worker is a function of their level of "ability". Ability is distributed over two dimensions: call them 'brawn' and 'brains'. Workers with relatively high brain-ability are more productive in a sector that produces an administrative good. Workers with relatively high brawn-ability are more productive in a sector that produces a manufactured good. The wages paid to each type of worker are a function of both their occupation and their level of ability in that sector. Administrative workers are skilled relative to manufacturing workers and acquiring education is costly in terms of forgone consumption. For the workforce as whole, the two types of ability levels may be positively, negatively or zero correlated at the individual level, the implications of which are discussed in the full paper. For the purposes of this exposition, we will assume that brain and brawn are not correlated; being a high ability brain worker does not suggest that the worker is either a high or low ability brawn worker. Finally, ability, over either dimension, is log-normally distributed.

Technological progress is skill-biased in that the productivity of skilled workers relative to unskilled workers, on average, increases when the level of technology increases. Technological

[4]The model is presented here for purely illustrative purposes. For the complete model please see the full version of the paper on the author's website at http://myweb.dal.ca/mr964257/

progress is also *ability-biased*. Workers with higher ability adjust more quickly in periods of rapid technological progress; adjustment is costly for low ability workers of either skill level. Where workers with higher brain-ability are more likely to become skilled workers, if technological progress is skill-biased, it is brain-ability-biased as well. If, on the hand, the ability bias is sufficiently high for unskilled workers, then technological change be complimentary to high ability unskilled workers as well. This interesting feature of model allows us to examine the distributions of income, both of within and between group, of workers of different skill types in face of rapid technological and educational achievement.

A large number of competitive producers use a constant returns to scale technology which combines capital (K) with human capital (H) in the production of a single final good. The technology is

$$Y_t = A_t F(K_t, H_t)$$

and can be written in the intensive form

$$y_t = \frac{Y_t}{H_t} = A_t f(k_t).$$

The wage paid to human capital is the marginal product of the intensive form production function

$$\begin{aligned} w_t &= A_t \left(f(k_t) - k_t f'(k_t) \right) \\ &= A_t w(k_t). \end{aligned}$$

We will assume that capital per unit of human capital is fixed so that $w(k_t) = \bar{w}$.

The growth rate to technology is simply

$$g_t = \frac{A_t - A_{t-1}}{A_{t-1}}.$$

The labour input combines the human capital of skilled workers (h_t) with the human capital of unskilled workers (l_t) and

$$H_t = \beta h_t + l_t (1 - g_t).$$

If we assume that the human capital of skilled labour is more productive than unskilled labour, then $\beta > 1$. The final term of the left-hand side imposes the condition that if technology is growing the labour input of unskilled workers is reduced relative to skilled workers, that is technology growth favours the productivity of skilled workers.[5]

Factor prices for each type of labour are given by the equations

$$\begin{aligned} w_t^s &= \beta \bar{w} A_t \\ w_t^u &= (1 - g_t)\, \bar{w} A_t \end{aligned}$$

where the superscript s denotes skilled workers and u denotes unskilled workers and the term $(1 - g)$ in the unskilled wage ensures that, on average, technological change is skill biased.

Where a^j, $j = [s, u]$, is an individual's ability level in either skilled or unskilled labour, and where the distribution of ability is log-normally distributed (such that $\ln a^j \sim N\left(\mu^j, \sigma^j\right)$), the efficient labour supply of unskilled worker i is

$$l_{i,t} = (a_i^u)^{p(g_t)}$$

and the efficient labour supply of skilled worker i is

$$h_{i,t} = (a_i^s)^{c(g_t)}.$$

Where both $p\,(g) \geq 1, c\,(g) \geq 1$, so that while technological change in on average skill biased, increases in the growth of technology favours high ability workers of either skill type. In fact if an unskilled worker's ability level is such that

$$\ln a_i^u > \frac{1}{(1 - g_t)\, p'\,(g_t)}$$

[5] In the full model human capital is further divided into male and female workers such that

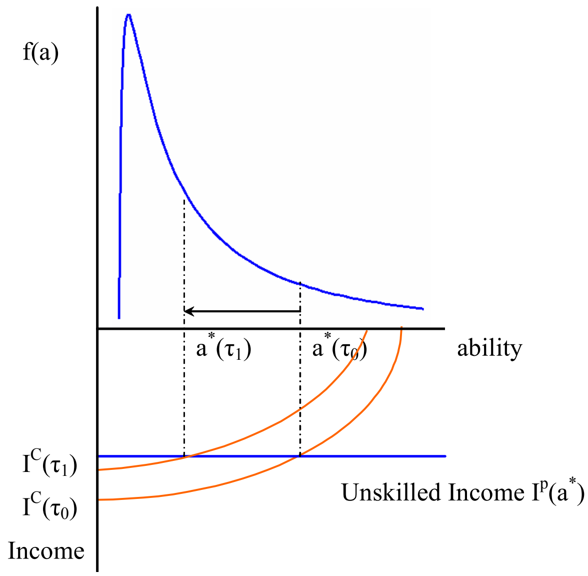
$$\begin{aligned} h_t &= h_t^m + h_t^f \\ l_t &= l_t^m + \gamma l_t^f, \end{aligned}$$

such that if $\gamma < 1$ male workers have a comparative advantage in unskilled labour.

the negative effect of the skill bias is dominated by the ability bias; the output (and income) of the worker increase in the face of accelerating technology growth.

The solution to the model describes the income distributions of both skilled and unskilled workers. These distributions are both a function of the cost of education and the of the growth rate of technology; any factor which alters the cost of education or the growth rate of technology will influence the relative income distributions of the two types of workers.

The mechanism through which the dynamic process is initiated is an exogenous decrease in the cost of education. The potential income of workers of all ability types, net of education costs, in the administrative sector increases relative to their potential income in the manufacturing sector. For a worker of any given brawn-ability level, say a^*, the probability that their brain-ability level now falls in the portion of the brain-ability distribution such is it profitable to invest in education is now higher. Those workers who might previously have chosen to remain unskilled become skilled and the average ability level of skilled workers falls. In addition to lowering the mean ability level in that sector, the decrease in τ, say from τ_0 to τ_1, puts upward pressure on the mean of the distribution of incomes. Depending on which effect dominates the over-all mean of the distribution of incomes might either increase or decrease. If the flow of workers into skilled employment is sufficiently large then the share of workers in the tail of the distribution of incomes of skilled workers in administration will fall relative to unskilled workers in manufacturing, that is an endogenous decrease in the cost of education reduces income inequality between the two sectors. This outcome is illustrated in Figures Three and Four where $I^P(a^*)$ represents the income level of a worker with brawn-ability a^*, and the area to the right of the dashed lines represent the portion of the brain distribution in which the worker would have to fall in order to find it profitable to invest in education. When the cost of education declines this line shifts to the left, and the probability that the work falls in that portion of the distribution increases. Where the worker did not find it profitable to invest in education prior to the fall in education costs it must be the case that her education level falls within the area of the two dashed lines and her ability level is, on average,



A decrease in the cost of education from τ_0 to τ_1 increases the probability that a worker with brawn ability a^* has a brain ability within the range sufficient to warrant investing in skills.

Figure 3: The effect on ability distributions with an exogenous decrease in the cost of education.

lower than that of the average skilled worker. This causes the mean ability of level of skilled workers to fall and the distribution of skilled wages to become more dispersed.

In the model the increase in investment in education feeds back into the economy and technology increases endogenously. For workers with low brawn-ability the outcome is illustrated in Figure Five; an increase in the growth rate of technology decreases income levels in manufacturing and increases the probability that a worker will have a sufficiently high level of brain-ability to find it profitable to invest in education. Again, while the increase in the growth rate of technology increases the income of skilled workers, with higher ability workers, who adapt more quickly to the technology, benefiting by more than low ability workers, the average ability level of workers in that sector falls. This effect is compounded if, as illustrated in Figure Six, high brawn-ability workers' manufacturing incomes increase when the growth rate of technology increases. In that

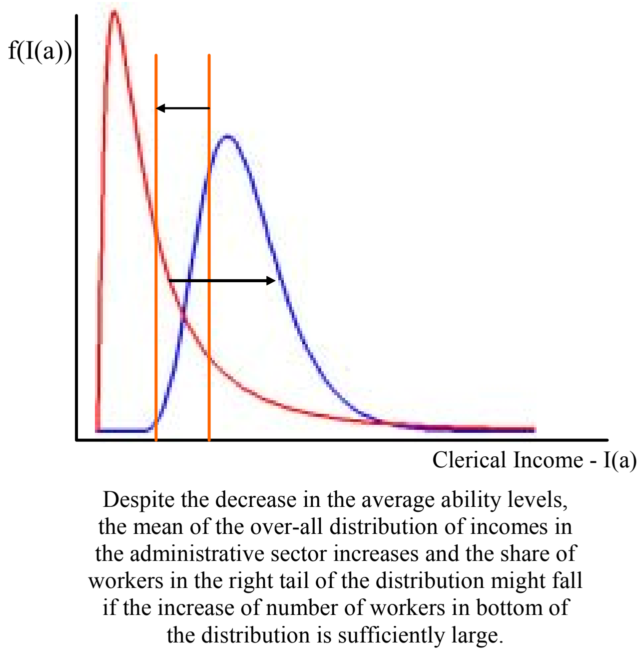


Figure 4: The effect on income distributions with an exogenous decrease in the cost of education.

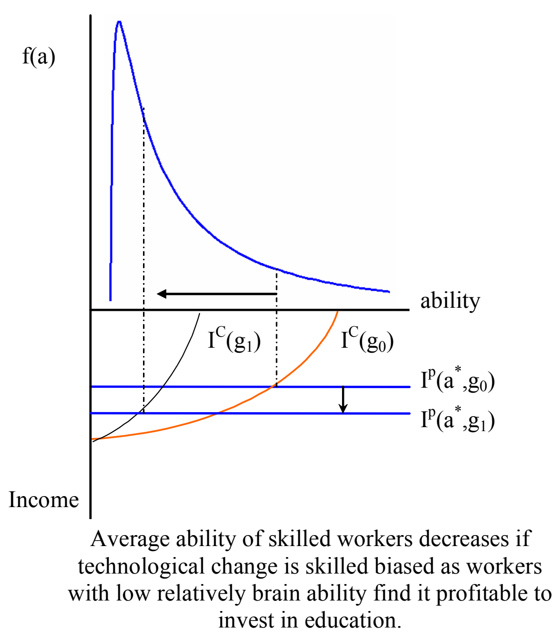
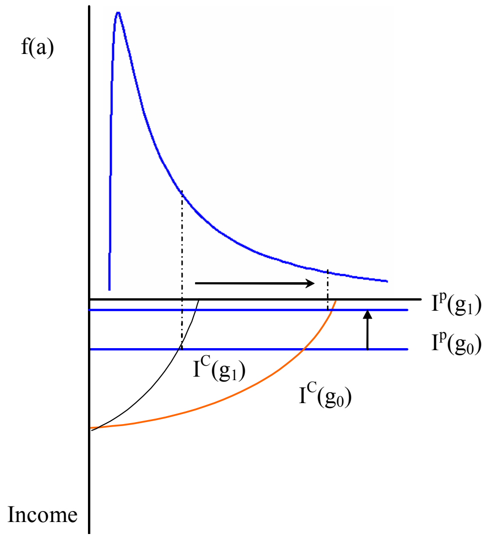


Figure 5: Th effect of an increase in the rate of technology growth with low brawn-ability workers.



If, due to the ability bias, the increase in technology growth rate drives up the relative income of the most able production workers, within occupation inequality will increase in manufacturing as more highly able unskilled workers choose to remain unskilled.

Figure 6: The effect of an increase in the rate of technology growth with high brawn-ability workers.

case the number of workers in the top of the brain-ability distribution falls, again putting downward pressure on the mean income. The effects on the variance of the distribution of incomes however is certain. In addition to the increase in workers on the low end of the distribution, the ability bias increases the relative income of workers on the high end of the distribution; again within group income inequality increases. For unskilled workers, despite the assumption of no correlation between ability levels, it is the relatively less able workers, in terms of manufacturing, who choose to become skilled. This should increase the mean ability in that sector and, depending on the level of ability-bias the distribution of income may increase, or decrease.

The composition of the workforce, in terms of the ability levels, changes within occupations as workers move from the manufacturing to the administrative sector, influencing the distribution of incomes of both occupations. An increase in the returns to investing in education will cause workers with lower brain type ability than the average administrative worker to become more educated and find employment in that sector. This decreases the average ability level in administration and widens the income distribution of the occupation. If technology is both skill-biased and ability-biased, however, the mean income in that occupation will not decrease.

3 Empirical Evidence

The Ohio Division of Labor Statistics' wage distributions have been used to estimate gender, occupation, and age specific mean log wages for each manufacturing industry included in the report using a standard Tobit model (adjusted to accommodate the open-ended upper interval).This estimation approach requires an assumption of log normality for each wage distribution. For industry-years in which workers' wages were only reported in one interval, the mean of the interval was used. In the rare cases where the workers' wages were only reported in the upper interval, the lower bound of that interval was used. The distributions of these wages for the years 1915, 1923, 1930 and 1937 are illustrated in Figures Seven through Ten below. In each graph the distribution of manufacturing wages is plotted along with its kernel density. I have also plotted the kernel density of clerical wages (which is, in every case, to the right of the manufacturing distribution). The evidence suggested in Figure One is again seen here; from 1915 to 1923 the distributions of wages between manufacturing and clerical workers moved closer together, and then from 1923 moved farther apart again. What was not evident from the aggregate data, however, is the evidence from the industry level data that suggest that, over the whole, pre-depression, period the distribution of wages of manufacturing workers narrowed relative to those of clerical workers. From this perspective, at least, it appears that while the shifting back of the distribution of incomes of clerical workers in the early period offset the effect of this relative compression in wages in manufacturing, as we move to the end of the decade this effect dominates, leading to an increase in the relative share of clerical workers in the right tail of the income distribution.

In addition to the wage and employment figures collected from the Ohio Division of Labor Statistics annual reports, we have matched the gender, occupation, and industry specific employment and wage data with information from the biennial Census of Manufactures for the state of Ohio. The census data and employment data overlap for four years during our sample period: 1914, 1923, 1929, 1931, 1933, 1935 and 1937.[6] We have used the four-digit SIC industry titles to match industries in the two data sets.

The specification of the model is:

$$I_{i,t}^{[f,m]} = \beta_0 + \beta_X \Sigma_X \ln X_{it} + \beta_S S_i + \beta_Z Z_j + +\varepsilon_{it},$$

where i identifies the four-digit industry code, j identifies the two-digit industry code, t identifies the year and $I_{i,t}$ is the inequality measure. X_{it} is a vectors which include the determinants of the wage distribution from the model, X_{it} also include a time parameter (t) that captures the effects of technological change as well as variable that measures the share of the workforce under the age of 18 in order to control for changes in child-labour laws over the period. The share of production workers with less than 12 years education in industry i in 1940 is S_i and Z_j is a vector of industry specific fixed effects included to control for cross panel heteroscedasticity. $\beta_X, \beta_{XY}, \beta_S$ and β_Z are vectors of parameters to be estimated. The model makes gender specific predictions for male and female workers, accordingly the exercise is repeated, dividing the workers by gender and allowing the share of clerical workers who are female to enter the equation. All labour inputs, capital, materials and output are in log form and are for workers over the age of 18.

The empirical results of this model are reported in Table Two. Male wage inequality decreased in male production workers but increased in all other workers. This is consistent with the additional result that inequality was decreasing in the volume of output; large production processes, with a large blue-collar workforce, most likely used a production technology that required the input of more skilled blue collar workers than small production process. This would increase the share of male production workers in the right tail of the income distribution. In fact increasing output decreased all levels of inequality, except for female occupational inequality where it is positive but

[6] For more information on data methodology, methods please see Adshade and Keay (2006).

insignificant. Capital appears to complement male clerical workers, even relative to female clerical workers and, although, capital does not appear to favour male production workers relative to male clerical workers, it does appear to favour male production workers relative to female production workers. Not surprisingly decreasing the share of children working increases inequality for men. As children left the workforce less skilled, low waged, manual jobs, previously undertaken by children, would have gone to adult workers, increasing the number of workers in the left tail of the income distribution. The result is the same for female workers, although the result is only significant at the 15% level. In terms of the theoretical model the evidence is consistent with the view that as more workers move into skilled employment (both male and female workers) the share of those types of workers in the top tail of the distribution increases relative to production workers. One final note. Movements in the gender wage gap for clerical workers appears to have little to do with changes in the female workforce. One plausible explanation is that as the clerical workforce expanded, in terms of both male and female workers, that male workers moved further into the top of the wage distribution as women occupied less skilled and, probably, low tenure jobs. Clearly these relationships warrant further analysis.

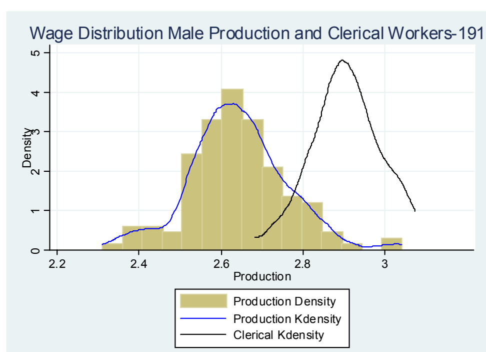


Figure 7: Density of industry specifc mean wages, by occupation, in 1915

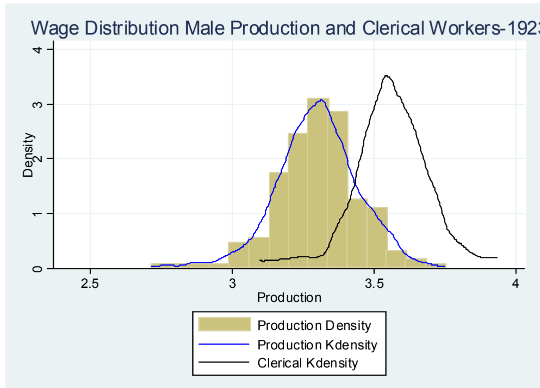


Figure 8: Density of industry specifc mean wages, by occupation, in 1923

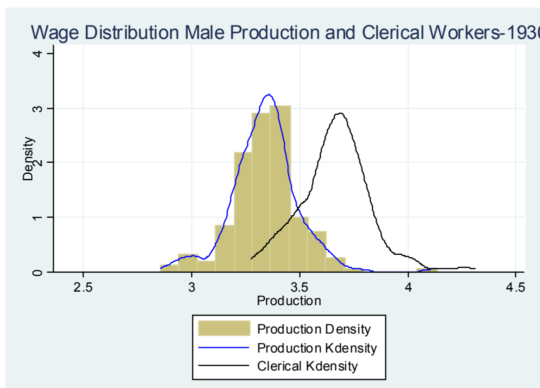


Figure 9: Density of industry specifc mean wages, by occupation, in 1930

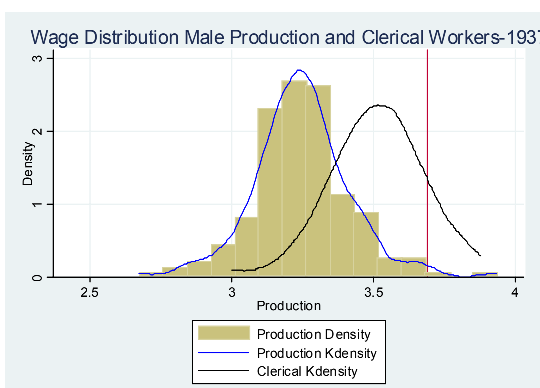


Figure 10: Density of industry specifc mean wages, by occupation, in 1937

Table One: Summary Statistics for Share of the Top of the Wage Distribution									
Year	n	Male Waged		Female Waged		Male Clerical		Female Clerical	
		$P^{w>a}/P$	s.d	$P^{w>a}/P$	s.d	$C^{w>a}/C$	s.d	$C^{w>a}/C$	s.d.
1914	87	0.23	0.10	0.01	0.06	0.42	0.18	0.28	0.26
1923	130	0.19	0.10	0.04	0.04	0.41	0.13	0.13	0.06
1929	102	0.24	0.10	0.04	0.05	0.51	0.08	0.18	0.06
1931	122	0.24	0.12	0.05	0.07	0.56	0.14	0.29	0.10
1933	90	0.17	0.11	0.05	0.05	0.56	0.16	0.35	0.11
1935	109	0.16	0.09	0.05	0.07	0.46	0.13	0.18	0.07
1937	116	0.17	0.09	0.04	0.04	0.42	0.14	0.12	0.06

Note: Observations are industry-year pairs. The mean share of workers in the top of the distribution ($P^{w>a}/P$ and $C^{w>a}/C$) are weighted by the total number of workers in the industry.

Table Two: Econometric Results of the Model

	Dependent variable measuring inequality between:							
	Clerical / Production Workers				Male / Female Workers			
	Male (I^m)		Female (I^f)		Clerical (G^C)		Production (G^P)	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
Year	0.002	0.002	-0.004***	0.001	0.001	0.001	-0.005***	0.001
Male Prod. Labour	-0.038***	0.008	-0.019***	0.007	-0.018***	0.007	-0.003***	0.005
Female Prod. Labour	0.010***	0.004	-0.001	0.003	0.004	0.003	-0.009**	0.002
Male Clerical Labour	0.063***	0.011	0.024***	0.009	0.041***	0.009	0.012	0.007
Female Clerical Labour	0.023**	0.011	0.024***	0.009	0.008	0.009	-0.002***	0.007
Capital	0.043***	0.016	-0.021	0.014	0.027**	0.013	-0.040***	0.011
Materials	0.189***	0.024	0.003	0.022	0.076***	0.020	-0.135***	0.016
Output	-0.257***	0.038	0.002	0.034	-0.107***	0.031	0.186	0.025
Share <18	-0.509**	0.223	-0.280	0.190	-0.069	0.186	0.096	0.151
Share < Grade 12	0.491***	0.096	0.080	0.056				
Depression Dummy	-0.021	0.022	0.094***	0.019	-0.070***	0.018	0.043***	0.015
R^2	0.4651		0.2677		0.3372		0.1363	
observations	755		712		755		712	

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