Gender Differences and Inequality in the U.S. Labor Market

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Gender differences in the labor market can be better understood by looking at specific trends within and between each gender group. In this paper, we look specifically at income inequalities that exist between certain segments of the male and female labor force in addition to examining inequalities that exist within each gender group. Dividing male and female workers into cohorts first by age, and then by characteristics such as marital status, unionization rates, and occupational category, we find evidence to support a number of leading hypotheses that help explain the narrowing of the gender gap in the American workforce between 1979-2013.

I. Introduction

The general facts and long-term trends regarding gender differentials in the American labor market are well documented. In 2016, female labor force participation in the United States stood at 56.8 percent compared to 69.2 percent for men, and a comparison of median earnings tells us that women in America are earning approximately 82 cents for every dollar earned by their male counterparts.

Overall, gender gaps within the American labor force have been narrowing. Although the labor force participation rate for women has recently fallen back down to its levels of the late 1980s and is down from its peak of 60 percent in 1999, female participation in the labor force has increased dramatically since the 1940s and 1950s when the participation rate was less than 38 percent. As more women have entered the labor force, more men have been dropping out of it. Male labor force participation was as high as 84 percent in 1951, but has fallen persistently since then. This fact has helped to close the gap in participation albeit in a less than desirable manner. The earnings gap between men and women has also narrowed in a similar fashion. Current Population Survey data show that real earnings for men increased throughout the 1960s and even into the 1970s, but since 1973, median earnings for men have mostly stagnated or fallen from year to year. Women, on the other hand, experienced strong spurts of growth in their

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earnings particularly in the 1960s and 1980s, and as a result, the ratio of earnings between women and men has increased significantly over the last few decades.

In labor force participation, in earnings, and even in areas such as educational attainment, women seem to have made noticeable strides, while men have helped to expedite the narrowing of gender gaps by often regressing or failing to extend their own trajectories of success and progress. As encouraging or discouraging as these findings are; however, these basic indicators and trends give us only the most generalized understanding of what is going with regards to gender differences and dynamics in the workforce. To better understand gender differentials in the labor market, we need to take a closer look at what is going on within sub-segments of the male and female workforce.

One way to study these gender differentials in greater detail is to consider what has happened between, as well as, within each gender group with regards to income inequality. We believe this is important to consider, since as the overall gender gap has been narrowing, economic inequality between different subgroups of men and women have also been changing. There has been both convergence and divergence of incomes amongst and between various subgroups of men and women, and by breaking down each gender group into smaller categories by age and race, as well as a number of other characteristics, we can begin to postulate some of the causes and consequences associated with the overall narrowing of the gender gap in the United States.

In this paper, we examine trends in income inequality amongst and between subgroups of working men and women in the United States labor force during the period 1979-2013. We begin by documenting some of these trends and offering a number of theoretical hypotheses that could help to explain them. We then use empirical analysis to determine whether gender differentials persist once controlling for a number of cohort characteristics.

II. Data

The data for our analysis comes from the Luxembourg Income Study (LIS) database, which provides harmonized micro-level income data from roughly 50 countries. LIS income data for the United States is based on the Current Population Survey (CPS), and for the period under our consideration, LIS provides data for the years 1979, 1986, 1991, 1994, 1997, 2000, 2004, 2007, 2010, and 2013. We use individual-level income data rather than household-level data for our analysis for the obvious reason that we are concerned with gender-specific characteristics, which cannot be observed at the household level.

Using individual-level income data from LIS, we begin our study by dividing our sample of individuals into age cohorts defined by five-year intervals. Our youngest cohort consists of 20- to 24-years olds, the next cohort includes 25- to 29-year olds, and so on. We then calculate within-age-cohort Gini coefficients for each of our age groups in 1979 and in 2013, and compare how within-age-cohort inequality has changed over time. We separate full-time workers into a cateogry of

their own to control for differences associated with large differences in the number of hours worked.

Our analysis begins as we further divide each of these cohorts by gender to compare trends in inequality amongst men and women of a similar age over time. The remainder of our analysis consists of trying to understand what causes the difference in inequality trends between men and women.

III. Gender and Inequality

Figure 1 shows the Gini coefficients across different age groups in 1979 and 2013 for all workers and for full-time workers only. You can see that while inequality has risen for all age groups, the change in within-group inequality varies across groups. For instance, the lowest increase belongs to the group of 35- to 39-year old full-time workers at 12.6 percent and the highest increase is for 55- to 59-year old full-time workers at 25.5 percent. Not surprisingly inequality among all workers is slightly greater than for just full-time workers.

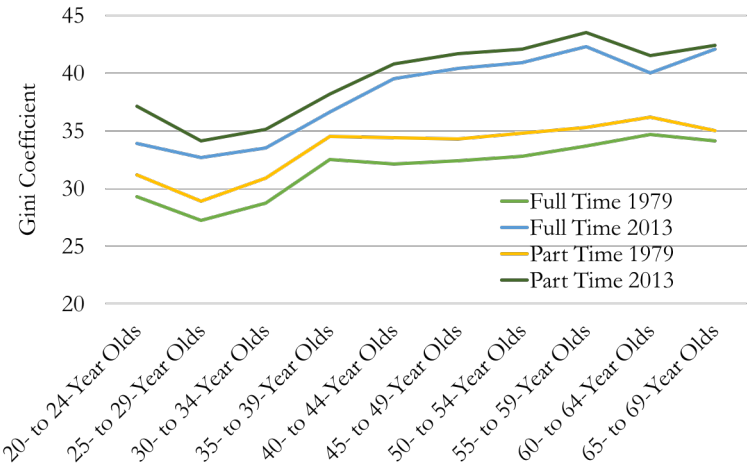

Figure 1. : Inequality among all and full-time workers across age groups: 1979-2013

Figure 2 represents the further decomposition of inequality into gender groups. For the sake of simplicity, we focus our attention on those working more than or equal to 20 hours per week. An interesting takeaway from the figure is that while inequality among most cohorts of women was higher than for cohorts of men in 1979, in 2013 the opposite was the case. Due to the larger increase in inequality among cohorts of men during this period, men are now more unequal than women. To demonstrate this contrast further we note that while the average increase in inequality across cohorts of men during this period was as high

as 32.3 percent, for women the average increase was 11.8 percent, one-third of men. Another interesting takeaway from Figure 2 is that the shape of within-age-cohort inequality among men and women in 2013 follow a similar pattern, i.e. the inequality across different age groups follows a similar pattern between men and women (higher inequality among older age cohorts). This was not the case in 1979, and this convergence of trend lines for men and women has been noticed by relatively few researchers.[1]

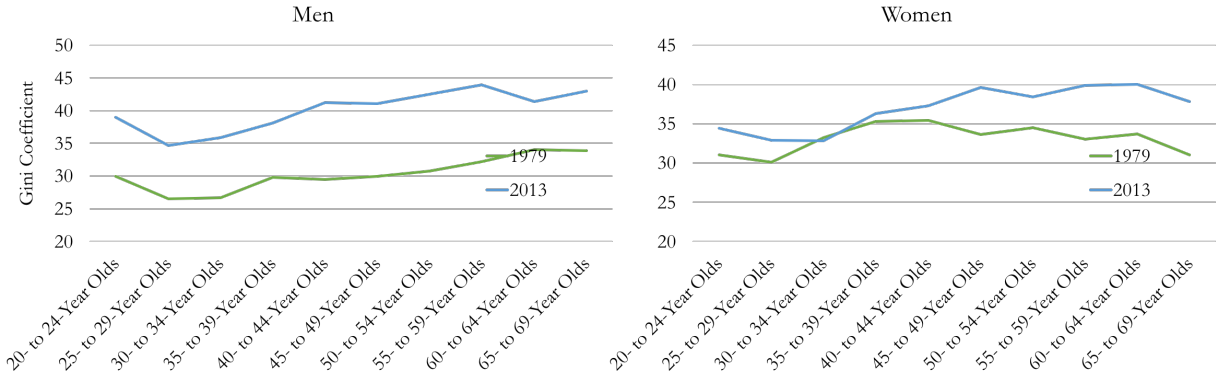

Figure 2. : Inequality among gender and age groups: 1979-2013

Moving from inequality that exists within age-cohorts of the same gender, we now turn our attention to inequality between age-cohorts of opposite genders. Going from Figure 1 to Figure 2, we can observe the inequality between men and women for each age group. A look at the gender gap for each age cohort reveals that the gender gap varies by age. Figure 3 represents the share of mean wages for women over mean wages for men across different age groups in 1979 and 2013. It is worth noting that although the inequality between gender groups has improved, in both years, the gender gap is largest among older cohorts and relatively small between young female and male workers.

Given these observations, the question we must ask is what could potentially explain the differences in levels and trends of age-cohort inequality between men and women. Answering this question requires extensive research on the causes of inequality in recent decades in the United States. In this paper, we try to empirically analyze this to some extent using regressions and also attempt to provide some hypotheses to explain the differences in inequality across cohorts of men and women.

[1]For instance see Osberg (2003) and Jenkins (1995)

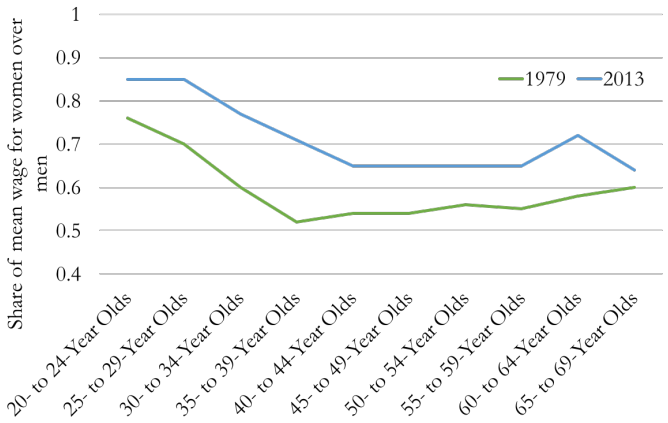

Figure 3. : Gender gap across age groups: 1979-2013

A. Female labor supply, marriage, and birth rate

Among the factors that are frequently used to explain the narrowing of the gender gap, changes in the labor supply of women due to changing patterns of marriage, divorce, and childbirth feature prominently. Johnson and Skinner (1986) found that both divorced women and women who were at higher risk of getting a divorce were more likely to participate and remain in the labor force. They postulated that these women were more likely to guard against shocks to their income related to divorce. Observations have also been made about changes in the labor supply patterns of married women. A greater share of white and high income married women are entering the workforce as they respond to growing skill premiums and tax incentives such as the Tax Reform Act of 1986 which reduced the marginal tax rate for the highest income bracket.[2] Meanwhile, policy changes such as the Temporary Assistance to Needy Families (TANF), and the expansion of the Earned Income Tax Credit Program (EITC) are thought to have negatively impacted the labor supply of low income minority women. Greenwood et al. (2016) have argued that assortative mating, divorce, and increases in the female labor supply together can explain one-third of the overall increase in income inequality in the United States from 1960 to 2005.

To observe changes in the effect of marriage patterns on inequality amongst working men and women, we can calculate within-gender-group Gini coefficients for working men and women according to marital status and compare these figures for 1979 to 2013. In doing so, we spot an important juxtaposition; inequality amongst married men, unmarried men, and unmarried women have all gone up, while inequality has actually declined amongst married women. Figure 4 demon-

[2]See Juhn and Potter (2006).

strates these patterns. While inequality among married women fell 10 percent during this period, inequality amongst married men increased by nearly 30 percent. In Figure 5, we see the within age-cohort inequality for the same groups observed in Figure 4. Even here we see a fall in inequality amongst all age-cohorts of married women. We can thus conclude that married women have played a role in equalizing incomes amongst women, whereas married men have contributed heavily to rising inequality within their own gender group.

Figure 4. : Inequality in terms of Gini coefficient for different marital and gender groups

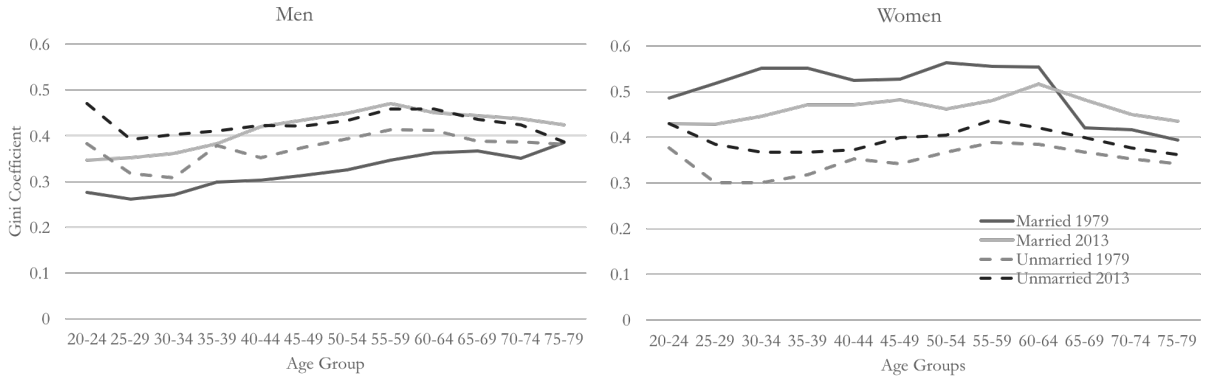

Figure 5. : Within age-cohort inequality in terms of Gini coefficient for different marital and gender groups

The lower inequality within cohorts of married women could have something to do with declining birth rates in recent decades. Women without children typically earn more than women with children. Goldin (2014) finds that women without

children worked roughly a quarter more hours per week than women who had children in 2012, and if we assume that women who don't have children work more hours, lower rates of childbirth could be thought to decrease inequality. Additionally, if more experience in the work force correlates to greater productivity, and if productivity is correlated with wages, then having children and reducing labor supply could decrease the wages of some women while not affecting the wages of others.(Lundberg and Rose, 2000).

In our data, we look to see if the number of children for working women has changed significantly over time, and find that the variance in the number of children for married, working women has fallen by about 8 percent between 1979 and 2013. For women 40- to 44-years old, this variance has dropped by 15 percent. For women in the 45- to 49-year old cohort it has dropped 17 percent, and for 50- to 54-year olds it has dropped by 14 percent. This supports the idea that falling rates of child birth can help to explain reductions in inequality even among married women. The big conundrum then is why this has not also helped to lower inequality among men. We can only speculate, but it could be the case that childbirth has opposing effects on maternal and paternal wages. Lundberg and Rose (2000) show that the birth of a first child is linked to a 5 percent decrease in maternal wages, but a 9 percent increase in paternal wages. It could be the case that fathers choose to work more to in the years of child rearing to support mothers who frequently choose to spend more time at home. Lower rates of childbirth, may have, in this case lowered the labor supply of fact...

B. The decline in the real value of the minimum wage

Although the nominal value of the minimum wage has gone up by 150 percent over the past three decades, the real value of the minimum wage has declined by about 22 percent as Figure 6 shows. In fact, the minimum wage would currently be at $9.39 had it been indexed to inflation in 1968 (Boushey, 2014). The value of tipped minimum wage[3] has declined by roughly 40 percent since early 1990s and is currently at a record low since its establishment in 1966.

How minimum wage affects inequality remains a controversial topic in economics. Lee (1999), in one of the first studies of minimum wage and inequality, used Current Population Survey data to show that the decline in the real value of the minimum wage largely explained the surge in inequality in the 1980s. In a recent paper, David, Manning and Smith (2016) use a longer span of time and find that minimum wage explains about 30-40 percent of the rise in income inequality. But if minimum wage has failed to keep up with the inflation rate, and if it is correlated with the recent rise in income inequality, how can we justify the rise in inequality among men but not women?

The answer to this is in the differences in trends of minimum wage earners

[3]The federal tipped minimum wage is the amount that combined with the employee's tips has to exceed the regular federal minimum wage.

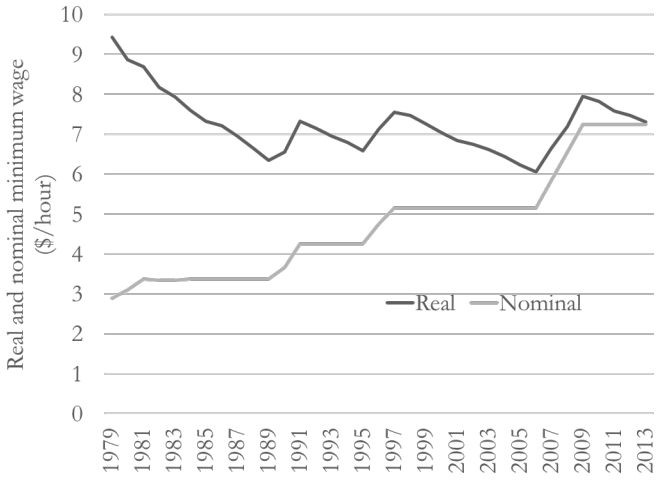

Figure 6. : Real and nominal values of the minimum wage: 1979-2013 Source: BLS Data

among men and women. As shown in Figure 7, the percentage of women who earn the federal minimum wage or less among hourly workers was about three times as high as their male counterparts in 1979 (20.2 versus 7.7 percent, respectively). However, by 2013 the share for women plummeted to 5.4 percent, which is a figure that is now much closer to that of men at 3.3 percent, as confirmed by David, Manning and Smith (2016).[4] They provide evidence that there has been a significant decline in the share of hours paid at or below the federal or applicable state minimum wage for female workers since 1979 and that the same share for male workers has remained relatively stable.

Thus, the evidence presented above is aligned with the inequality trends within female workers during the 1979-2013 period. The decrease in the real value of minimum wage is coupled with a sharp decline in the share of female workers who earn at or below the wage floor and a relatively stable share for male workers. This leads to a decline in inequality among women and a rise in inequality among men.

C. Deunionization

There is no hard evidence on the causal relationship of unionization rates in the United States and the rise in income inequality. Some studies, however, have found negative correlations between union membership rates and inequality

[4]They argue that due to the stable share of hours at or below minimum wage for male workers, any minimum-wage related impact on inequality should be due to spillover effects, i.e. the minimum wage mainly affects the wages of workers paid above the minimum wage. This effect is intensified when the minimum wage increases unemployment. See also Card, Katz and Krueger (1993).

Figure 7. : Percentage of workers earning federal minimum wage or less by gender
Source: BLS

measures such as the income share of the top 1 percent or the 50th over 10th percentile income ratio. Unions can also indirectly impact wage distribution through spillover effects, effects that unionization might have on non-union members.

The labor unions that gained so much power after the New Deal era until the early 1970s,[5] lost most of their gains during the three decades beginning in the early 1970s. What followed was an era known for the filibuster of the labor law reform of 1978, the suppression of the Professional Air Traffic Controllers Organization strike during the Reagan administration, and the passage of trade deals with China and Mexico that were unfriendly to workers. This deunionization trend was different for men and women. As you can see in Figure 8, the gap between private-sector union membership rates between men and women has decreased from roughly 17 to 4 percentage.[6]

It is often argued that the effect of deunionization on wage inequality is smaller among women than men. Card, Lemieux and Riddell (2003) find that the falling unionization rate is responsible for roughly 14 percent of the growth of male wage variance between 1973 to 2001 with a much smaller effect for women. DiNardo, Fortin and Lemieux (1995), Card (2001), and Gosling and Lemieux (2004) all find no (or negligible) effect of deunionization on wage inequality among women. Western and Rosenfeld (2011) calculates that 20 percent of the increase in wage inequality among men is caused by deunionization while they find no significant link between unions and wage inequality among women. Card, Lemieux and Riddell (2003) discuss three reasons for the asymmetric effects of unionization on

[5]Union membership reached 40 percent of the labor force by early 1970s.

[6]A similar trends in unionization between men and women in countries like the United Kingdom and Canada has been observed.

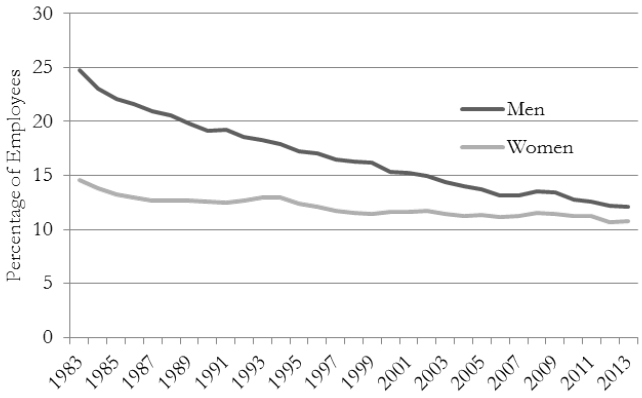

Figure 8. : Union membership rates for men and women: 1983-2013 Source: The Center for Economic and Policy Research and Current Population Survey

income inequality for men and women: 1) concentration of unionized women is higher in the upper end of the wage distribution than men. 2) union wage gap is larger for women than for men, which results in a larger between-sector effect. 3) the union wage gap is relatively larger for low-skilled men than high-skilled ones, but this skill effect if negligible for women.

In addition to raising the wage floor, unions are often found to have helped bring down the wage ceiling. Bivens and Mishel (2013) claim that efforts in blocking unions in companies that keep the wages paid to workers at low levels, lead to increase in returns to shareholders and to higher pay for corporate managers. This claims has been empirically supported by DiNardo, Hallock and Pischke (1997) who find evidence of a negative correlation between unionization and executive pay both across countries and across U.S. firms. For instance, they find that CEO pay is 2 percent lower for each additional 10 percent increase in unionization rate across firms in the United States.[7]

Altogether, we hypothesize that the combination of the larger decline in unionization among men than women and arguably the larger negative impact of deunionization on wage inequality for men than women is consistent with the observation that inequality among men has increased but it has decreased among most cohorts of women.

D. Technology and automation

A fourth category of factors that cannot be ignored are the effects of technology and automation on labor outcomes. It has been almost eight decades since John Maynard Keynes coined the term "technological unemployment," and since then

[7]For a more recent empirical analysis see Gomez and Tzioumis (2013).

the idea that machines will eventually displace workers and create "superstars" or "winners" has been popular both inside and outside of academia. Brynjolfsson and McAfee (2012), in their book, *Race Against the Machine*, discuss how technological change can lead to a rise in inequality among workers. Here again, we take a look at how these changes could impact inequality within the gender groups of the labor force.

We begin by looking at some of the different ways that technology impacts different sectors of employment. David Autor has argued that the effects of automation on employment are not uniform across all occupations, and he has divided jobs into three categories according to these differences. He differentiates between a) *routine* jobs or jobs that follow an exhaustive set of rules such as bookkeeping, clerical work, and repetitive production tasks, b) *manual* jobs or jobs that require situational adaptability, visual and language recognition, and in-person interactions such as food preparation, serving jobs, cleaning, and maintenance, and c) *abstract* jobs or jobs that require problem-solving skills, intuition, creativity, and persuasion such as managerial, technical, and professional occupations (Autor, 2014). Autor then argues that manual and abstract skills that demand more flexibility, judgement, and common sense skills are the ones that are less likely to be replaced by machines. While computers are good substitutes for routine jobs, they mostly complement abstract jobs and may have ambiguous effect on manual jobs. As a result, if automation replaces routine jobs and increases productivity of workers in manual and abstract jobs, the result is a job polarization in which there is a growth in employment in high-education, high-income and low-education, low-income jobs and a decline in employment in middle-education, middle-income jobs. These findings are empirically supported by Goos and Manning (2007). This job polarization can have a direct impact on the distribution of income in the economy. But we can only understand the consequences of this job polarization for wage inequality through the elasticity of demand and supply of jobs.

If we look at abstract jobs, the fact that the accumulation of skills and human capital is slow makes the supply of workers in abstract jobs very inelastic. As a result, an increase in demand for abstract jobs (potentially due to rises in productivity) is not usually followed by an influx of workers to supply those jobs. Evidence suggest that computerization has benefited all workers in abstract jobs by raising their wages (Autor, 2014). However, the story is different for women. The large number of idle women who have been recruited to the labor force makes supply of women (both skilled and unskilled) more elastic. Blundell and MaCurdy (1999) finds that the own-wage labor supply elasticity of women is almost tenfold that of men. The inelastic supply of male abstract workers and more elastic supply of female abstract workers lead to an increase in wages in managerial jobs done by men and a decrease in wages in those done mainly by women.[8] Due to

[8]In fact, it seems that the rise in the demand for skilled labor is positively correlated with automation and and computerization. Weinberg (2000) finds evidence for a positive correlation between computer

the already high wages in these sectors, the compound effect is higher inequality among men and lower inequality among women.

On the other hand, since computers do not necessarily complement (or substitute) manual jobs, the productivity gains in those jobs are negligible. We argue that the demand for manual tasks are relatively income elastic. Therefore, a growth-induced increase in the aggregate income can lead to a rise in demand for manual occupations. Now, due to the high elasticity of supply in those jobs a wage rise in manual jobs is naturally compensated with more supply of workers. Consequently, unlike abstract jobs, the effect of computerization on manual skills is not necessarily positive for both men and women.

Lastly, high substitution rate between routine jobs and computerization means lower wages for those working in the related sectors. Figure 9 shows the employment shares of occupational categories for both men and women. We have added two more categories: (1) cognitive routine jobs, which are jobs that require more cognitive skills, include sales and office occupations, and (2) manual routine jobs, which are routine jobs that require physical skills more than cognitive skills, include construction, transportation, production and repair occupations. As figure shows, women has reduced their employment in manual routine jobs at a higher rate than men (30 versus 15 percentage points between 1979 and 2014).

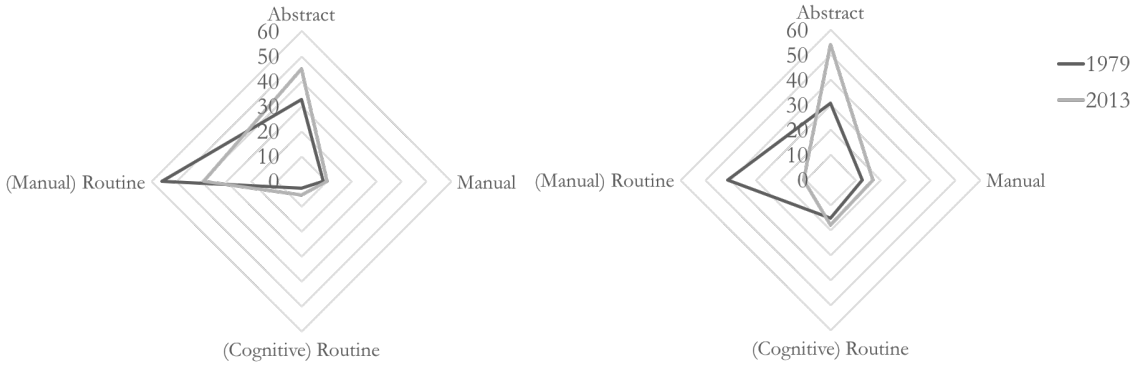

Figure 9. : Changes in occupational distribution for major occupational groups by gender between 1979-2014 Source: data from LIS Note: Abstract jobs contain managerial, professional, and technical occupations. Cognitive routine jobs are sales and office-related occupations. Manual routine jobs are production, transportation, and material moving occupations as well as natural resources, construction, and maintenance occupations. Manual jobs are cleaning, personal, and protective services.

In conjunction with the dynamic of employment shares, the ever decreasing

investment at the industry level and demand for female labor.

decline in wages for routine jobs has led to an increase in inequality among men and a decrease in inequality among women between 1979 and 2013. Note that the share of women in abstract jobs has increased over the period. Also it is important to notice that for men the changes in employment shares are quite negligible. Figure 10 depicts the percentage change in mean annual wages by occupational categories for men and women. The only negative growth in wages for women is in manual routine jobs, whereas, the only positive growth in wages for men is seen in abstract jobs. The increase in annual wages in managerial and professional jobs for women is as high as 25 percent. Consistent with elastic supply of workers for manual jobs, as employment rose for this occupation category, wages declined for men. Overall, the wage growth in routine category has been very modest for women and highly negative for men.

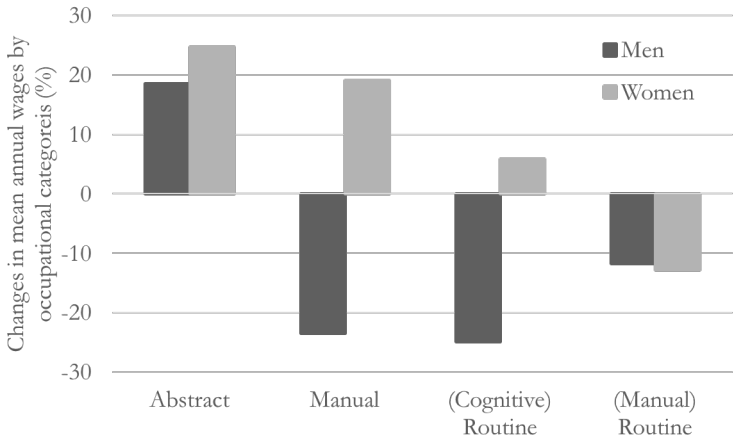

Figure 10. : Changes in mean annual wages by occupational categories and gender, Note: data from LIS

IV. Empirical Analysis

Our next question is whether the gender differences in inequality is due persists once we control for other cohort characteristics. Let us first look at the main factors that can explain such differentials in inequality using the following regression.

$$\text{WGI}_{it} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Female}_i + \beta_3 \text{Race}_i + v_t + \epsilon_{it}$$

Here i represents the *i-th* cohort, t represents year t, and v_t captures year effects. *Age*, *Female*, and *Race* enter the equation as vectors of dummies for cohort i. The dependent variable is the inequality in terms of Gini coefficient in cohort i at time

t. Table 1 shows the regression results for when we only consider individuals who work longer than 20 hours per week.

The coefficient on female changes significantly during the period 1979 to 2013. In 1979, the Gini coefficient for female workers is 2 points higher than for men. However, by 2013 it is men who are more unequal than women. The results also show that once we control for other factors, over the whole period the different in cohort inequality between men and women is insignificant. Model 11, shows that older workers tend to be more unequal than younger counterparts. Overall, looking at the constant, we can see that there has been a noticeable increase in inequality across all cohorts between 1979-2013.

The next step is to check whether we see the same trend when we look at the wages of full-time workers. This is shown in Table 2. The difference in inequality between cohort inequality of men and women seems to be much smaller for those who work more than 35 hours per week (notice the small coefficients for female in all years). What this suggests is that most of the inequality among women is due to the inequality in terms of working hours. Again, as in the case of Table 1, the gap in terms of cohort inequality between men and women gets smaller over time until in 2013 that men become significantly more unequal (the gap becomes equal to around 4 Gini points in 2013). Inequality within younger cohorts is smaller. Furthermore, both tables show that whites are more equal than blacks and Hispanics.

Lastly, as we previously discussed, there are other factors that can explain the differences in inequality of cohorts of men and women. We try to show this in columns 3-6 of Table 3 as much as data availability allows. We use share of married individuals in each cohort and variance of the number of children as factors that affect labor supply. Due to the ever-increasing return to college, we think a factor that can explain within-cohort inequality is the share of highly educated individuals in each cohort. This is calculated as the share of those with college and more. To investigate the effect of automation in the labor force and wage differentials in terms of occupations, we add to the regression the share of those in abstract, manual and cognitive routine jobs as discussed in previous sections. The omitted category is the share in manual routine jobs.

Note that after adding more control variables, cohorts of men turn out to be more unequal by 3 Gini points for both those working more than 20 hours and those working more than 35 hours. The coefficient on gender is significant in almost all regressions. Both share of married people and variance of the number of children in each cohort do not seem to be important indicators of within-cohort inequality, pointing out to the fact that variations in labor supply reflected by these factors does not determine inequality within cohorts. However, share of highly educated individuals is important in regressions 3 and 4 (but not in 5 and 6). For instance, for every 10 percent increase in the share of highly educated people in the cohort, inequality increases by 2 Gini points, according to models 3 and 4. Moreover, adding occupational shares to the regression proves that

Table 1—: Regression results for workers who work longer than 20 hours per week

	(1) 1979	(2) 1986	(3) 1991	(4) 1994	(5) 1997	(6) 2000	(7) 2004	(8) 2007	(9) 2010	(10) 2013	(11) All Years
Female	0.0217**	0.0233***	0.000743	-0.00417	0.00655	-0.0176*	-0.0236**	-0.00105	-0.0283***	-0.0295***	-0.00520*
	(3.48)	(4.35)	(0.12)	(-0.50)	(0.53)	(-2.20)	(-2.99)	(-0.12)	(-4.41)	(-4.80)	(-2.01)
25- to 29-Year Olds	-0.0361*	-0.0189	-0.0165	-0.0197	-0.0304	-0.0131	-0.0561**	-0.00157	-0.0338*	-0.0427**	-0.0269***
	(-2.59)	(-1.58)	(-1.23)	(-1.06)	(-1.10)	(-0.73)	(-3.17)	(-0.08)	(-2.35)	(-3.11)	(-4.64)
30- to 34-Year Olds	-0.0221	-0.0158	0.00400	-0.0202	-0.00299	0.00211	-0.0412*	0.00282	-0.0318*	-0.0371**	-0.0162**
	(-1.58)	(-1.32)	(0.30)	(-1.08)	(-0.11)	(0.12)	(-2.33)	(0.14)	(-2.21)	(-2.70)	(-2.80)
35- to 39-Year Olds	-0.000397	-0.00611	0.0137	0.0136	0.0257	0.0132	-0.0196	0.0135	0.00462	-0.0169	0.00414
	(-0.03)	(-0.51)	(1.02)	(0.73)	(0.93)	(0.73)	(-1.11)	(0.68)	(0.32)	(-1.23)	(0.72)
40- to 44-Year Olds	-0.00689	-0.000350	0.0167	0.0148	0.0169	0.0209	0.00158	0.0263	0.00859	0.00241	0.0101
	(-0.49)	(-0.03)	(1.24)	(0.80)	(0.61)	(1.16)	(0.09)	(1.31)	(0.60)	(0.18)	(1.74)
45- to 49-Year Olds	0.00141	-0.00640	0.0177	0.0211	0.0289	0.0480*	0.00415	0.0372	0.0204	-0.000310	0.0172**
	(0.10)	(-0.53)	(1.32)	(1.13)	(1.05)	(2.67)	(0.24)	(1.86)	(1.42)	(-0.02)	(2.97)
50- to 54-Year Olds	0.00311	-0.00262	0.0329*	0.0432*	0.0250	0.0315	0.00389	0.0346	0.0306*	0.00758	0.0210***
	(0.22)	(-0.22)	(2.45)	(2.32)	(0.91)	(1.76)	(0.22)	(1.73)	(2.13)	(0.55)	(3.62)
55- to 59-Year Olds	0.00668	0.0102	0.0334*	0.00823	0.0489	0.0388*	0.0142	0.0402*	0.00843	0.0229	0.0232***
	(0.48)	(0.85)	(2.49)	(0.44)	(1.78)	(2.16)	(0.81)	(2.01)	(0.59)	(1.67)	(4.01)
60- to 64-Year Olds	0.0122	0.0197	0.0352*	0.0229	0.0338	0.0107	0.0158	0.0336	0.0215	0.0201	0.0226***
	(0.87)	(1.65)	(2.62)	(1.23)	(1.23)	(0.60)	(0.90)	(1.68)	(1.50)	(1.46)	(3.90)
65- to 69-Year Olds	-0.00220	0.0290*	0.0231	0.0337	0.0478	0.000527	-0.0120	0.0717***	0.0319*	0.00992	0.0233***
	(-0.16)	(2.42)	(1.72)	(1.80)	(1.74)	(0.03)	(-0.68)	(3.58)	(2.21)	(0.72)	(4.03)
Black	0.00490	0.00641	0.0197*	0.0207*	0.0564***	0.0359***	0.0283**	0.00365	0.0309***	0.00269	0.0209***
	(0.64)	(0.98)	(2.67)	(2.02)	(3.74)	(3.65)	(2.92)	(0.33)	(3.92)	(0.36)	(6.60)
Hispanic	0.0140	-0.000130	0.0167*	0.0310**	0.0580***	0.0506***	0.0355***	0.0197	0.0378***	0.0251**	0.0288***
	(1.83)	(-0.02)	(2.27)	(3.04)	(3.84)	(5.15)	(3.67)	(1.80)	(4.79)	(3.34)	(9.09)
Constant	0.294***	0.319***	0.305***	0.330***	0.298***	0.319***	0.356***	0.327***	0.340***	0.375***	0.285***
	(26.08)	(33.04)	(28.21)	(21.96)	(13.39)	(22.05)	(25.03)	(20.26)	(29.32)	(33.83)	(46.86)
Year Fixed Effects	No	No	No	No	60	60	No	No	No	No	Yea
Observations	60	60	60	60	60	60	60	60	60	60	600

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2—: Regression results for workers who work longer than 35 hours per week

	(1) 1979	(2) 1986	(3) 1991	(4) 1994	(5) 1997	(6) 2000	(7) 2004	(8) 2007	(9) 2010	(10) 2013	(11) All Years
Female	0.00595	0.00550	-0.00763	-0.0186	-0.0134	-0.0303***	-0.0350***	-0.0102	-0.0391***	-0.0430***	-0.0186***
	(0.97)	(0.76)	(-1.34)	(-1.95)	(-1.50)	(-3.72)	(-4.42)	(-1.07)	(-5.84)	(-5.95)	(-7.18)
25- to 29-Year Olds	-0.0317*	-0.0133	-0.000292	-0.0166	-0.0209	-0.00167	-0.0475**	0.00957	-0.0246	-0.0268	-0.0174**
	(-2.32)	(-0.82)	(-0.02)	(-0.78)	(-1.04)	(-0.09)	(-2.69)	(0.45)	(-1.64)	(-1.66)	(-3.00)
30- to 34-Year Olds	-0.0201	-0.00310	0.0163	-0.0161	0.00659	0.0149	-0.0331	0.0178	-0.0187	-0.0196	-0.00551
	(-1.48)	(-0.19)	(1.28)	(-0.76)	(0.33)	(0.82)	(-1.87)	(0.83)	(-1.25)	(-1.21)	(-0.95)
35- to 39-Year Olds	0.00377	0.00473	0.0307*	0.0165	0.0351	0.0246	-0.00837	0.0219	0.0176	0.00190	0.0149*
	(0.28)	(0.29)	(2.41)	(0.77)	(1.75)	(1.36)	(-0.47)	(1.02)	(1.18)	(0.12)	(2.57)
40- to 44-Year Olds	-0.00725	0.00917	0.0344**	0.0188	0.0246	0.0288	0.0104	0.0416	0.0229	0.0226	0.0206***
	(-0.53)	(0.57)	(2.70)	(0.88)	(1.23)	(1.59)	(0.59)	(1.94)	(1.53)	(1.40)	(3.56)
45- to 49-Year Olds	0.00361	0.00840	0.0344**	0.0227	0.0420*	0.0607**	0.0133	0.0476*	0.0345*	0.0210	0.0288***
	(0.26)	(0.52)	(2.70)	(1.06)	(2.10)	(3.34)	(0.75)	(2.22)	(2.31)	(1.30)	(4.98)
50- to 54-Year Olds	0.00611	0.00672	0.0472***	0.0473*	0.0323	0.0438*	0.0147	0.0514*	0.0449**	0.0276	0.0322***
	(0.45)	(0.42)	(3.71)	(2.21)	(1.61)	(2.41)	(0.83)	(2.40)	(3.00)	(1.71)	(5.56)
55- to 59-Year Olds	0.00624	0.0205	0.0493***	0.0113	0.0633**	0.0475*	0.0212	0.0502*	0.0201	0.0406*	0.0330***
	(0.46)	(1.27)	(3.87)	(0.53)	(3.16)	(2.61)	(1.20)	(2.34)	(1.35)	(2.51)	(5.70)
60- to 64-Year Olds	0.0214	0.0284	0.0494***	0.0220	0.0403	0.0180	0.0251	0.0468*	0.0337*	0.0416*	0.0327***
	(1.57)	(1.76)	(3.88)	(1.03)	(2.01)	(0.99)	(1.42)	(2.19)	(2.25)	(2.58)	(5.64)
65- to 69-Year Olds	0.0251	0.0255	0.0591***	0.0458*	0.0237	-0.00811	-0.0000967	0.0856***	0.0492**	0.0382*	0.0344***
	(1.84)	(1.58)	(4.64)	(2.14)	(1.18)	(-0.45)	(-0.01)	(3.99)	(3.29)	(2.37)	(5.94)
Black	0.0117	0.00305	0.0182*	0.0235	0.0382**	0.0386***	0.0289**	-0.0000780	0.0290***	0.00305	0.0194***
	(1.56)	(0.34)	(2.61)	(2.01)	(3.48)	(3.87)	(2.99)	(-0.01)	(3.53)	(0.34)	(6.12)
Hispanic	0.0102	0.000201	0.0148*	0.0319**	0.0515***	0.0490***	0.0342***	0.0155	0.0340***	0.0225*	0.0264***
	(1.37)	(0.02)	(2.13)	(2.73)	(4.70)	(4.92)	(3.53)	(1.32)	(4.15)	(2.55)	(8.32)
Constant	0.283***	0.303***	0.276***	0.320***	0.295***	0.304***	0.342***	0.309***	0.320***	0.350***	0.271***
	(25.70)	(23.26)	(26.83)	(18.59)	(18.25)	(20.76)	(24.02)	(17.90)	(26.55)	(26.90)	(44.57)
Year Fixed Effects	No	No	No	No	60	60	No	No	No	No	Yea
Observations	60	60	60	60	60	60	60	60	60	60	600

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

inequality is the highest for manual routine jobs. Every 10 percent increase in the share of workers in abstract jobs raises within-cohort inequality by 2 or 1 Gini points according to models 5 and 6, respectively. The share in cognitive routine jobs does not affect inequality significantly, which is in accordance with our hypothesis stated in the previous section.

V. Concluding Remarks

While inequality has risen among cohorts of men, I show, quite paradoxically, that inequality among women has not risen as much over the past three decades. These trends in combination with the higher inequality among women in late 1970s has resulted in inequality levels almost similar for cohorts of both men and women. In this paper we investigate the factors that can explain these trends. We hypothesize that factors such as marriage rate, trends in inequality in terms of the number of children, the decline in the real value of minimum wage, deunionization, and automation in the workplace and its imbalanced impact on occupational categories are suspects. All these factors, have affected wage inequality within cohorts of men and women differently. For instance, the percentage of women who earn the federal minimum wage or less was about three times higher for women than for men in 1979 (20.2 versus 7.7 percent). However, by 2013 the share for women plummeted to 5.4 percent, a number closer to that of men at 3.3 percent. Therefore, we argue that the decrease in the real value of the minimum wage in combination with these trends has resulted in a decline in inequality among women and a rise among men. A similar pattern is observed in terms of unionization. Lastly, relying on Autor (2014) detailed analysis of computerization and the labor force, I analyze the different effects it might have for gender groups. Autor categorizes jobs into abstract, routine, and manual and argues that computers have worked as substitutes for routine jobs but have complemented abstract jobs. I find that the dynamic of supply and demand for each job category has favored women by reducing inequality among them.

To investigate the inequality differences between men and women, we perform an empirical analysis by calculating the within-cohort Gini coefficients and dividing the population into 60 cohorts based on gender, age, and race. Regression analysis gives a better picture of the gap between men and women in terms of inequality. By controlling for different factors, we find that the gap indeed is smaller than in appears and has dwindled over time. Although, a more thorough analysis is needed to study the trends in within-cohort inequality (for instance, looking at educational policy and how it has impacted different subgroups of the population and retirement decisions to name a few), the analysis in this paper paves the way for a more granular study of inequality in which we focus on how different economic and social trends have differently impacted different demographic groups, more specifically men and women.

Table 3—: Regression results for additional controls

	(1) 20 Hours	(2) 35 Hours	(3) 20 Hours	(4) 35 Hours	(5) 20 Hours	(6) 35 Hours
Female	-0.00520*	-0.0186***	0.00273	-0.0121***	-0.0332**	-0.0356**
	(-2.01)	(-7.18)	(0.84)	(-3.81)	(-2.82)	(-3.07)
25- to 29-Year Olds	-0.0269***	-0.0174**	-0.0618***	-0.0530***	-0.0544***	-0.0509***
	(-4.64)	(-3.00)	(-5.58)	(-4.92)	(-4.72)	(-4.48)
30- to 34-Year Olds	-0.0162**	-0.00551	-0.0537***	-0.0449***	-0.0457**	-0.0427**
	(-2.80)	(-0.95)	(-4.00)	(-3.44)	(-3.23)	(-3.06)
35- to 39-Year Olds	0.00414	0.0149*	-0.0359*	-0.0260	-0.0260	-0.0231
	(0.72)	(2.57)	(-2.55)	(-1.90)	(-1.73)	(-1.56)
40- to 44-Year Olds	0.0101	0.0206***	-0.0326*	-0.0241	-0.0227	-0.0218
	(1.74)	(3.56)	(-2.37)	(-1.80)	(-1.52)	(-1.48)
45- to 49-Year Olds	0.0172**	0.0288***	-0.0252	-0.0138	-0.0130	-0.0103
	(2.97)	(4.98)	(-1.96)	(-1.11)	(-0.92)	(-0.73)
50- to 54-Year Olds	0.0210***	0.0322***	-0.0222	-0.0109	-0.0103	-0.00891
	(3.62)	(5.56)	(-1.89)	(-0.95)	(-0.77)	(-0.68)
55- to 59-Year Olds	0.0232***	0.0330***	-0.0158	-0.00333	-0.00479	-0.00249
	(4.01)	(5.70)	(-1.47)	(-0.32)	(-0.38)	(-0.20)
60- to 64-Year Olds	0.0226***	0.0327***	-0.0141	-0.00130	-0.00509	-0.00187
	(3.90)	(5.64)	(-1.38)	(-0.13)	(-0.42)	(-0.16)
65- to 69-Year Olds	0.0233***	0.0344***	-0.0150	-0.00195	-0.00706	-0.00191
	(4.03)	(5.94)	(-1.48)	(-0.20)	(-0.60)	(-0.17)
Black	0.0209***	0.0194***	0.00287	0.0232	0.00379	0.0169
	(6.60)	(6.12)	(0.15)	(1.23)	(0.19)	(0.88)
Hispanic	0.0288***	0.0264***	-0.00141	-0.00222	-0.000578	-0.00573
	(9.09)	(8.32)	(-0.18)	(-0.29)	(-0.07)	(-0.72)
Share Married			0.000131	0.000113	0.000165	0.000112
			(0.85)	(0.76)	(1.08)	(0.75)
Var. of of Children			-0.0146	-0.00322	-0.0110	-0.00624
			(-0.85)	(-0.19)	(-0.64)	(-0.37)
Share Highly Educated			0.00247***	0.00230***	0.000856	0.000879
			(4.92)	(4.70)	(1.19)	(1.24)
Share in Abstract					0.00206***	0.00165**
					(3.84)	(3.13)
Share in Manual					0.00178**	0.000410
					(3.16)	(0.74)
Share in Cog Routine					0.000379	0.000436
					(0.72)	(0.84)
Constant	0.285***	0.271***	0.263***	0.247***	0.181***	0.210***
	(46.86)	(44.57)	(20.40)	(19.70)	(7.18)	(8.45)
Observations	600	600	420	420	420	420

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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