Anatomy of Income Inequality in the United States: 1979-2013

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Abstract

In this paper, I analyze the evolution of income inequality in the United States between 1979-2013. I offer a more granular analysis by looking at inequality that exists within and between multiple demographic groups instead of looking at single statistics. To understand concretely the forces that are at work in shaping the distribution of income, one needs to factor in the changes that have happened in different divisions and groups in American society. I pursue this by decomposing the Gini coefficient into different sub-groups using Pyatt decomposition method. Some stylized facts are 1) a stable and relatively high within-cohort share of overall inequality in the U.S. compared to most advance countries, 2) greater rise in inequality within the very young and the very old between 1979-2013, 3) a rise in inequality among men but a decline among women. I further investigate these evidences and provide hypothesis that may explain them.

JEL classification: D31, D63, J11.

Keywords: Inequality Decomposition; Within Group Gini Coefficient; Income Distribution.

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1. Introduction

All indicators of inequality remind us that income disparities in America have grown since the late 1970s. The Gini coefficient has increased by 8-18 percent in the past three decades according to data retrieved from the All the Ginis database hosted by the World Bank.$^1$ Data from the Luxembourg Income Study give a sense of how incomes at the top of the income distribution have grown in comparison to those at the bottom. Between 1979 and 2013, the ratio of household incomes in the 90th percentile to those in the 10th percentile rose from 4.55 to 5.81. Similarly, the ratio comparing the 80th percentile to 20th percentile has risen from 2.66 to 3.15. During this same period, median equivalent household income increased by 259 percent, while the mean household income increased by almost 300 percent.

But what do these numbers tell us? These numbers, as widely as they are being used, do not tell us much about the underlying causes and the consequences of the increase in income inequality. To understand the forces at work in shaping the distribution of income, one needs to look below the surface at what has happened over time within different subgroups in American society. This study attempts to do this by looking at inequality measures decomposed between multiple subgroups of the American population. Instead of looking at a single number, the main focus of this study is to dissect the evolution of personal income inequality since 1979 by breaking down inequality measures into different groups based on age, gender, race, and education.

The need for this dissection is multifold. First, demographic changes are partially responsible for the change in inequality over the past three decades. As we will see in this paper, demographic transitions can partially explain existing income inequality within countries, as well as, differences in inequality measures between countries. Changes in redistribution policies that disproportionally target individuals of different ages can largely affect the distribution of income. Second, due to the existence of age-income profiles —the evolution of income with respect to a person’s experience and age— even under perfect equality of opportunity and a social policy for reducing inequality, the Gini coefficient will never be close zero. I calculate that even if every worker’s income follows the cross-sectional trajectory of the life-cycle income in 2013, the Gini coefficient will still be about $0.13^2$. This is due to the apparent differences in incomes between young and old workers that are inherent in most societies. Although most of us do not believe in a policy scheme that equalizes the incomes of the young and the mature, such differences do show up in inequality measures. It could be argued that since individuals typically expect to receive higher incomes as they age,

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$^1$See http://bit.ly/1pE3YeX. The Ginis vary based on which income measure is used.

$^2$This calculation is done by using cross-sectional income and age data in 2013. Calculations are not provided here but are available upon request.
inequality due to differences in age can be justified. Third, inequality within various cohorts can inform us about the effect different policies have had in reducing (or increasing) inequality within those cohorts. Experts in the field of inequality usually relate rising inequality to financialization, weakening of anti-poverty measures, reductions in redistributive policies, globalization and the movement of capital, the growing importance of technical skills, soaring compensations for the top 1 percent (and in general changes in pay norms), dynamic changes in the labor market, immigration, changes in household structure, and reduction in economic mobility (which itself is caused by multiple factors). However, looking at a single number impairs our understanding of the combination of the factors that have been largely in effect.

These three grounds are the motive of analysis in this paper. I will start by decomposing the Gini coefficient into two components: a within-age-cohort component and a between-cohorts component. The within-cohort component is a weighted average of inequality within each of the age cohorts, while the between-cohort component measures inequality that exists between those age cohorts. It will be informative to see how these components have evolved over time in the United States and how they compare to other countries. As it turns out, there are large variations among countries in terms of the share of within and between cohort inequality.

After decomposing the Gini Coefficient, we see that the upward trend in income inequality in the United States can be separated into three effects: changes in inequality within age groups, changes in inequality between age groups, and changes in the size of each age group. Inequality can be affected by each of these factors and depending on which factor is stronger, we might have a different interpretation of the causes and the consequences of changes in the level of inequality. While inequality in educational opportunities, parenting, and nutrition are the main drivers of inequality within cohorts, recessions and unemployment fluctuations affect the inequality between cohorts. There are factors such as unionization, minimum wage policy, skill-biased technological change that affect both within and between cohort inequality (Gottschalk and Smeeding 1997). Lastly, demographic changes such as changes in fertility, mortality, and immigration rates can change the population share of each age group.

Using the same decomposition technique, I next look at inequality within and between various other subgroups of the population such as men versus women, educated versus less educated, blacks versus whites, etc.. Again, I control for the effect of variations in age among the different groups. Few attempts have been made at decomposing inequality measures for smaller subgroups. Deaton and Paxson (1994) find a dramatic increase in consumption inequality by age using data from the 1980s in the United States, the United Kingdom, and
Taiwan. Their results are consistent with the Permanent Income Hypothesis (PIH) originally proposed by Eden (1980) and further studied by Deaton and Paxson (1993). PIH states that inequality within a specific age cohort increases as cohort ages. Heathcote, Storesletten, and Violante (2005) theorize the impacts cohorts have on the age profiles of inequality. They find that attributing the rising inequality in the United States solely to cohort effects is also misleading and one has to consider time effects as well. Juhn, Murphy, and Pierce (1993) study more narrowly-defined groups of male workers in the United States and attribute most of the increase in wage inequality for males to increased returns to skills. Osberg (2003) looks at inequality among different age groups of the population in the United States and some selected countries. He argues that the decline in average family size in recent decades, which is the result of unequal changes at different points in the age distribution, is likely to be responsible for changes in the distribution of income.

This study is the first attempt (to my knowledge) that studies the inequality between and within different age, gender, racial, and educational groups of the American society by decomposing the Gini coefficient. A great deal of interesting observations emerge by decomposing the Gini coefficient, some consistent with previous studies, and some that are yet to be discussed in inequality literature. The overall finding of this paper is that there is a lot more behind a single number.

The structure of the paper is as follows: In 2 I discuss the role of age-income profiles in the measurement of inequality and the limitations of traditional inequality measures. I also review different methods in decomposing the Gini coefficient into within- and between-cohort components. Next in Section 2.2 I discuss the data used in this study. I use Luxembourg Income Study data, an extensive and harmonized dataset based on personal and household income surveys across a large set of countries. In the sections that follow, I then discuss multiple observations that the decomposition of inequality reveals and I try to offer some hypotheses that may explain those findings. In Section 3.1 I overview the within and between age cohort inequality in the United States and how they compare to a sample of countries. In Section 3.2 I expose and analyze the inequality among different age groups in the United States. This includes some interesting trends in inequality among the very young and the very old cohorts. Section 3.3 examines opposing trends in inequality among men and women. Finally, in Section 4 I further scrutinize other striking evidence that emerges from decomposing inequality even further into educational and racial groups, and later I conclude the results.
2. Methodology and Data

In order to understand why the decomposition of inequality measures is both necessary and useful, consider how inequality is typically measured today. The Gini coefficient, the most widely used measure of inequality, is based on the cumulative distribution of income and is calculated as the area between the cumulative distribution curve (called the Lorenz curve) and the perfect equality line (the 45-degree line). The Gini coefficient is simple, has an intuitive interpretation, and is nicely scaled between zero and one with a Gini of zero representing a perfectly equal society and a Gini of one representing a perfectly unequal one. The simplicity of the coefficient, however, glosses over the fact that we may not, in reality, associate perfect equality with a completely equal distribution of incomes as measured at any particular moment in time. The basic intuition behind the 45-degree line of equality (henceforth the line of equality) is that, ideally, everyones income should be equal to, or at the very least, compared against the average income in society. This would be misleading and could be considered a gross oversimplification if we accept that there are reasonable differences of income in society that are due, in particular, to life-cycle differences in income. If this is the case, even in societies we consider to be very equal, we would not expect to find that all individual incomes are closely aligned with the average societal income.

If we want to adjust our inequality measures to account for reasonable life-cycle differences in income, we must start by looking at the overall age-income profile and the overall age distribution of the societies or countries under consideration. An age-income profile illustrates the relationship between a persons income and their age. Consequently, the overall age-income profile of a society is the aggregate of the individual age-income profiles of all adults. The overall age distribution will also have important consequences for measured inequality. For instance, as societies transition from old to young, as a result of changes in factors such as fertility rates, immigration, retirement etc., they may witness higher inequality measures. Both of these factors are not accounted for in our standard Gini calculations, which hinders our ability to draw meaningful inequality comparisons across time, as well as, across countries that exhibit fundamental differences in their demographic structures. By decomposing the Gini coefficient into within-age-cohort and between-age-cohort components, we may be able to overcome these issues.

In an ideal case, we would want to generalize the evolution of income of a sample of individuals over their lifetime to obtain the societal profile. Therefore, longitudinal data are needed in order to estimate the profile for a society and any attempt to derive the age-income profile in a country based on cross-sectional data suffers from biases due to cross-cohort discrepancies due to differences in years of schooling, post-graduation experiences, economic conditions, technological changes, etc. Obtaining age-income profiles based on longitudinal data is, however, an impossible task simply due to the fact that they are non-existent, at least for cross-country comparisons.
2.1. Decomposition of Inequality Measures

Unfortunately, the Gini coefficient cannot be easily decomposed. One of the earliest attempts to use the Gini coefficient to measure inter-cohort dispersions in income has been the work by Paglin (1975). Paglin’s work proposed a method to reconstruct the line of perfect equality. This new line, which he called the P-reference line (henceforth the P-line), was defined in a way which conforms to what casual users of the [Lorenz] curve might infer is the meaning of equality: equal lifetime incomes but not with the added constraint of a flat age-income profile.

The P-line is a breakdown of the line of equality for each age cohort. The construction of the new P-line is done by taking the average income in each age group and ranking these groups by their mean incomes. The next step is to calculate the cumulative share of the population and share of the total incomes according to the ranking in the previous step. This new curve is used as the line of equality against the standard Lorenz curve to calculate a modified Gini coefficient, which has been called the P-Gini. The line of equality, the P-line, and the Lorenz curve are depicted in Figure 1. The area $\alpha$ represents the portion of the Gini coefficient that is due to between-group inequalities and the area $\beta$ represents the area that is due to within-group inequalities.

The improvement from the line of equality to the P-line can be best summarized in an example of two societies represented in Figure 2. Imagine two societies, one with an arched age-income profile A and one with a flat age-income profile B, in which individuals’ income does not change over the course of their lifetime. Assuming the same distribution of income at any point in time will result in exactly the same Gini coefficients for both societies. However, by replacing the line of equality by the P-line yields a lower Gini for society B than society A.

Table 1 uses the notations on the graph to show the different versions of the Gini coefficient. It is clear that the Lorenzian Gini is the sum of the P-Gini or the within-cohort Gini and the Age-Gini or the between-cohort Gini coefficients. Applying this methodology on family income data from CPR P-60 series, Paglin showed that the traditional Gini coefficient was 50 percent higher than the P-Gini in 1972.

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<tr>
<th>Table 1: Pagin’s Gini versus the Lorenzian Gini</th>
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<tr>
<td><strong>Gini Coefficients</strong></td>
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<tr>
<td>------------------------</td>
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<tr>
<td>Lorenzian Gini</td>
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<td>Age-Gini (Between Groups)</td>
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</table>
Fig. 1. Lorenz Curve

Fig. 2. Typical age-income profile
Among the wide criticism that Paglin received on his alternative calculations of the Gini coefficient there are three that deserve the most attention. The first of these criticisms was the sensitivity of the P-Gini coefficient to the definition of the age cohorts. As Formby, Seaks, and Smith (1989) show, inequality measures based on the P-Gini methodology change drastically by varying the width of the age groups making the choice of the age cohort widths arbitrary. For instance, using March Current Population Survey (CPS) data for families in the United States, the P-Gini coefficient in year 1986 can range from 0.259 to 0.312 depending on whether we choose a 1-year or 20-year age cohort width. However, this criticism can be disregarded as one notices smaller variations between a more realistic range for age cohort width. For instance, the choice of 1-, 2-, or 5-year intervals.

The second important criticism of the P-Gini calculation is that the method lets data dictate the actual differences in lifetime incomes to us when calculating the P-line. A more precise P-line should be calculated using longitudinal data to derive the age-income profile. However, with our data limitations, we should realize that those alternatives are impractical and that the P-Gini coefficient is still a major improvement from the Lorenzian Gini. Even with applying the coefficient on experience in the Mincerian wage equation, we are applying a cross sectional data to all years, and potentially, all countries. The age-income profile for individuals of different generations constantly changes over time. For instance, Sapelli (2011) observes that in the case of Chile there has been some flattening of the profile and he holds responsible education and returns to experience for the dynamic. Another related issue with the P-Gini is that the calculation is made under the assumption that individuals in each cohort keep the same within-group order along the age-income profile. In other words, cohorts are stationary. Again, this issue, like the one mentioned before, is related to data constraint.

Lastly, as Nelson (1977) notes, the decomposition of the Gini coefficient into within- and between-age cohort components still suffers from the problem of ignoring overlapping income differences. The overlap terms rise due to the fact that some members of an older cohort are poorer than some members of a younger cohort. In other words, groups overlap when the relative positions of individuals in each group distribution is not the same as their position in the total income distribution. It is apparent that even the youngest and the oldest groups overlap. Nelson shows that if age-income distributions overlap, the P-Gini will be affected by cohorts’ mean income and populations weights. Altogether, Paglin’s decomposition of the Gini coefficient into within and between groups was never persuasive enough to make its way into studies of inequality. Yitzhaki and Lerman (1991) and Yitzhaki (1994) argue that the overlap component is an essential part of the within-group inequality.

For a more detailed discussion of the latter issue refer to Johnson (1977).
Nevertheless, Paglin drew attention to life cycle effects on inequality and the limitations of the Gini coefficient. Despite the criticism he received on the P-Gini, his method was discussed, used, and was updated over time. For instance, one of the latest additions to the calculation of the P-Gini was suggested by Formby and Seaks (1980) which was based on the fact that the P-Gini only approached the value of 1 if $\alpha = 0$. Looking back at Figure 1, they claim that since the area $\alpha$ reflects the effects of the age-income profile, it is not relevant in measuring the P-Gini. They suggest that the P-Gini be calculated as $\beta/[(\beta + \gamma)]$ instead of $\beta/[(\alpha + \beta + \gamma)]$. The argument for their modification is that if the area $\alpha$ is omitted from the numerator we should not include it in the denominator either. This modified P-Gini then lies between the Lorenzian Gini and P-Gini coefficients and measures the “ratio of the deviation of the actual income distribution from the P-curve relative to the income which could be equally distributed given the age-income profile” (Formby and Seaks, 1980). The P-Gini only measures the ratio of the deviation away from the P-curve relative to a flat age-income profile. However, one should note that this version of the P-Gini and the age-Gini no longer additively constitute the Lorenzian Gini.

Considering the limitations of the Gini coefficient and the issues with the P-Gini coefficient, let us now turn to another representation of the Gini coefficient offered by Kendall and Stuart (1977). This approach suggests that the inequality among a set of numbers $x_1, x_2, x_3, \ldots, x_n$ can be expressed, in terms of the Gini coefficient, as

$$Gini = \frac{\frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} |x_j - x_i|}{\frac{1}{n} \sum_{j=1}^{n} x_i}$$

In other words, Gini can be written as the ratio of the mean absolute difference between each income pair in the society $(x_i, x_j)$ over twice the average level of all incomes $\bar{x}$. Note that the Gini formula above can also be written as

$$Gini = \frac{2(\frac{1}{n^2}) \sum_{(i=1, j=1)}^{n^2} max(0, x_j - x_i)}{\frac{1}{n} \sum_{j=1}^{n} x_i}$$

This approach is similar to a game suggested by Pyatt (1976) in which he suggested that the Gini coefficient can be written in terms of the expected value (in the statistical sense) of a game where individuals compare themselves to other randomly drawn individuals from the population. Imagine a game conducted for each individual in which individual $i$ randomly picks person $j$ from the population. If person $j$’s income is greater than his own income, he will switch to that income, otherwise he will keep his own income. Therefore, no individual can lose from participating in this game. As a result, the expected gain for individual $i$ is
\[ \frac{1}{n} \sum_{j=1}^{n} \max(0, x_j - x_i) \text{ for all } i \]

If now, we average the expected gains over all individuals, we obtain the following expression

\[
\text{Average Expected Gain} = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \max(0, x_j - x_i)
\]

Note that this is the numerator of the Gini formulation introduced above. This formula is similar to the calculation of the aggregate deprivation, where deprivation is defined as what the individual does not have but sees as feasible when comparing herself to other persons in the society. Now the Gini coefficient can be interpreted as the average expected gain (in the income comparison game), expressed in (or normalized by) the mean income. A higher expected gain means that the individual would be better off in someone else’s shoes, therefore, it corresponds to a higher Gini coefficient. You can expect the poorest person in the population to have the highest expected gain and equal to the mean income, and the richest person to have an expected gain of zero.

Suppose now the population has been divided into \( m \) mutually exclusive and exhaustive groups, or in our case, age cohorts. We can now look at the average expected gain for individual in group \( i \) drawing incomes at random from group \( j \)

\[
\text{Average Expected Gain} = \sum_{i=1}^{n} \sum_{j=1}^{n} E(gain|i \rightarrow j) \Pr(i \rightarrow j)
\]

\( E(gain|i \rightarrow j) \) is the average expected gain, taken over all individuals in group \( i \), when they draw a member of group \( j \) to compare within the game setup. It is easy to see that \( \Pr(i \rightarrow j) = p_ip_j \) where \( p_i \) and \( p_j \) are population shares of groups \( i \) and \( j \), respectively. Gini coefficient in matrix form can be written as

\[
Gini = \left( \frac{1}{n} \right) \sum_{i=1}^{n} x_i = \frac{s'Ep}{s'p} = (s'p)^{-1}p'Ep
\]

Where \( s \) and \( p \) are vectors of income shares and population shares of each group, respectively. \( E \) is an \( m \times m \) matrix with diagonal elements representing within-group expected gains and off-diagonal elements representing between-group expected gains. A reformulation of the Gini coefficient can be obtained by defining \( \pi = (s'p)^{-1}s \) where \( \pi \) is a column vector with the \( i \)-th row being the proportion of group \( i \)'s income from the aggregate income. Therefore,

\footnote{For a more detailed discussion on deprivation see Runciman (1966).}

\footnote{Amartya Sen has a similar interpretation of the Gini coefficient. He states that “in any pair-wise comparison the man with the lower income can be thought to be suffering from some depression on finding his income to be lower. Let this depression be proportional to the difference in income. The sum total of all such depressions in all possible pair-wise comparisons takes us to the Gini coefficient” Sen (1973).}
\[ Gini = \pi' s^{-1} Ep = \pi' E^* p \]

Where \( E^* = s^{-1} E \). Matrix \( E^* \) is simply a normalization of the matrix \( E \) by the mean income of each population group. Now, the decomposition of the Gini coefficient is done in two steps. In the first step, we calculate a matrix \( E_2^* \), which is the normalized expected gains under the assumption that the members of each cohort have incomes equal to the mean income of their cohort. This should remind us of the corresponding P-equality line in Paglin (1975). As one would expect, the diagonal elements of \( E_2^* \) are all zero (since it is assumed that no inequality exists within each group), and so are those off-diagonal elements \((i, j)\) for which mean income of group \( i \) is bigger than mean income of group \( j \). The second step is to calculate matrix \( E_1^* \) as follows

\[ E_1^* = E^* - E_2^* \]

The diagonal elements of \( E_1^* \) are the Gini coefficients of within-group inequality as in matrix \( E^* \). We would expect the off-diagonal elements of \( E_1^* \) to be all zero in case the groups do not overlap. Those off-diagonal elements represent the inequality associated with those who are lagged behind. The overlapping terms can be thought of as the “across groups” contribution to the within-Gini coefficient.\(^7\)

In calculating the within-group inequality, it is a mistake to only focus on the diagonal elements elements of matrices \( E^* \) and \( E_1^* \) and toss everything else.\(^8\) This approach in treating the overlap terms is “equivalent to putting blinders around members of each cohort as that they can only compare themselves with others in the same cohort” (Paglin 1977). Based on this approach the within-cohort Gini can be calculated as follows

\[ \text{Within-Gini} = \pi' E_1^* p \]

This version of the within-Gini coefficient is superior to the P-Gini coefficient since it takes into account the lagged individuals, a non-negligible part of the overall inequality. In the following section, we will use the Pyatt method in decomposing the Gini coefficient into within and between components.

2.2. Data

I use Luxembourg Income Study (LIS) data to find within- and between-cohort inequalities in the United States, and I compare these to the same figures in other countries. The LIS

\(^7\) A detailed explanation of the matrices can be found in Pyatt (1976).

\(^8\) This is what Nelson (1977) suggests.
Database is one of the largest available income databases of micro-level panel data collected from multiple countries over a period of decades and are harmonized for cross-country comparisons. The data set contains income (among many other variables) at both the individual and household level.

Discussions around the choice of consumption unit should be an integral part of any inequality study. I will justify the use of personal-level data as opposed to household-level data due to the fact that the very purpose of this study is to look at age, gender-specific, educational, and racial groups, which are hard to define for a family or household.

Furthermore, as Deaton and Paxson (1993) note, "unlike individuals, households form and dissolve over time." This may lead to shaky results since when we track households through the age of the head of the household, it is hard to assume that the sampling population in successive years remains the same. This is a more binding problem with older households that are more prone to changes such as death, the departure of children from the household, etc.. Another important consideration when using the household as a consumption unit is the choice of the equivalence scale for calculating income per member of the family. For instance, one can simply divide the total household income by the number of household members. However, scholars often suggest to take into account the economy of scale in families. The most used scale by researchers is the square root of the number of household members. Still, while the choice of the scale can affect the inequality measures, it is arbitrarily chosen and it is hard to defend that it should be the same across a group of countries. Working with individual level data does not require such arbitrariness in calculation of individual-equivalent incomes. Gottschalk and Smeeding (1997) argue that "economic and demographic decisions within households are endogenous and so complex that empirical research is far from being able to sort out the linkages from individual earnings to household disposable income."

Our decision has its vices too. By using individual level data, I ignore the family structure in which each individual is situated (number of dependents, etc.). It is obvious that such considerations are important in order to understand how much a person needs in terms of annual income.

Since one of the problems with cross-country comparisons is the heterogeneity in standards of data collection and constituting variables, the LIS data is advantageous since it minimizes those discrepancies and harmonizes the surveys. I use disposable income for individuals of age 20 to 79, where disposable income is defined as the sum of monetary and non-

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9 Other researches have, nonetheless, used the age, gender, education, and race of the head of the household, which seems irrelevant as it is hard to justify a society that comprises of only "heads of households."

10 For a thorough analysis of the equivalence scale read Buhmann, Rainwater, Schmaus, and Smeeding (1988).
monetary income from labor, monetary income from capital, monetary social security transfers (including work-related insurance transfers, universal transfers, and assistance transfers), and non-monetary social assistance transfers, as well as, monetary and non-monetary private transfers, less the amount of income taxes and social contributions paid. I have excluded those who report negative or zero disposable income from our analysis.

I define cohorts along 5-year intervals. Therefore, the youngest cohort in our sample contains individuals in the age range 20-24 and the oldest cohort includes individuals aged 75-79.

3. The Evolution of Inequality Within American Cohorts

3.1. Observation One: Overall within-age-cohort inequality in the United States has been high and steady

Using the Pyatt decomposition method mentioned in the previous section, we begin our analysis of inequality in the United States by calculating "between" and "within" inequality measures that are based on age. In this section, we will briefly compare these figures to the same decomposition measures calculated for a number of other countries between 1979 and 2013. As previously mentioned, our age cohorts are defined by 5-year intervals with the youngest cohort consisting of individuals aged 20-24 and the oldest cohort consisting of individuals aged 75-79.

Figure 3 shows the share of overall income inequality that is due to within-age-cohort income differences in each of these countries. Looking at this figure, we can see that the within-cohort share of inequality in the United States is in the range of 71-74 percent of overall income inequality. This rate has been consistently higher than it has been in most other countries, especially the Scandinavian countries. In Denmark, for example, the within-age-cohort share of inequality has been between 50-60 percent. It appears that only Canada and France lead the United States in their share of within cohort inequality in 2010. The share of within-age-cohort inequality in the United Kingdom has risen from 57.5 percent in the late 1970s to almost as high as the United States (73.2 percent) in 2013.

The cross-country differences in Figure 3 leave us with two fundamental questions. First, what explains cross-country differences in the within-cohort share of overall income inequal-

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11 It goes without saying that the constructing such variable requires careful harmonization across countries.

12 The within cohort share of inequality in Canada in 2010 reaches a surprisingly high value of 91.3 percent from 70.8 percent in 2007.
Fig. 3. Within Age-Cohort Share of Inequality (Gini), Note: Due to the unavailability of disposable income, for Spain, France, The Netherlands, and Germany market income has been used.
ity? And second, why has this share remained at a high and constant level in the United States, while it has increased (and in some cases fluctuated quite dramatically) in other countries? The answers to these questions are not simple and will require further scrutiny, but similar factors may be in effect for both questions.

We will focus on how the Pyatt decomposition is conducted. Putting the overlap term aside, inequality can be dissected into population-weighted within-cohort components and between-cohort components. As a result, three factors can change the overall level of inequality: 1) the inequality between cohorts which is a reflection of the age-income profile, 2) the population share of each cohort, and 3) the inequality within each cohort.

3.1.1. Age-Income Profile

As discussed at the beginning of this paper, age-income profiles (henceforth income profiles) and the evolution of an individuals’ earnings over their lifetime require a reconsideration of our measures of income inequality. The income profiles of most societies are typically inverse U-shaped curves with a positive relationship between earnings and age up to the peak of income (usually around the age of 40-50, but varying greatly across societies), and a negative relationship between the two variables afterward. The explanations for the positive sloping part of the income profile are as follows: first, income goes up as age increases due to the augmentation of human capital and experience, which can be due to more on-the-job training. Promotions, professional networking effects, and psychological development are also responsible for the increase in income over a lifetime. Other factors such as paying off student loans, mortgages, and other forms of liabilities contribute to the increase in the incomes of workers before the tipping point. After the peak of the profile, the negative slope of the income profile can be explained by depreciation of human capital, cognitive and non-cognitive skills, and physical abilities, as well as, decline in hours of work before retirement and natural reductions in income after retirement.

Although the income profile is usually interpreted as the evolution of an individual’s earnings over time, in the context of inequality, it is often interpreted as the differences between the incomes of individuals of different ages. In other words, what we define as the income profile in this study, is mainly the income profile measured using cross-sectional data.

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13The share of the overlap term tends to be relatively constant over time for most countries and very similar across countries. For the sake of space, we do not report the overlap terms independently.

14These profiles can also be different depending on the occupations; occupations that are physical skill-intensive have a lower tipping point and tend to be different in shape (slope) than those that require more cognitive abilities of individuals. Additionally, if the income profile is based on disposable income, the shape relies heavily on government programs.

15Mincer (1974) attributed most of the decline in earnings after the peak of income to the fall of working hours rather than a fall in hourly wages.
Fig. 4. Age-Income Profile in the United States, United Kingdom, Canada, and Denmark

rather than longitudinal data. This is an important difference. The dynamic of the income profile in the original definition has been discussed by many researchers.\textsuperscript{16} It is interesting to test whether the income profiles over the period 1979-2013 have changed in the United States and how the U.S. compares to the other countries in our sample. This is shown in Figure 4, which shows the income profile for all workers aged 20-79 in the United States, United Kingdom, Canada and Denmark. The average income of each cohort is compared to the average income in the highest earning age group in that year, and the graph is smoothed. Again, note that these profiles are calculated using cross-sectional data from LIS and are not based on panel data.

What is apparent from the figure above is a very slight steepening of the income profile in the United States between 1979 and 2013 for the first half of the life cycle and a slight flattening for the second half of the life cycle. The overall change in the income profile complies with the observation that the between-cohort share of inequality in the United States has remained relatively constant. On the contrary, the within-cohort share of inequality in Canada and the United Kingdom has changed quite dramatically during the past few decades and so have the income profiles in those countries.

\textsuperscript{16}See Kambourov and Manovskii (2005).
Figure 4 also demonstrates another finding. In all the sample countries, the income profile has flattened for older workers and steepened for younger ones. For instance, the income ratio of the oldest group to the highest earning group has decreased by roughly 100 percent from 0.3 to 0.6 in the United Kingdom. This can arguably be attributed to improvements in the social security system. It is also noteworthy that in recent years, the ratio of the oldest income earners to the highest earners has been the same in all the four countries at around 0.6.

In general, when return to experience is higher in a society, the income profile is steeper (especially in the first half of the life cycle). In societies where there are better social programs for the elderly after their retirement years, the income profile is flatter in the second half of the life cycle. Higgins and Williamson (1999) suggest that changes in the share of older cohorts can directly affect the income profile in a society by affecting the experience premium. This is simply due to the supply effect; when there are more people in a specific age cohort, wages of that age group dwindle. Changes in family structures, too, may impact the income profile.

It may be interesting to look at the income profile for men and women separately. Figure 5 shows the income profile of American men and women between 1979 and 2013. There are two main takeaways from the figure. First, the income profile for women is flatter compared to men in both years. Second, the income profile for women has steepened dramatically between 1979 and 2013. The ratio of the lowest earning cohort to the highest earning cohort declined roughly from 0.75 to 0.45, a 40 percent decrease. The implication of the flatter income profile for female workers is that women contribute less to the overall between-cohort inequality than men do. In other words, the overall within-cohort inequality is larger among women than it is among men. We will discuss the differences between within-cohort inequality between men and women in more detail in future sections.

3.1.2. Demographic dynamics

Demographic differences among countries and changing demographics over time are likely responsible for part of the dynamics of income distribution in countries. Figure 6 depicts variations of the median age in countries around the world. The median age can be as low as 15-16 years (in countries such as Niger, Uganda, and Mali) and above 45 years (as is the case in Monaco, Japan, and Germany). As the share of younger individuals in low-income and lower-middle-income countries has increased over time, the opposite trend has been observed in more developed countries. In high-income countries, the share of individuals in the age group 45-49 and 50-54 combined rose from 11.1 to 14.6 percent between 1950 and 2015. In upper-middle-income countries, the share of the groups 40-44 and 45-49 increased by 2.3
Fig. 5. Age Income Profile for men and women in the United States, 1979 and 2013

and 2.8 percentage points, respectively. Since individuals in the middle-aged groups are supposedly among the medium to high earners in most countries, an increase in their share of the population can have significant effects on the income distributions in those countries.

In the United States, the median age has increased by 32 percent from 28 years to almost 37 years. The share of 45-64 year-old individuals has increased from 20.6 to 26.4 percent, and the share of younger cohorts has decreased significantly. This is shown in Figure 7.

The main effect of demographic transition, more specifically transition from a younger society to an older is on the within cohort component of inequality by increasing the population weight of the older groups. Therefore, the main question is why an increase in the share of older individuals increases the overall inequality. This can be explained by the permanent income hypothesis (PIH), originally introduced by Eden (1980) and further investigated by Deaton and Paxson (1993), which states that inequality among individuals of the same age (or same age range) increases as the cohort ages. Therefore, two factors are in play for high within-cohort inequality in the United States. First, is the fact that the baby boomer generation is in its 50s and 60s. Second, inequality within a cohort is highest when the cohort reaches those years, as explained by the PIH and as shown in this study.

Our results based on LIS confirm the PIH hypothesis in the United States as shown in Figure 8. The graph shows each cohort tracked through time. The cohort that was 20-24 years old in 1974 is 40-44 in 1994 and so on. As shown, inequality within cohorts of

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17 The theory has been tested for various countries. For instance, see Blundell (2014) and Heathcote et al. (2005).

18 The years are chosen in 10-year intervals but are not exact since it jumps from 1974 to 1986 to 1994 to 2004 and finally 2013.
Fig. 6. Median age in the world, 2014 Source: CIA Factbook and Wikipedia Commons Licensed under Public Domain

Fig. 7. Age Distribution in the United States, Source: Age and Sex Composition, U.S. Census Bureau, 2010
different ages in 1974 increases as cohorts age, however, the only difference between our results and those confirmed by other researchers is the decrease in inequality within the same cohorts as they reach their 60s\textsuperscript{19}. This could be a result of improvements in the social security programs in the United States\textsuperscript{20}. In countries where the distribution of the pensions of the retired follows the same distribution as the pre-retirement income, inequality within the group of elderly does not change that much or might even increase. Whereas in countries where incomes get boosted after retirement, inequality among the elderly might decrease. For instance, in Canada, the bottom decile is better off in retirement years than in their working years.

Multiple factors can explain why within-cohort inequality increases as the cohort ages. Among them we believe accumulation of income, the role of credit constraint in access to higher education, assortative mating, better access to credit for high-income individuals, and better mental and physical health are the most important factors. Increase in the average age in a society can also push income inequality upward if there are strong intergenerational transfers where bequests are important (Deaton and Paxson\textsuperscript{1994}). Higgins and Williamson\textsuperscript{1999} argue that slower population growth that shifts the population age distribution toward older, more experienced cohorts, may potentially reduce the experience premium, which then lowers aggregate inequality.

Another impact of an aging population on income inequality is the burden that a higher share of elderly puts on younger workers. Many researchers have pointed out the shrinking

\textsuperscript{19} Prus\textsuperscript{2000} finds similar results for Canada.
\textsuperscript{20} Explain this further
ratio of workers to retirees. This ratio, also called the “support ratio,” measures the number of individuals aged 20-64 divided by the number of individuals aged 65 and over. A higher ratio means that more workers share the burden of supporting the elderly. This ratio tends to be fairly low among countries in the developed world. However, the United States enjoys a higher ratio among them.\footnote{Reznik, Shoffner, and Weaver (2005) estimate that in 2005 with the scheduled tax rates and benefits, the social security program needed a support ratio of about 2.8 to function at a pay-as-you-go level.\footnote{So that the tax revenue roughly equals benefit payments.} It is projected that by 2040 this ratio will fall to only 2.1 putting even more burden on the young population and causing income inequality to increase.}

In this section, we looked at the overall between- and within-cohort components of inequality. More specifically, the within-cohort component is the expected average across different age groups, so it does not fully capture the dynamic of within-cohort inequality. It will be difficult, and to some extent devoid of any meaning, to try to explain forces that resulted in changes in such a single number. In the next section, we will provide a detailed analysis of the inequality within various age groups and the role they play in the evolution of inequality.

3.2. Observation Two: Unbalanced rise of inequality across age cohorts

In this section, we will look at the trends in inequality within different age groups in American society between 1979 and 2013. Understanding the evolution of inequality between these years requires an inspection of inequality within each of these age groups. As discussed briefly in the previous section, there are multiple factors in play that affect the within-cohort component of the overall inequality in a country. What has precipitated high inequality among older cohorts is different than the factors responsible for the inequality among younger cohorts. In order to disregard the effect of life-cycle differences in earnings (the effect of the income profile), we need to decompose the overall within cohort component of inequality into different age groups. We define age cohorts as individuals belonging to 5-year age intervals starting from 20 years of age. Thus our cohorts will be 20-24, 25-29, 30-34, and so on.\footnote{The results in this section and the following sections are robust to the length of the intervals.}

Figure 9 shows the inequality within each of these age cohorts in 1979 and in 2013 for employed workers in the United States. Note that the overall within-cohort component of inequality calculated in the previous section is a weighted average of inequality within each age group. It is obvious that the growth in inequality during the period is different across
Fig. 9. Inequality Measured in terms of Gini for each age cohort between 1979-2013

cohorts. Interestingly, the growth in within-cohort inequality ranges from -1 percent for 35- to 39-year olds to 14.5 for 70- to 74-year olds. Most of the increase in inequality in the period 1979-2013 is due to increases in within-cohort inequality among the elderly and middle-age workers. Increases in inequality among the young is not as drastic as other age groups.

There are multiple findings from the graph that need to be addressed. We first discuss and provide evidence for why inequality has grown among older individuals. Three arguments can be made in explaining the causes of this increase: increases in life expectancy among black Americans, changes in social security programs since the early 1980s, and inequality in hours of working among the elderly. We then try to provide some hypotheses mostly on the grounds of inequality of opportunity and mobility to explain the increase in within-cohort inequality among younger cohorts. In order to understand these two phenomena, we may need to look at more granular groups divided based on gender, educational groups, race, and immigration status, which will be further investigated in the future.

3.2.1. Increases in life expectancy of black Americans

Extension in life expectancy for minorities and those at the lower bottom of the income distribution is closely tied to income inequality. On the one hand, life expectancy is lower in more unequal societies and on the other hand, the dynamic of life expectancy can affect the distribution of income in a society. Mainly, the latter explanation is important in our context. In the period 1979-2013, life expectancy at birth increased by almost 8 years for the population as a whole. The racial differences narrowed but never vanished. In 1970, the gap in life expectancy between a black male and white female was as high as 15 years but narrowed to 9 years in 2013. These trends are shown in the Figure [10].
As depicted, while the average life expectancy for black females exceeded the age 70 in 1974, for black males this only happened after 2007. This increase in average life expectancy for black Americans, who tend to come from the lower bottom of the income distribution may explain the rise in inequality among the older cohorts.

### 3.2.2. Changes in social security policies

Studies on poverty and inequality among the elderly that use market income are far from being accurate since a large portion of individuals’ income in this group are transfers and non-cash income. With an emergence of a large lower class, mostly blacks, single women, and those with little education, the dependence on government social programs has been ever increasing. For instance, a large portion of American elderly are using Medicare. It is projected that by 2030, about three-fourth of the elderly will receive social security benefits and pension and asset income. However, estimates show that there will not be much changes in the amounts (percentage of total income) paid to the elderly.\(^{24}\) One of the advantages of the LIS data is the existence of detailed sources of incomes for individuals of different ages.

Changes in social security and pension plans can have two impacts on the inequality among the elderly: change in labor participation, and changes in disposable income after retirement. For instance, Krueger and Pischke (1992) compare men born in 1911-15, who were in their early 60s during the 1970s hype of Social Security benefits in the U.S., to men

\(^{24}\text{Boomers Approaching Midlife: How Secure a Future?, Public Policy Institute of AARP, 1998}\)
born five years earlier. They find that participation rates for the age group 60-64 fell 6.4 percentage points relative to their older peers. Anderson, Gustman, and Steinmeier (1999) show that changes in Social Security and pension plans account for about a quarter of the decline in participation of men in their early 60s but they found almost no effect on labor market participation of 65 and older men. Most of the decline has been attributed to the overall decline in demand for less-skilled workers. Autor and Duggan (2003), too, find that loosening of eligibility rules for Social Security Disability Insurance benefits, together with reduction in demand for low-skilled workers, have induced a fall in participation rates among the elderly.

The retirement plans has moved away from employer bearing most of the risk toward individuals bearing greater responsibility. Defined benefits plans that consisted a majority of pension plans are mostly replaced with defined contribution plans. According to the U.S. Department of Labor, defined benefit plans that were dominant in the period leading to 1984, were largely replaced with defined contribution plans. It is argued that the decline in defined benefit plans was mostly a result of weekend unions in the manufacturing sector and shift in plans offered by small employees.

To sum up, compared to late 1970s, the increase in Social Security’s full retirement age, reduction in participation in retirement benefits, transition from defined benefit plans to defined contribution plans, fall in the share of employers that offer retiree health benefits, and increase in average total out-of-pocket spending on services and premiums by Medicare beneficiaries could be all suspects in the rise in inequality among the American elderly in the past few decades. However, a full picture of inequality among the elderly requires an analysis of the role of gender in inequality. We will discuss this in Section 3.3.

3.2.3. Inequality in working hours

It is important to note that the inequality trends presented in Figure 9 are based on annual earnings. The variances of income is largest at either end of the working life (Blundell 2014). The income differences have among the youth have become more pronounced due to increases in college enrollment. At the end of the working life, health shocks and the dynamic of retirement decisions are likely to explain income inequality. Therefore, it is very important as to how much of the inequality shown among different cohorts is due to enrollment or retirement decisions.

Kuhn and Lozano (2008) find that among men, industries with more pay inequality are also less equal in terms of hours worked. This is seen across the income ladder. They noticed that in 1979 the bottom 20 percent of the earners were more likely to work longer hours compared to those at the top. Something that was theoretically suggested by Thorstein
Veblen that the poor works longer hours in order to keep up with their richer peers. However, more recently the reverse is evident in data. Those at top of the income distribution spent more hours. It is argued that skilled workers now have better incentives to put in longer hours since for them it means higher bonuses and job promotions. Others have argued that the culture around working longer hours has also had an important effect in reversing the trend.

In terms of retirement age, too, it is important that older men have been retiring at ever-earlier ages starting the late nineteenth century. This could be due to the introduction of the social security programs, the rise of incomes and consequently savings, and lifestyle changes in older ages during the same period. This decline was steeper during the early 1970s and 1980s and it fell from 83.4 percent in 1969 to 67.2 percent in 1989 [Juhn and Potter 2006]. However, labor force participation among older men stabilized by later 1980s and early 1990s and has even slightly increased since then. Part of this recent trend can be attributed to age composition. In fact, if we keep the age composition constant, we notice even larger increases in labor force participation among older cohorts.

Therefore, before making any judgement on the dynamic of inequality for each cohort, we first need to take a look at the inequality in terms of working hours among American workers. This is especially salient for older cohorts where inequality in hours of works due to health conditions can potentially be larger. The LIS data set provides statistics on hours of worked for each individual. The data shows the regular weekly hours worked at first/second job including family work and overtime. We can use this data in order to find inequality in terms of working hours for each cohort in 1979 and 2013 shown in Figure 11.

There are multiple findings from the figure above. First and the most trivial is that the average working hours is highest among middle-aged workers. Second, between 1979 and
2013 average working hours has slightly increased but the increase is more noticeable for older cohorts. Third, the standard deviation of working hours is the highest among younger and older cohorts in 2013, which confirms our hypothesis that variations in working decisions are greater among those cohorts. Lastly, we notice that the variations in working hours has decreased for all cohorts during the period. The reduction in inequality of hours is in contrast to the increase in overall inequality among the youth and the elderly. This means that most of the increase in inequality in annual income is in fact due to increase in inequality in hourly wages.

Another consideration by most researchers is to look at what has happened to inequality among full time workers instead of all workers in the economy. This resembles an apples-to-apples comparison. In this regard we calculate inequality within cohorts of workers who work more than 20 and 35 hours per week. Figure 12 shows the inequality among such workers. Moving from including all workers to only those who work beyond 20 or 35 hours has drastic implications on inequality. First, overall inequality decreases by 11.1 Gini points in 1979 and by 6.7 Gini points in 2013 if we exclude workers who work less than 35 hours per week. Second, as the figure shows, interestingly, the dynamic of cohort inequality alters from what we saw in Figure 9. The increase in inequality within middle-aged workers is not the highest, while inequality among older cohorts hasn’t changed much.

3.2.4. The large gender gap among the elderly

One hypothesis that may explain the increase in inequality among the elderly is an increase in gender gap among the elderly between 1979-2013. The "great gender convergence"
has become a theme in most gender gap studies. The decline in gender disparity has happened in multiple arenas including labor force participation, paid hours of work, education, and hourly earnings. In the past decades, a plateau in labor participation has happened in most age and education groups and years of education for women increased more than it did for men. A combination of both has brought about a decrease in annual income gap between men and women. On the other hand, the 59-cents-on-the-dollar gap between women and men in the 1970s became a 77-cents-on-the-dollar gap in recent years. According to data from Bureau of Labor Statistics, in 28.1 percent of American families, where both husband and wife had earnings, wife had a higher income than the husband, a 7.2 percentage-point increase from two decades earlier. We discuss briefly the role of the gender gap in inequality and its dynamic over time.

However, gender gap is not uniform across the age distribution. Previous studies suggest that the gender gap increases by age, i.e. it is higher among older workers. To check this, we use the same Pyatt’s decomposition method in order to find the inequality between men and women of different age groups as depicted in Figure 13. There are some interesting observations. First, the gender gap is larger for older cohorts in 2013 but not in 1979. The between gender inequality for 65- to 79-year olds is almost three times the between gender inequality between 20- to 24-year olds. Second, the gender gap has gone down for all cohorts between 1979 and 2013 with the exception of 70- to 74-year olds and 75- to 79-year olds.

Another implication of Figure 13 is that the gender gap would have been much lower had it not have been for the babyboomers. Since the ratio of female to male earnings decreases as each cohort ages, a society with aging population can see the a relatively less impressive reduction in gender gap.

Gender differences in education and experience, especially the one that exists among the elderly, can also be partially responsible for the gender gap. We end the conclusion that the increase in gender gap among the elderly can explain why inequality among the older cohorts have risen more than middle-aged workers.

3.3. Observation Three: Inequality among men has increased but it has decreased among women

An important suspect in connection to the ever increasing inequality in the United States is gender. In order to better understand the sharp increase in inequality between 1979-2013 among the youth and the elderly, an analysis of inequality based on gender groups is required.

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25 For a thorough analysis of the gender gap see Goldin (2014).
26 For instance, see Goldin (2014).
Fig. 13. Inequality between men and women of different age groups in 1979 and 2013. Source: LIS Data

Fig. 14. Changes in inequality within men and women between 1979 and 2013. Source: LIS Data

Such a breakdown reveals that inequality between men and women has declined from 39.1 percent of overall inequality to 23.3 percent. As a result, it is safe to assume that inequality within cohorts of men and women is the main contributor to the rise in overall inequality. However, a closer look at the figures shows that it is the inequality among men that makes up most of the increase in inequality over the past few decades. While the Gini coefficient among American men was 0.36 in 1979, it increased to 0.45 in 2013. At the same time, inequality among women, which was initially higher than men during the same time, decreased from 0.47 to 0.45 to a level slightly smaller than that of men as shown in Figure 14.

After breaking down inequality by gender groups we face two questions. One concerns the decrease in the gender gap and the other is why inequality within men and not women...
has increased significantly. We discussed the question regarding the gender gap in Section 3.2.4. The second question is of more importance in our analysis mainly due to the fact that it has slipped researchers attention. We will need to further break down inequality by age groups to have a better understanding of inequality within cohorts of men and women. The inequality among all cohorts of men has gone up significantly since late 70s but has gone down for most cohorts of women during the same time as shown in Figure 15. The figure shows the change in inequality, measured in terms of Gini coefficient, within cohorts of men and women between 1979 and 2013. In fact, the inequality within some cohorts of women has indeed fallen by as much as 14 percent. For men, the increase in inequality among some cohorts (for instance 30- to 34-year olds and 40- to 44-year olds) reaches almost 37 percent. This has been noticed by few researchers\(^{27}\) and the “swimming against the tide” phenomenon among women has not been investigated as much as it deserves. Also note that we no longer see a large increase in inequality among the older men and women as we saw in Figure 9 since an increase in gender gap in older cohort can cause the overall inequality among older cohorts to go up regardless of any change within each of the genders.

Another observation from the figure is the similarity of within-cohort inequality between men and women in 2013. The shape of the two graphs are almost identical in 2013. Understanding this phenomenon requires more analysis which is beyond the scope of this paper. In what follows we investigate factors that can explain why inequality among women has had an opposite trend as the inequality among men.

\(^{27}\)For instance see Osberg (2003) and Jenkins (1995)
3.3.1. Labor force participation

The U.S. labor force dynamics has witnessed prolonged changes since the turn of the twentieth century. While 82 percent of the American workforce were male in 1900, this share dropped to 54 percent in 2013. It is often argued that the spike in female labor supply is one of the main factors that has precipitated the increase in inequality among men. Welch (2000) emphasizes that the increase in inequality among men and the narrowing of the gender gap are “two sides of the same coin.” By categorizing skills into hard (physical) and soft (intellectual) skills, he argues that if the latter is less equally distributed than the former, then an increase in the relative value of soft skills (caused by more higher female labor supply) will increase wage dispersion (among men).

Acemoglu, Lyle, et al. (2004) study female labor force participation through the exogenous shocks on female labor supply of variations in mobilization for the war among men across states.28 The effects on states with larger female participation are summarized as: 1) lower wages for women, 2) reduction in male wages, and 3) asymmetric effect on male wages across the skill distribution (most of the effect was on medium-skilled men since they were closer substitute for women). However, there is no consensus among researchers as to which group of men has been affected the most. Grant and Hamermesh (1981) argue that female labor has traditionally been a closer substitute for low-skilled male worker. This in turn renders a higher inequality among men by increasing the returns to skills among men. Topel (1997) asserts that the rise in supply of college-educated women in the 1970s and 1980s kept the wage of male high school dropouts. Blau and Kahn (1997), have a completely different view. They do not associate the ever increasing rise in inequality among men to female labor supply. They argue that the largest degree of substitutability is between men and women within the same skill group. For a survey of the links between female labor supply and wage inequality among men see Katz et al. (1999).

We know relatively little about the consequences of the increase in female labor force participation on inequality among women. This convergence in labor force participation between men and women is mainly driven by the recent cohorts of women and their job market decisions after child-bearing years. The dipping off of labor market engagement during child-bearing years has become less acute in more recent cohorts of women.

The relevant statistics for labor force participation is the share of civilian non-institutional population of at least 16 years of age that is considered either employed or unemployed. In 2012 the civilian non-institutional population consisted of about 243 million people out of

28This was due to variations in drafting laws. They show that on average women worked about 1.1 more weeks in a state that had a 10 percentage-point higher mobilization rate during the war, which corresponded to a 9 percentage-point lump in female labor supply.
which 155 million were in the labor force (therefore a total labor force population of 63.7 percent). While labor force participation has surprisingly remained constant between 1979 and 2012 a closer look reveals that it has had opposing trends for men and women as shown in Figure 16. Between 1979 and 2012, the labor force participation rate among men has gone down by 9.7 percent while it has gradually increased by 13.3 percent for women. This increase in female labor force participation is equivalent to 28.5 million increase in female workers in the population in 2012 numbers.

Changes in labor force participation rate can be decomposed into two components: changes in the participation rate of each subgroups and changes in the population weights of each group. Therefore, if we were to divide the female working age population into age groups, the 13.3 percent increase in labor force participation rate among women can be due to the increases within each of those age groups and due to the demographic changes in the female population over time.

The expansion in female labor supply has been mainly driven by changes that have occurred in job market decisions of married women, more specifically married white women who traditionally used to be mainly working at home. Researchers also associate the increase in labor force participation among this group to policy changes that mostly affected women of color in the United States. Among them are the transformation of the old Aid for Families with Dependent Children (AFDC) program into more temporary and conditional assistance in the Temporary Assistance to Needy Families (TANF) program that happened in 1996 as well as the expansion of the Earned Income Tax Credit program (EITC). On the other hand, women from high-income households were mainly motivated to join the labor market by the ever-increasing skill premium and the Tax Reform Act of 1986, which reduced the
top marginal tax rate from 50 to 28 percent\textsuperscript{29}

Other factors such as divorce rates, changes in household technology and changes in husband’s income have been characterized as some of the possible explanations for the increase in female labor force participation rate. According to Johnson and Skinner (1986) divorced women are more likely to participate in the labor market and an increase in the risk of divorce may also increase married women’s participation since they may choose to stay in the labor force to hedge against future income risk associated with divorce.

How is this increase in female labor force participation important in answering the decrease in earning inequality among women? Answer to this question lies in the way inequality measures work. Imagine a population of 100 individuals who do not participate in the labor market and, therefore, whose earnings are zero. By every measure, the existing inequality is zero in this population. Then, imagine one of these individuals enters labor market and earns income (for simplicity the minimum wage). In this case, inequality will no longer be zero. Now, as more and more individuals enter the labor market and earn wages, it is understood that the inequality should go up. However, we also know that as soon as everyone enter the labor market and earns the same minimum wage (therefore, there would be no one with income of zero), our inequality measure should go back to zero. As a matter of fact, most inequality measures exhibits the kind of behavior explained above. The same argument goes for labor force participation. If no female is in the labor force, inequality among women is small. If more and more women join the labor force (up until almost half of them are in labor force), inequality continues to increase. If labor force participation increases further than that, inequality decreases until it reaches a low level when most women are in the labor force. This is shown in \textsuperscript{17}. Of course, this is a simplified version of reality since we have ignored the wage heterogeneity among women and the fact that most inequality measures are more sensitive to transfers of incomes either at the bottom or the top\textsuperscript{30}

Does this mean that the ever increasing labor force participation by women mean inequality among women will decrease even further? Juhn and Potter (2006) predict that the growth in female labor force participation will slow down from roughly 2 percent in 2005 to levels observed in the late 1990s. Most of the increase in female labor force participation will be due to higher participation by single mothers and older workers due to more flexible work arrangements by employers and the expansion of the Earned Income Tax Credit.

\textsuperscript{29}See Juhn and Potter (2006).

\textsuperscript{30}The Gini coefficient is more sensitive to the incomes at the bottom of the distribution. Other measures such as Atkinson are more sensitive to the incomes at the top. For a detailed analysis of this see Amiel and Cowell (1999) pages 78-86.
3.3.2. Marriage and parenthood

There has been a battery of empirical studies on the effect of marriage on inequality. Numerous studies are conducted on the effect of assortative mating on inequality, especially those calculated based on household incomes. Greenwood, Guner, Kocharkov, and Santos (2016) show that assortative mating, divorce, and female labor supply accounted for about one-third of the increase in income inequality in the United States from 1960 to 2005. However, there is not a great deal of analyses on the effect of marriage on inequality within male or female workers.

Most of the impact of marriage on inequality, especially among women, is through labor market participation. Juhn and Potter (2006) show that although general increases in wages have caused all women to supply more hours than before, women who marry to high-wage husbands, on average, increase their labor supply even faster than those married to low-wage husbands. They report that women married to men in the bottom quintile of earnings increased their labor force participation rate from 46 percent in 1969 to 66 percent in 1999. On the other hand, those married to men in the top quintile of earnings increased their labor force participation rate from 31 to 66 percent during the same period. Gottschalk and Smeeding (1997) argue that married women’s labor force participation rates, hours, and wages have increased in almost all countries during the 1980s. They also find that the correlation between husbands and wives earnings has increased during the same time.

Include statistics about labor force participation of married and unmarried workers

If we analyze the trend in inequality among married and unmarried workers by gender, we observe peculiar trends. Although, inequality within married and unmarried men as well as unmarried women have all gone up, inequality within married women has declined between 1979 and 2013. Figure [18] depicts the Gini coefficient for each group. While inequality within married men soared by almost 30 percent between the two years, it decreased by about 10
percent for married women. Figure 19 represents within age-cohort inequality for the same groups. A noticeable trend is again the decline in the inequality within almost all cohorts of married women. We could safely assume that it is married women that have driven down the overall inequality among women. Among men, most of the inequality is driven by married men.

This reduction in inequality among married women could be directly correlated with a reduction in the number of children per woman during recent decades. If women without children have generally higher earnings (due to longer hours of work and higher labor force participation) than those with children, a general declining trend in childbirth per woman can reduce inequality. Goldin (2014) reports that women with children work around 24 percent fewer hours per week than women without children in 2012. Finding the link between wage and number of children is harder to establish due to selection, however, most causal estimates point to a negative relationship between the number of children and wages in most countries.
Numerous factors can be suggested for the existence of this negative relationship. If female wages are correlated with their market productivity, then reduction in work experience, loss of specific human capital, atrophy of market skills while not working, and reduced incentive to invest in training that may bring a payoff in the future during the childbearing and parenting period can ebb wages for maternal parents (Lundberg and Rose, 2000).

Let us first calculate the inequality in terms of number of children for married workers. Among married workers, inequality in terms of number of children has decreased from 0.28 to 0.26 measured in terms of the Gini coefficient between 1979-2013. In particular, the inequality of number of children per woman declined by 15 percent for 40- to 44-year olds, by 17 percent for 45- to 49-year olds, and by 14 percent for 50- to 54-year olds. Altogether, this suggests that childbirth rate partially explains the reduction in inequality among married women.

The question that arises is why the reduction in the number of children per family contributed to a decline in wage inequality among women but not men. We hypothesize that the family gap and its uneven effect on women and men is a suspect. It has been argued that childbirth leads to salient reallocations of time and effort for married couples. It tends to impose a wage penalty on maternal wage while it may cause an increase in the paternal wage. Lundberg and Rose (2000) find that the birth of the first child is associated to a 5 percent decrease in the mother’s wage while it is linked to a 9 percent increase in father’s wage. This may be due to the fact that fathers may need to work longer hours to compensate for the mother’s time spent at home and not at work. The decline in childbirth, especially among lower-income families, may have caused a reduction in fathers’ hours of work and, therefore, their wages which may in turn increase inequality. On the other hand, the same factor may have caused women of lower income to spend more hours at work that consequently leads to closing the wage gap within women.

Another hypothesis that explains the reduction in inequality among married women is the disconnect between women’s wages and their husbands’ earnings. Leibowitz and Klerman (1995) report that the sensitivity of married women’s labor supply decision to their husbands’ wages went down between early 1970s and 1990. As a result, this may be suggestive that the employment (and therefore wages) of married women become loosely connected to the highly unequal wage distribution of their husbands.

3.3.3. Minimum Wage

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. [David, Manning, and Smith (2016)] in a recent paper, use a longer span of time and find that minimum wage explains about 30-40 percent of the rise in income inequality.

Let us begin with the trend in the real value of the minimum wage during the time period of this paper. As Figure 20 shows, although the nominal value of the minimum wage has gone by 150 percent up over the past three decades, the real value of the minimum wage has declined by about 22 percent. In fact, if the minimum wage had been indexed to inflation starting in 1968, it would currently be at $9.39 ([Boushey] 2014). The value of tipped minimum wage has declined by roughly 40 percent since early 1990s and is currently at a record low since its establishment in 1966.

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 among men and women. As shown in Figure 21, the percentage of women who earn federal minimum wage or less among hourly workers was about three times 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 in 2013, a number that was much closer to that of men at 3.3 percent. [David et al (2016)] confirm this trend. [32] They provide evidence that there

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

32 They argue that due to the stable share of hours at or below minimum wage for male worker, any
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 evidences presented in Figures 22-23 are 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. The ramification is nothing but a decline in inequality among women and a rise in inequality among men.

3.3.4. Unionization

There is no hard evidence on the causal relationship of unionization rate in the United States and the rise in income inequality. Most studies, however, find negative correlations between union membership rates and inequality trends 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 early 1970s\(33\) lost most of its gain during the three decades beginning early 1970s. What followed was an era known for the filibuster of the labor law reform of 1978, the suppression of the PATCO 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).

\(33\)Union membership reached 40 percent of the labor force by early 1970s.
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 22, the gap between private-sector union membership rates between men and women decreases from roughly 17 to 4 percentage points. One can observe this similar trends in unionization between men and women in countries like the United Kingdom and Canada as well.

On the other hand, 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 falling unionization 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 et al. (2003) discuss three reasons for the asymmetric effects of unionization on income inequality within men and women: 1) concentration of unionized women is higher in the upper end of the wage distribution than men. This is especially important when controlling for the skill composition of the workforce. 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.\footnote{For a more recent empirical analysis see Gomez and Tzioumis (2013).}

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

3.3.5. **Technology and Automation**

It has been almost eight decades since Johan Maynard Keynes coined the term "technological unemployment." Since then the idea that machines will eventually displace workers and create "superstars" or "winners" has been popular both inside and outside academia. Brynjolfsson and McAfee (2012), in their book, *Race Against the Machine*, discuss how technological changes can lead to a rise in inequality among workers. The best place to start for understanding within-gender inequality trends in the United States is to look at how technology affects employment in different sectors.

David Autor, a leading economist in the area of technology and labor market, argues that the effect of automation on employment is not uniform across all occupations. He divides jobs into three categories: 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 et al., 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 direct impact on the distribution of income in the economy. But we can only understand wage consequences of this job polarization through the elasticity of demand and supply of jobs.

Let us start with 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 et al., 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 ten-fold 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. Due to the already high wages in these sectors, the compound effect is higher inequality among men and lower inequality among women.

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 investment at the industry level and demand for female labor. DiNardo and Card (2002) report that women use computers at work at a significantly higher rate than men.

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, if computerization raises aggregate income, it 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 23 shows the employment shares of occupational categories for both men and women. We have added two more categories: 1) cognitive routine jobs, which include sales and office occupations and 2) manual routine jobs, which 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).

In conjunction with the dynamic of employment shares, the ever decreasing decline in
wages for routine jobs has led to an increase in inequality among men and a reduction 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 24 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. Consistent with elastic supply of workers for manual jobs, as employment rose for this category between 2000 and 2007 wages declined.

3.4. Regression Analysis

A useful framework for isolating different factors that have shaped inequality in the United States is to partially examine them through a sample wage equation. To do this, we find the effect on within-cohort inequality of factors such as marriage rate, variance of number of children, share of individuals in abstract jobs, share of individuals who are foreign born among other cohort characteristics. We follow Juhn et al. (1993) and Heathcote et al. (2005) and assume that those effects of cohort characteristics and time effects (year effects)
To do this, we first group individuals in each year into age, gender, and racial groups. Since racial categories in 1979 only include whites, blacks, and hispanics, we exclude other racial categories that are added in earlier years. We also use 12 age categories as defined in previous sections. As a result, there are 72 cohorts in each year. The data includes years 1979, 1986, 1994, 2000, 2007, and 2013. Table 2 shows the regression coefficients of within cohort Gini on basic group characteristics. Each column represents data from a specific year. Last column is aggregated data for all the years.

The variable age is the average age of the cohort, therefore, it is 22 for the age group 20-24 and so on. As it appears, this variable is not significant in any of the models 1-7. Age appears to be not an important determinant of within-cohort Gini, which could be due to the way it appears in the regression model. As you can see the difference between within-cohort inequality of female versus male cohorts ranges from 8 Gini points in 1979 to almost 0 in 2013, which suggests that the importance of gender in terms of cohort inequality is declining. Whites seem to be the most unequal and blacks the most equal groups.

Show that the effect of gender is declining throughout time.

In Table 3 we add other factors such as share of cohort with college or graduate degrees; share of cohort who hold abstract jobs including management, professional, and related jobs; share of cohort who are married; logarithm of the variance of number of children in each cohort, and share of the cohort that are foreign born. Regression model 1 uses share

\[35\] Data for immigration status is not available for 1979 and 1986 in LIS dataset.
Table 2: Factors defining within-cohort Gini coefficients

<table>
<thead>
<tr>
<th></th>
<th>(1) 1979</th>
<th>(2) 1986</th>
<th>(3) 1994</th>
<th>(4) 2000</th>
<th>(5) 2007</th>
<th>(6) 2013</th>
<th>(7) 1979-2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.000204</td>
<td>-0.000568</td>
<td>-0.000488</td>
<td>0.000336</td>
<td>0.000640</td>
<td>0.000228</td>
<td>-0.00000936</td>
</tr>
<tr>
<td></td>
<td>(-0.59)</td>
<td>(-1.99)</td>
<td>(-1.51)</td>
<td>(1.36)</td>
<td>(2.92)</td>
<td>(1.10)</td>
<td>(-0.07)</td>
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<tr>
<td>Female</td>
<td>0.0854</td>
<td>0.0752</td>
<td>0.0425</td>
<td>0.0156</td>
<td>0.0195</td>
<td>0.000889</td>
<td>0.0398</td>
</tr>
<tr>
<td></td>
<td>(7.13)</td>
<td>(7.64)</td>
<td>(3.80)</td>
<td>(1.83)</td>
<td>(2.57)</td>
<td>(0.12)</td>
<td>(9.10)</td>
</tr>
<tr>
<td>White</td>
<td>0.0188</td>
<td>0.00846</td>
<td>0.0185</td>
<td>0.0198</td>
<td>0.0185</td>
<td>0.0177</td>
<td>0.0170</td>
</tr>
<tr>
<td></td>
<td>(1.28)</td>
<td>(0.70)</td>
<td>(1.35)</td>
<td>(1.90)</td>
<td>(1.99)</td>
<td>(2.02)</td>
<td>(3.16)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.0165</td>
<td>-0.0126</td>
<td>0.0000417</td>
<td>-0.0138</td>
<td>-0.00204</td>
<td>0.00679</td>
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<td></td>
<td>(-1.12)</td>
<td>(-1.04)</td>
<td>(0.00)</td>
<td>(-1.32)</td>
<td>(-0.22)</td>
<td>(0.77)</td>
<td>(-1.18)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.345</td>
<td>0.383</td>
<td>0.407</td>
<td>0.382</td>
<td>0.365</td>
<td>0.401</td>
<td>0.380</td>
</tr>
<tr>
<td></td>
<td>(16.51)</td>
<td>(22.26)</td>
<td>(20.81)</td>
<td>(25.59)</td>
<td>(27.59)</td>
<td>(32.04)</td>
<td>(49.74)</td>
</tr>
</tbody>
</table>

| Observations | 72 | 72 | 72 | 72 | 72 | 72 | 432 |
| $R^2$         | 0.460 | 0.494 | 0.222 | 0.189 | 0.239 | 0.074 | 0.195 |

$t$ statistics in parentheses
of cohort with college or graduate degree to control for the education level of the cohort. However, it does not appear to have a large impact on inequality. Model 2 includes age but as categories and in model 3 we add more variables such as share of cohort who are married, are foreign born, or work in abstract jobs, as well as the variance of number of children in cohort. This variables are added in order to control the factors discussed in previous sections. In both model 2 and 3, inequality tends to be higher among middle-ages workers and lower at the two ends of the age spectrum with the exception of the 20- to 24-year olds. For instance, controlling for gender, race, and education among other factors, inequality among the cohort of 30- to 34-year olds appears to be about 8 Gini points lower than the reference age group of 20- to 24-year olds based on model 3. Other factors such as share of cohort in abstract jobs are not found to be significant determinants of within-cohort inequality.

4. Conclusion

In this paper, we have analyzed the evolution of income inequality in American society between 1979-2013. We offer a more granular analysis by looking at inequality that exists within and between multiple demographic groups instead of looking at single statistics. We pursue this by decomposing the Gini coefficient into different sub-groups using a Gini decomposition method introduced by Pyatt (1976). The advantage of Pyatt’s decomposition method is that it takes into account the overlapping part of inequality after we decompose inequality into different age groups. These overlapping terms are important and exist in most societies. The reasons that we advocate decomposing inequality into smaller age and gender groups are: 1) we can gain greater insights into the causes (and consequences) of inequality by looking at smaller groups of the population, 2) changes in inequality within a country and differences among countries can be partially caused by the demographic dynamics of those countries, and 3) inequality measures do not reflect reasonable differences in income among groups of different ages that exist due to life cycle effects.

Using data from Luxembourg Income Study (LIS), we first define age groups as cohorts of five-year intervals and decompose the Gini coefficient into within- and between-age-group components. The first finding after this decomposition is that, while in most countries, the part of inequality that is due to differences within age groups has fluctuated over the period 1979-2013, in the United States, this share has remained relatively stable. In the U.S., the within-cohort share of inequality has not exceeded the range of 71-74 percent of overall inequality, but this range is among the highest compared to a sample of countries we used in this study. As a point of reference, the within-cohort share of inequality in the United
Table 3: Factors defining within-cohort Gini coefficients

<table>
<thead>
<tr>
<th>Factor</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.0000892</td>
<td>0.00411</td>
<td>0.0416</td>
</tr>
<tr>
<td>Female</td>
<td>(9.47)</td>
<td>(11.25)</td>
<td>(6.01)</td>
</tr>
<tr>
<td>White</td>
<td>0.00309</td>
<td>-0.00169</td>
<td>0.0310</td>
</tr>
<tr>
<td>Black</td>
<td>(-1.82)</td>
<td>-0.0110</td>
<td>0.0434</td>
</tr>
<tr>
<td>Share with college or graduate degrees</td>
<td>0.000933</td>
<td>0.00125</td>
<td>-0.0000152</td>
</tr>
<tr>
<td>Age group 25-29</td>
<td>-0.0565</td>
<td>-0.0733</td>
<td>(-5.78)</td>
</tr>
<tr>
<td>Age group 30-34</td>
<td>-0.0512</td>
<td>-0.0857</td>
<td>(-5.09)</td>
</tr>
<tr>
<td>Age group 35-39</td>
<td>-0.0368</td>
<td>-0.0795</td>
<td>(-4.77)</td>
</tr>
<tr>
<td>Age group 40-44</td>
<td>-0.0302</td>
<td>-0.0746</td>
<td>(-4.24)</td>
</tr>
<tr>
<td>Age group 45-49</td>
<td>-0.0167</td>
<td>-0.0616</td>
<td>(-3.72)</td>
</tr>
<tr>
<td>Age group 50-54</td>
<td>-0.00605</td>
<td>-0.0562</td>
<td>(-3.62)</td>
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<tr>
<td>Age group 55-59</td>
<td>0.0120</td>
<td>-0.0406</td>
<td>(1.27)</td>
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<tr>
<td>Age group 60-64</td>
<td>0.0128</td>
<td>-0.0420</td>
<td>(1.37)</td>
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<tr>
<td>Age group 65-69</td>
<td>-0.0112</td>
<td>-0.0568</td>
<td>(-1.22)</td>
</tr>
<tr>
<td>Age group 70-74</td>
<td>-0.0395</td>
<td>-0.0850</td>
<td>(-4.34)</td>
</tr>
<tr>
<td>Age group 75-79</td>
<td>-0.0584</td>
<td>-0.0994</td>
<td>(-6.46)</td>
</tr>
<tr>
<td>Share Married</td>
<td>0.00124</td>
<td>(4.74)</td>
<td></td>
</tr>
<tr>
<td>Share in abstract jobs</td>
<td>0.000388</td>
<td>(1.11)</td>
<td></td>
</tr>
<tr>
<td>Log of variance of number of children</td>
<td>-0.0126</td>
<td>(0.86)</td>
<td></td>
</tr>
<tr>
<td>Share foreign born</td>
<td>0.000586</td>
<td>(1.43)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<td>0.390</td>
<td>0.335</td>
</tr>
<tr>
<td>Observations</td>
<td>432</td>
<td>432</td>
<td>288</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.215</td>
<td>0.447</td>
<td>0.495</td>
</tr>
</tbody>
</table>
Kingdom has soared from a low value of 57.5 percent in the late 1970s to a level as high as the United States in 2013.

We first show that in the United States the overall shape of the age-income profile has not changed significantly between 1979 and 2013. By looking at the age-income profile for men and women we find that the profile for women is flatter compared to men in a given year and that it has steepened dramatically for women during the period under observation. One reason that my be responsible for relatively high within-cohort inequality in the United States is the combination of population dynamics and the Permanent Income Hypothesis. The hypothesis states that inequality within a specific cohort of a population increases as the cohort ages. Our results using LIS data support this hypothesis in the United States. This effect compounded with the aging of the babyboomer generation (and, therefore, a larger elderly share) has resulted in an increase in the between-cohort share of overall inequality in recent decades.

We further investigate the changes in income inequality for each of the age cohorts. An interesting observation is that most of the increase in inequality in the past three decades is due to increases in within-cohort inequality among the youngest and oldest age groups. In fact, while inequality among middle-aged Americans has remained the same or ha changed little, it has increased by 9 and 5 percent respectively among 20- to 24-year olds and 25- to 29-year olds. Similarly it has gone up by 8 percent for 65- to 69-year olds, by 15 percent for 70- to 74-year olds, and by 11 percent for 75- to 79-year olds. We raise six hypotheses in order to explain these trends.

Our first hypothesis is that a rise in life expectancy among black Americans and more explicitly among black men is responsible for increased within-cohort inequality amongst the elderly. While 1974 was the first time that the average life expectancy among black females surpassed the age 70, this only happened for black men in 2007. This increase in life expectancy among black Americans, who tend to be among the low-earners in the income distribution, can explain the rise in income inequality among the elderly.

We then test whether inequality in terms of working hours can be another factor in explaining the rise in inequality among the elderly. We find that although inequality in terms of working hours is the highest among the elderly, it has decreased by about 26 percent in the period 1979-2013, contrary to our hypothesis. Our hunch is that changes in social security policies that have resulted in decline in participation in retirement benefits and a fall in the share of employers that offer retiree health benefits can be responsible for the rise in inequality. More importantly, we find that a rise in the gender gap among the elderly has aggravated income inequality within older cohorts. We provide evidence that, although the gender gap averaged over all cohorts has gone down, the gender gap among
the elderly has worsened between 1979 and 2013. In 1979, the gender gap was the highest among middle-aged workers, but by 2013, it was the elderly who suffered most from gender differences in incomes. We find that the gender gap among 65- to 79-year olds is now almost three times greater than the gender gap among the 20- to 24-year olds.

For the increase in inequality among the youth, we believe that lower mobility rates as suggested by Kopczuk, Saez, and Song (2007), lower inequality of opportunity, and changes in educational policy have precipitated the rise in youth inequality. Relying on multiple factors, we show that changes in family composition (high rate of single-parenthood) and inequality in terms of number of children in American families, black parents’ incarceration rate, and disparities in time spent with children at home are important factors. For instance, the percentage of children born to unmarried mothers has increased from 20 percent in 1979 to about 41 percent in 2010. The number of black children under 18 with a parent in prison or in jail is now about six-times the rate in 1980 (Pettit, Sykes, and Western, 2009). Research shows that children with incarcerated parents are more prone to developmental delays and behavioral problems.

Higher education as an equalizing factor has drawn much attention among economists, however, recent studies show that hikes in tuition rates and the shift in educational policies from need-based to merit-based policies together with the decline in the real value of such policies have proven that differences in educational outcome have helped the rise in inequality. It is estimated that such differences (together with experience) are responsible for about one third of overall income inequality (Krueger et al., 2002). We show that there has been significant shifts in the way educational aid is distributed. According to data from the National Center for Educational Statistics, 57 percent of merit-based aid and 21 percent of the total need-based aid goes to children of high- and high-middle-income families. Other forms of aid such as tuition credits have proved to be serving advantaged children more often than their disadvantaged counterparts. One can argue that since more talented youth generally come from more affluent families that do not need any stimulus to pursue higher education, merit-based aid may only exacerbate inequality.

Finally, we discuss the last finding of this study - that men are the main contributor to the increase in overall inequality. While inequality has risen among cohorts of men, we show, quite paradoxically, that inequality among women has declined over the past three decades. We show that while the Gini coefficient among American men was 0.36 in 1979, it increased to 0.45 in 2013. At the same time, inequality within cohorts of women that was initially higher than that of men, decreased from 0.47 to 0.45. This is an observation that has slipped away from most inequality studies. We find that the rise in inequality has been the highest among middle-aged men. On the other hand, with the exception of older women, inequality
for all cohorts of women have declined with the highest decline for 30- to 39-year olds and 50- to 54-year olds. The other important finding is the divergence in the shape of within-cohort inequality for men and women.

In trying to explain the above phenomena, we offer five possible explanations. The first and the most obvious is the increase in female labor force participation. We discuss how inequality measures follow an inverse-U shaped curve when more women join the labor market, i.e., inequality increases as we move from labor participation of zero to almost 50 percent and decreases as almost all women are in the labor force. The ever-increasing trend of women in the labor force (that changed from almost 50 to 60 percent) and the decreasing trend among men (from 78 to 70 percent) support this hypothesis. We then break down the inequality trend to married and unmarried workers and notice that married women are the main contributor to the decline in inequality among women. This can be attributed to lower inequality in terms of number of children. If women without children have generally higher earnings, then a general decline in childbirth per women, especially among lower-income women, can decrease inequality among married women.

Our next explanation for the decline in inequality among women is the opposing trends of minimum wage earners among men and women. 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 an rise among men. A similar trend is observed in terms of unionization. While unionization among men was much higher than among women in the early 1980s, they both fell to a similar level by 2013. We argue that this deunionization trajectory that was more dire for men than for women contributed to the rise in inequality among men but not women.

Lastly, relying on [Autor et al. (2014)] detailed analysis of computerization and the labor force, we 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. However, since the supply of abstract jobs are more inelastic for men than for women, an increase in demand for abstract jobs can be translated into higher wages in managerial and technical jobs typically done by men and smaller rises in those done by women. Considering that these types of jobs are typically on the top of the income distribution, a wage polarization among men happens as a result of computerization. We show that the substitution of workers with machines in routine jobs has a similar ramification. If computers have served as a substitute to workers in those jobs,
wages in this sector that typically constitute administrative and office related jobs should go down. However, since the share of women in routine jobs has declined at a much faster rate than men, the disqualifying effects are stronger for men than women.

Overall we show that each of the trends mentioned above have different effects on inequality among men and women. This study is not exhaustive in assessing all factors that can explain the trends in inequality. To further understand the trend in inequality among American cohorts, especially for men and women, the further analysis of educational groups is required. We believe more interesting results will appear if we further dissect inequality into smaller cohorts.

We believe studying the evolution of income inequality in the United States, or any other country, requires the detailed analysis of cohorts rather than looking at single numbers. The dissection of inequality can lead to more insights into what has caused inequality and what to do about it.
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