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Essays on Economics of Inequality

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Abstract

ESSAYS ON ECONOMICS OF INEQUALITY

by

ABOOZAR HADAVAND

Adviser: Professor Wim Vijverberg

This dissertation consists of three chapters all around the subject of inequality. The first chapter provides a novel analysis of the trend in income inequality in the United States between 1979–2013. There are two ways in which this chapter contributes to the literature. First, I analyze how much of the existing inequality in the U.S. is due to the demographic changes that happened over this period. Using microdata from Luxembourg Income Study and after decomposing inequality into within- and between-age group components, I find that the within-group share of overall inequality in the U.S. is high and steady compared to other developed countries. I also find that about 17 percent of the rise in inequality in this period is due to the between-group component (life-cycle effects). Second, I provide a regression analysis to explain cross-group variations in inequality during the period. I estimate that most of the rise in inequality has happened among middle-aged men while inequality among women, especially among married women has, in fact, decreased. This more granular analysis of inequality can help us investigate the causes of inequality, which would be impossible if we only look at a single inequality statistic.

The second chapter focuses on an important aspect of economic inequality – the question of how people perceive inequality and whether these perceptions deviate in any meaningful way from statistical measures of inequality. Perceptions of inequality have been shown to affect happiness, job satisfaction, and political support for redistribution, and studies have also shown that individuals tend to ‘misperceive’ inequality. Using a novel approach
I find that individuals across different countries are able to correctly estimate the shape of the income distribution of the country where they reside. I also find that perceptions of inequality are frequently shaped by reference groups such as those formed according to educational attainment, age, and gender. Across countries, I find that education is a more important reference group where access to education (more specifically to higher education) is better. In addition, I find that age-related reference groups are more important in societies with higher intergenerational mobility. Lastly, gender reference groups are more relevant in countries where gender disparities are more accepted and more pronounced.

In the third chapter, using model in which the assignment of skills to tasks is determined by relative productivities and are endogenously determined by ability, access to higher education, and technology, I find the effect of different educational aid schemes (including need-based aid, merit-based aid, or a combination of the two) on the distribution of wages. I calibrate the model using NLSY97 data and find that in general, determining what policy minimizes inequality depends on the elasticities of demand for higher education of each ability/human capital group, the labor shares of each group, and the share of resources devoted to each group. Given the model parameters, both merit-based and need-based policies are preferred to a policy based on both merit and need. Moreover, under the model parameters, a need-based policy reduces wage inequality more than a merit-based policy.
Acknowledgments

To Sarah who has been with me through Ph.D.’s thin and thick years and without whom this essay would not be readable (will you be my lifetime editor and partner?)

To my parents, obviously. I would have never come this far without them.

And to my advisor, Wim Vijverberg, one of the wisest and most humble humans I know.
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Chapter 1

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

1.1 Introduction

Many indicators tell us that income inequality in the United States has risen since the late 1970s. Data retrieved from the All the Ginis database show that over the past three decades the Gini coefficient has risen by 8-18 percent depending on what type of income measures are used.\(^1\) Data from the Luxembourg Income Study (LIS) show that 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 the 20th percentile rose from 2.66 to 3.15. One could also compare changes in the median equivalent household income to changes in the mean household income to demonstrate that there has been faster growth at the top of the income distribution relative to the rest of the distribution. Between 1979 and 2013, the median equivalent household income increased by 259 percent, while the mean household income increased by almost 300 percent.

\(^1\)See http://go.worldbank.org/9VCQW66LA0
CHAPTER 1. ANATOMY OF INCOME INEQUALITY

What do all of these measures tell us? They certainly can signal a broad shift in the overall level of inequality, but they do not tell us much about the underlying mechanisms that contribute to such shifts. In order to better understand specific transformations of income distributions across space and time, we must look under the hood of the income distribution and observe what has been happening within and across various subgroups of the populations we are studying. When it comes to the recent rise in income inequality in the United States, it is relevant to first understand how changes in the overall age distribution have affected inequality and to understand the different degrees to which various subgroups of the population have been affected by the recent rise in inequality. This study attempts to analyze and explore beneath the surface of traditional inequality measures. I do this by calculating inequality within and between various cohorts of the American population. I decompose inequality into within- and between-group components, where the within-cohort component is a weighted average of inequality within each cohort and the between component measures inequality that exists between cohorts. I find that the share of the within-cohort component of overall inequality in the United States has been steady and high compared to most developed countries. I also find that about 83 percent of the rise in inequality between 1979-2013 is due to changes in within-cohort inequality.

The importance of such decompositions is multifold, but a few points will help demonstrate why decompositions are central to deepening our understanding of income inequality. First, it is easily recognized that demographic changes are partially responsible for differences in inequality across space and time. The importance of demographic dynamic in inequality is mainly due to the Permanent Income Hypothesis (PIH) as it applies to inequality, which states that inequality within a specific age cohort increases as the cohort ages (Eden, 1980). Therefore, differences in measured inequality between two countries—one with a relatively young population and the other with an aging population for example—could, in fact, be explained by the differences in the demographic traits of each country. Likewise, a single
country that ages over time may experience a *natural* rise or fall in inequality that is largely a result of the demographic shift. When looking at differences in inequality across space and time it would be useful to be able to estimate the difference that results from these types of basic demographic incongruities.

Related to this point is the fact that in every country, differences in income due to an age-income profile can partially explain the magnitude of inequality. Such a profile illustrates the typical evolution of income with respect to a person’s experience and age. In most countries, this profile, when graphed, is an arched curve where income peaks around the late middle-aged years. It is considered reasonable that workers are rewarded somewhat proportionally according to their age and/or experience. Thus, we would expect that even in societies that many consider to be very equal, we would find some reasonable differences in income across individuals according to these traits. If this is the case, even under perfect equality of opportunity and a regime of social policies aimed at reducing inequality, the Gini coefficient would never be close to zero. In fact, I calculate that even if every American worker’s income follows the cross-sectional trajectory of the life-cycle income in 2013, the Gini coefficient would still be about 13.0.\footnote{This calculation is done by using cross-sectional income and age data in 2013. Calculations are not provided here but are available upon request.} Many people do not believe in a policy scheme that equalizes the incomes of the young and the mature, and yet, such differences do show up in traditional inequality metrics. One could argue, therefore, that since individuals typically expect to receive higher incomes as they age, inequality due to differences in age can be justified to a degree and that this notion should be reflected in the way we measure and discuss income inequality.

Finally, decomposition analysis can extend to different subgroups of the population based on gender, race, education, and occupation. By measuring inequality within these various groups, we can learn about the effects that different policies or economic phenomena have had
in reducing (or increasing) inequality within those cohorts. Experts in the field of inequality usually relate rising inequality to various factors such as financialization, weakening of anti-poverty measures, reductions in redistributive policies, globalization, 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, our standard statistics for measuring inequality are single numbers that obscure our understanding of how these many factors combine and contribute to overall inequality. It is these three considerations that have motivated the decomposition analysis in this essay. A second contribution of this essay is a detailed analysis of cross-cohort differences in within-cohort inequality among cohorts categorized by gender, education, and race among other factors.

This study is the first attempt (to my knowledge) that uses a decomposition of the Gini coefficient to study inequality between and within different age, gender, occupational, and educational groups. My analysis reveals a great deal of interesting findings, some of which are consistent with previous inequality studies, and some of which have yet to be discussed in the inequality literature. There have been some attempts in the past to decompose inequality measures according to age and geographic regions. 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. Heathcote et al. (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 et al. (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.

In spite of all these studies, there is a lack of coherent analysis of the evolution of inequality in the United States across different subgroups. The main challenge in my analysis is in figuring out how to calculate inequality measures for and between the various subgroups of the population.

In Section 1.2 of the paper I discuss the data used in my analysis. I use data from the LIS, which provides a large set of micro-level data collected from household surveys conducted across several countries. The data has already been harmonized for the sake of cross-country comparisons. Section 1.3 reviews the academic literature in this area and highlights some of the main attempts that have been made at adjusting and decomposing inequality measures. In this section, I also provide an age-cohort analysis of inequality in the United States. In Section 1.4, I use regression analysis to study why inequality in some cohorts has increased significantly while in others has declined. I do this while controlling for age differences among these various groups. The paper ends with a brief summary of my findings and a discussion about further applications of this method. Section 1.5 concludes the paper.

### 1.2 Data

The data used in this study is from Luxembourg Income Study (LIS) database, which is one of the largest available income databases of micro-level 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. LIS data for the United States is a reconstructed and a harmonized version of the Current Population Survey (CPS). However, between 1979-2013 only years 1979, 1986, 1991, 1994, 1997, 2000, 2004, 2007, 2010, and 2013 are included in LIS.
Discussions around the choice of the unit of analysis should be an integral part of any inequality study. I justify the use of personal-level data as opposed to household-level data with 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.\(^3\) Furthermore, as Deaton and Paxson (1994) 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 sampled 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 economies of scale in families. The most used scale by researchers is the square root of the number of household members.\(^4\) 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 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."

My 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. On the other hand, equality of income does not imply equality of standard

\(^3\)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."

\(^4\)For a thorough analysis of the equivalence scale read Buhmann et al. (1988).
CHAPTER 1. ANATOMY OF INCOME INEQUALITY

of living when family structure varies.

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 after-tax incomes for individuals of age 20 to 79, where income it is defined as the sum of monetary and non-monetary income from labor, and monetary income from capital. 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.

1.3 Inequality within and between age cohorts across the world

In this section, I begin my analysis of inequality in the United States by calculating ”between” and ”within” inequality measures that are based on age. I will briefly compare the within and between-age-cohort shares of inequality in the United States to the same shares calculated for a number of other countries between 1979 and 2013. To understand the importance of life-cycle effects in inequality calculations, let us first focus on the most widely used measure of inequality, the Gini coefficient, and how it is calculated. The Gini coefficient 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, every person’s 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 our consideration. The overall age-income profile of a society is the aggregate of the individual age-income profiles of all adults.\footnote{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.}

Paglin (1975) 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 1.1. 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
The improvement from the line of equality to the P-line can be best summarized in an example of two societies represented in Figure 1.2. 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 coefficient for both societies. However, replacing the line of equality with the P-line yields a lower Gini for society B than society A.
Table 1.1: Paglin’s Gini versus the Lorenzian Gini

<table>
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<th>Gini Coefficients</th>
<th>Area</th>
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<tbody>
<tr>
<td>Lorenzian Gini</td>
<td>((\alpha + \beta)/(\alpha + \beta + \gamma))</td>
</tr>
<tr>
<td>P-Gini (within Groups)</td>
<td>(\beta/(\alpha + \beta + \gamma))</td>
</tr>
<tr>
<td>Age-Gini (Between Groups)</td>
<td>(\alpha/(\alpha + \beta + \gamma))</td>
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Table 1.1 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 to family income data from the CPR P-60 series, Paglin showed that the traditional Gini coefficient was 50 percent higher than the P-Gini in 1972.

Since the introduction of Paglin’s decomposition approach, other methods have been introduced due to some major caveats. One of the most important contributions, is a method introduced by Pyatt et al. (1976) which is the method used in this essay. Pyatt used this approach and 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. A detailed explanation of the Pyatt’s method is explained in Appendix A. As previously mentioned, age cohorts in this analysis 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.

Using Pyatt’s method, Figure 1.3 below shows the share of overall income inequality that is due to within-age-cohort income differences in selected countries. It is important to note that what I am comparing here is the share of overall inequality that can be explained by within-age-cohort differences in income. Looking at this figure, we can immediately see that the within-cohort share of inequality in the United States has stayed in the range of 71-74.

---

Some of these issues are: (1) the P-Gini coefficient is sensitive to the boundaries of the age cohorts, (2) the Paglin’s method ignores overlapping income differences. It is apparent that even the youngest and the oldest groups overlap. Nelson (1977) shows that if age-income distributions overlap, the P-Gini will be affected by cohorts’ mean income and population weights.
Figure 1.3: Within Age-Cohort Share of Inequality

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 1.3 leave us with two questions. First, what explains cross-country differences in the within-cohort share of overall income inequality? And second, why has this share remained at such a high and constant level in the United States, while it has increased (and in some cases fluctuated quite dramatically) in other countries? The full analysis of these two questions is left for future research, as their analysis

8The within cohort share of inequality in Canada in 2010 reaches a surprisingly high value of 91.3 percent from 70.8 percent in 2007.
requires an additional qualitative investigation into policy and other socioeconomic trends in these various countries. For now, we continue our investigation by looking at the age-income profile and demographic trends as potential explanations.

So far, I have observed that the within-age-cohort share of inequality has been both high and steady in the United States. To corroborate this observation, I first examine changes in the age income profile for some of the countries in our sample. Changes in the income profile will provide a sense of how the between-age-cohort component of inequality has changed over time, and will therefore, provide some validation for the trends we observe in Figure 1.3. An analysis of basic demographic shifts, on the other hand, will help us account for some of the observed increases in both overall inequality and within-age-cohort inequality in the United States over time.\(^9\)

**Age-income profile**

Age-income profiles demonstrate the evolution of individual earnings over the course of a lifetime. The income profiles of most societies are typically inverse-U shaped curves with a positive relationship between earnings and age up until the point where incomes peak (usually around the age of 40-50, but varying greatly across societies) and a negative relationship between the two variables afterward.\(^{10}\)

In the context of inequality, the income profile can be used to examine the difference

---

\(^9\)The share of the overlap term tends to be relatively constant over time for most countries and very similar across countries, so the overlap term is not considered. For the sake of space, I do not report the overlap terms independently.

\(^{10}\)The explanations for the positive sloping part of the income profile are as follow: 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. Mincer (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.
in income between individuals of different age groups. In other words, the income profile can be understood as a reflection of the between-age-cohort component of inequality. In general, a steeper income profile suggests a high between-age-cohort share of inequality, and conversely, a flatter income profile indicates that the within-age-cohort share of inequality is higher. Additionally, if we see a dramatic change in the shape of the income profile over time, we would expect to see a corresponding change in the within-share of inequality.

Figure 1.4 below shows the income profile in 1979 and 2013 for all workers aged 20-79 for the United States, United Kingdom, Canada, and Denmark. In each case, the average income of each cohort is compared to the average income in the highest earning age group of that year in that country; the profiles are smoothed. What we see in Figure 1.4 is a very slight steepening of the first half of the income profile in the United States between 1979 and 2013 and a slight flattening in the second half of the life cycle. Overall, however, the shape of the income profile in the U.S. has not changed much. This is consistent with the observation that within-age-cohort inequality in the United States has not changed much over this period. Meanwhile, the income profiles in the United Kingdom and Canada have changed much more noticeably. In both countries, the income profile has flattened, which implies that the between-cohort component of inequality in both country has declined. We can confirm this trend by looking at Figure 1.3. For both countries, the within-cohort share of inequality has risen dramatically.

Figure 1.4 also demonstrates another finding that will become relevant to our discussion later on in this essay. In each of the four 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 increased by roughly 100 percent from 0.3 to 0.6 in the United Kingdom. Changes in family structures, too, may impact the income profile. 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.
Demographic dynamics

Demographic differences among countries and changing demographics over time are responsible for part of the dynamics of income distribution in countries. The fact that median ages across countries ranges from 15 (in countries such as Niger, Uganda, and Mali) to 45 (as is the case in Monaco, Japan, and Germany) reflects these demographic disparities. 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 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 in the past four decades. 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 1.5.

The effects of this demographic transition, namely an aging of the U.S. population, play out in two ways which I will discuss briefly here. Primarily, it impacts the inequality within each cohort and does so through the Permanent Income Hypothesis (PIH) as it has been applied to income inequality. The Permanent Income Hypothesis (PIH), which was originally applied to questions of inequality by Eden (1980) and further investigated by Deaton and Paxson (1994), suggests that inequality among individuals of the same age (or same age range) should increase as the cohort ages.\textsuperscript{11} This observed trend implies that an aging society may experience rising inequality simply due to the fact that older cohorts tend to be less equal.

\textsuperscript{11}The theory has been tested for various countries. For instance, see Blundell (2014) and Heathcote et al. (2005).
CHAPTER 1. ANATOMY OF INCOME INEQUALITY

If this is the case, then moving to an older society is associated with a rise in income inequality within cohorts. Secondly, an aging population increases the population weights of older cohorts. As a result, the older groups that tend to be more unequal based on PIH contribute more to the overall within-cohort inequality. The combined effect of these two trends is to increase overall inequality by way of increasing the within-age-component of inequality.

My results based on LIS confirm the PIH hypothesis in the United States as shown in Figure 1.6. 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.\textsuperscript{12} As shown, inequality within cohorts of different ages in 1974 increases as cohorts age; however, the only difference between my results and those confirmed by other researchers is the decrease in inequality within the same cohorts as they reach their 60s.\textsuperscript{13} 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, I 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, 1994). Higgins and Williamson (1999) argue that slower population growth that shifts the population age distribution toward

\textsuperscript{12}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.

\textsuperscript{13}Prus (2000) finds similar results for Canada.
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. The social security taxes, levied on younger workers to support older retired members of society, depress the disposable income of the young. Many researchers have pointed out the shrinking 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 compared to other developed countries.\textsuperscript{14} Reznik et al. (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.\textsuperscript{15} It is projected that by 2040 this ratio will fall to only 2.1, putting

\textsuperscript{14}According to OECD, the support ratio in the U.S. was the fourth largest among the OECD countries and only Turkey, Israel, and Luxembourg had a higher support ratio than the U.S.

\textsuperscript{15}So that the tax revenue roughly equals benefit payments.
even more burden on the young population and creating a larger age-gap, and therefore, causing overall income inequality to increase.

1.4 Cross-group empirical analysis

The analysis in previous section reflects the importance of inequality decomposition into within- and between-cohort components. A further step is to look at inequality within each age cohort. Figure 1.7 reveals that the inequality within each of these age cohorts has changed differently. Interestingly, the growth in within-cohort inequality ranges from -1 percent for 35 to 39-year olds to 14.5 percent 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 among other age groups. We do see an increase within the youngest cohort (20 to 24-year olds), but this can be explained by differences in work and educational choices. Note that the overall within-cohort component of inequality calculated in the previous section is a weighted average of inequality within each age group.
What factors can explain the variations in terms of change in inequality across the age groups mentioned above? What has precipitated high inequality among older cohorts is different than the factors responsible for the inequality among younger cohorts. A useful framework for isolating different factors that have shaped inequality in the United States is to partially examine them through a simple wage equation. To do this, in the next section I find the effect on within-cohort inequality of factors across age, gender, and racial groups and in the section that follows I look at additional factors such as marriage rate, variation in number of children, etc. as determinants of cross-group inequality differences.

### 1.4.1 Basic Model

I use each cohort as a unit of analysis. I follow Juhn et al. (1993) and Heathcote et al. (2005) and assume that those effects of cohort characteristics and time effects (year effects) are additively separable. To do this, I first group individuals in each year into age, gender, and racial groups. Since racial categories in 1979 only include whites, blacks, and Hispanics, I exclude other racial categories that are added in earlier years. I also use 12 age categories defined as 5-year intervals.\(^{16}\) As a result, there are 72 cohorts in each year. The data includes years 1979, 1986, 1991, 1994, 1997, 2000, 2004, 2007, 2010, and 2013. Table 1.2 summarizes the within groups inequality (WGI) in terms of Gini coefficient for different years. It is interesting to find that although average inequality across cohorts has increased over the period 1979-2013, cross-cohort variations has decreased during the same period. In the following section I review gender and race as the most important factors explaining cross-group differences in inequality.

\(^{16}\)Thus cohorts will be 20-24, 25-29, 30-34, and so on. The results in this section and the following sections are robust to the length of the intervals.
CHAPTER 1. ANATOMY OF INCOME INEQUALITY

Table 1.2: Inequality in different groups: 1979-2013

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>S.D.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
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<tr>
<td>1979</td>
<td>37.9</td>
<td>6.7</td>
<td>27.3</td>
<td>51.7</td>
</tr>
<tr>
<td>1986</td>
<td>39.1</td>
<td>5.7</td>
<td>27.8</td>
<td>51.0</td>
</tr>
<tr>
<td>1991</td>
<td>40.0</td>
<td>4.4</td>
<td>30.7</td>
<td>50.8</td>
</tr>
<tr>
<td>1994</td>
<td>41.0</td>
<td>5.2</td>
<td>26.8</td>
<td>52.5</td>
</tr>
<tr>
<td>1997</td>
<td>40.9</td>
<td>4.8</td>
<td>31.5</td>
<td>50.8</td>
</tr>
<tr>
<td>2000</td>
<td>40.8</td>
<td>3.9</td>
<td>32.1</td>
<td>49.4</td>
</tr>
<tr>
<td>2004</td>
<td>41.6</td>
<td>3.9</td>
<td>33.5</td>
<td>54.0</td>
</tr>
<tr>
<td>2007</td>
<td>41.2</td>
<td>3.6</td>
<td>34.7</td>
<td>52.5</td>
</tr>
<tr>
<td>2010</td>
<td>41.3</td>
<td>3.3</td>
<td>33.9</td>
<td>48.0</td>
</tr>
<tr>
<td>2013</td>
<td>42.1</td>
<td>3.1</td>
<td>35.3</td>
<td>48.7</td>
</tr>
<tr>
<td>All Years</td>
<td>40.6</td>
<td>4.7</td>
<td>26.8</td>
<td>54.0</td>
</tr>
</tbody>
</table>

Gender

The question we are facing is whether within cohort inequality is different for men and women and whether it has changed over time. To investigate this, I further decompose the Gini coefficient for male and female individuals. Inequality among cohorts of women that was much higher than men in 1979 seems to have declined to a level close to that of men in 2013 as shown in Figure 1.8. In fact, the within-cohort inequality within cohorts of women has become surprisingly similar to the shape of within-cohort inequality among men in 2013. The decline in inequality among women and the rise in inequality among men can explain this trend. If we look closer we see that 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 a few researchers.\(^1\) However, the decline in inequality among cohorts of women has not been investigated as much as it deserves.

Note that we no longer see a large increase in inequality among the older men and women as we saw in Figure 1.7. The answer to this contradiction is the rise in inequality between

\(^{1}\)For instance see Osberg (2003) and Jenkins (1995)
Figure 1.8: Change in inequality within cohorts of men and women between 1979-2013

Figure 1.9: Inequality between men and women of different age groups in 1979 and 2013

men and women of older ages during the same period. The closing of the gender gap is not uniform across all age groups. Previous studies suggest that the gender gap increases by age, i.e., it is higher among older workers. As Figure 1.9 presents 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.

\[\text{For instance, see Goldin (2014).}\]
Race plays a big role in determining income. A large body of academic work is devoted to racial differences in income. If income differences are equal across racial groups, how are inequality levels different within each group? Figure 1.10 shows WGI for different racial groups in 1979 and 2013. One can see the variations between these racial groups. For instance, in 1979 there is almost 4.0 Gini points difference in WGI among blacks and whites. Between 1979-2013, while inequality among blacks has gone up by about 86 percent, it has increased by 3.3 percent among Hispanics.

Race can also explain variations in inequality among age groups through life expectancy. Income inequality and life expectancy are closely tied to one another. 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. The latter explanation is mainly 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 1.11.

![Figure 1.11: Life expectancy at birth in the United States between 1970-2013. Source: Centers for Disease Control](image)

As depicted, while the average life expectancy for black females exceeded the age of 70 in 1974, for black males this only happened after 2007. This increase in average life expectancy for black Americans, who tend to be found in the lower end of the income distribution may explain the rise in inequality among the older cohorts.

### 1.4.2 Regression Analysis

To begin with our regression analysis, I first look at how the main factors explained above contribute to the cross-cohort inequalities both individually for each year and pooled for all years with dummy year effects.

\[
WGI_{it} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Female}_i + \beta_3 \text{Race}_i + v_t + \epsilon_{it} \tag{1.1}
\]

where \( i \) represents the \( i\)-th cohort, \( t \) represents year \( t \), and \( v_t \) captures year effects. \( \text{Age} \), \( \text{Female} \), and \( \text{Race} \) are vectors of dummies for cohort \( i \). The dependent variable is the inequality
in terms of Gini coefficient in cohort $i$ at time $t$. Table 1.3 shows the regression coefficients. Last column is aggregated data for all years but controls for year effects. The variable age is a dummy variable representing each age group.

As it appears most variables are significant predictors of within-group Gini coefficient in the aggregated model. The coefficient reflecting the additional inequality within women compared to men has declined over time. The coefficient is as high as 8.0 Gini points in 1979 but declines to about zero in 2013, pointing to the fact that women and men have become equally unequal in recent decades. The most equal age groups are the age groups 25-29, 30-34, and 75-79 year olds. On the other hand, the most unequal age groups are middle-aged Americans of age range 55-64. This is consistent across during the period. In terms of racial groups whites are the most unequal. In the aggregated sample of all years, whites tend to be 2.0 Gini points more unequal that blacks, while Hispanics, tend to stand in between. Over time, however, Hispanics have become as equal as blacks. The constant terms has increased from 33.6 to 44.1 (by about 10.0 Gini points) pointing out the overall trend in inequality in the same period. The same analysis holds for within-group Theil index and P90/P10 income ratio as shown in Table 1.4 columns 1 and 2.
Table 1.3: Cross Cohort Inequality Dynamic, Gini Coefficient

<table>
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<tr>
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<tbody>
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<td>Gender</td>
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</tr>
<tr>
<td>Female</td>
<td>0.085***</td>
<td>0.075***</td>
<td>0.050***</td>
<td>0.042***</td>
<td>0.031***</td>
<td>0.016**</td>
<td>0.007</td>
<td>0.020***</td>
<td>0.003</td>
<td>0.000</td>
<td>0.033***</td>
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</tr>
<tr>
<td>25-29</td>
<td>-0.049*</td>
<td>-0.033*</td>
<td>-0.045**</td>
<td>-0.041**</td>
<td>-0.058***</td>
<td>-0.035*</td>
<td>-0.064***</td>
<td>-0.029*</td>
<td>-0.059***</td>
<td>-0.054***</td>
<td>-0.047***</td>
</tr>
<tr>
<td>30-34</td>
<td>-0.037</td>
<td>-0.026</td>
<td>-0.020</td>
<td>-0.034*</td>
<td>-0.027</td>
<td>-0.026</td>
<td>-0.052***</td>
<td>-0.021</td>
<td>-0.056***</td>
<td>-0.048***</td>
<td>-0.035***</td>
</tr>
<tr>
<td>35-39</td>
<td>-0.012</td>
<td>-0.022</td>
<td>-0.009</td>
<td>-0.004</td>
<td>-0.000</td>
<td>-0.011</td>
<td>-0.036**</td>
<td>-0.018</td>
<td>-0.031**</td>
<td>-0.042***</td>
<td>-0.019***</td>
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<td>40-44</td>
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<td>-0.007</td>
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<td>-0.002</td>
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<td>-0.008</td>
<td>-0.016</td>
<td>-0.007</td>
<td>-0.028**</td>
<td>-0.025*</td>
<td>-0.014**</td>
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<td>45-49</td>
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<td>-0.013</td>
<td>-0.000</td>
<td>-0.007</td>
<td>-0.002</td>
<td>0.023</td>
<td>-0.022</td>
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<td>-0.014</td>
<td>-0.018</td>
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<td>50-54</td>
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<td>0.013</td>
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<td>0.038*</td>
<td>0.033*</td>
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<td>-0.011</td>
<td>0.013</td>
<td>0.021***</td>
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<tr>
<td>60-64</td>
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<td>0.024</td>
<td>0.037**</td>
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<td>0.027</td>
<td>0.013</td>
<td>0.028*</td>
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<td>0.006</td>
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<td>65-69</td>
<td>-0.030</td>
<td>-0.024</td>
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<td>-0.003</td>
<td>0.005</td>
<td>-0.001</td>
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<td>70-74</td>
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<td>-0.059***</td>
<td>-0.019</td>
<td>-0.059***</td>
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<td>-0.008</td>
<td>-0.020</td>
<td>-0.004</td>
<td>-0.019</td>
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<td>-0.029***</td>
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<tr>
<td>White</td>
<td>0.035**</td>
<td>0.021**</td>
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<td>0.018**</td>
<td>0.038***</td>
<td>0.034***</td>
<td>0.016</td>
<td>0.021**</td>
<td>0.020**</td>
<td>0.011*</td>
<td>0.022***</td>
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<td>0.013</td>
<td>-0.000</td>
<td>0.033***</td>
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<td>0.008</td>
<td>0.002</td>
<td>0.010</td>
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<tr>
<td>Constant</td>
<td>0.336***</td>
<td>0.360***</td>
<td>0.375***</td>
<td>0.394***</td>
<td>0.376***</td>
<td>0.386***</td>
<td>0.422***</td>
<td>0.393***</td>
<td>0.423***</td>
<td>0.441***</td>
<td>0.364***</td>
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</table>

Yr Dummies | N | N | N | N | N | N | N | N | N | N | Y |
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<td>Obs.</td>
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<td>72</td>
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<td>72</td>
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<td>720</td>
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<tr>
<td>Adj. $R^2$</td>
<td>0.524</td>
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<td>0.544</td>
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<td>0.335</td>
<td>0.208</td>
<td>0.383</td>
<td>0.574</td>
<td>0.508</td>
<td>0.441</td>
</tr>
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</table>

* p < 0.1, ** p < 0.05, *** p < 0.01
It is important to note that the coefficients represented in Table 1.3, are based on annual incomes. The variance of income is largest at either end of the working life (Blundell, 2014) due to work, school or work, and retirement decisions. The income differences among the youth have become more pronounced due to increases in college enrollment. On the other hand, health shocks and the dynamic of retirement decisions likely explain income inequality at the end of the working life. Therefore, it is very important to look at how much of the inequality among different cohorts is due to enrollment or retirement decisions.

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 in labor force participation 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.

Therefore, it is useful to see the within-cohort dynamic of inequality among employed and full-time workers. I first replicate the analysis for employed workers controlling for the dynamic of labor market. Since this highly limits the number of people in the older groups, I limit the sample to individuals of age 69 and younger. Column 3 in Table 1.4 uses the within-group Gini coefficient for employed individuals only. Once I limit the sample to employed workers, the within-cohort inequality gap between men and women vanishes. Age does not seem to be a significant determinant of across-cohort variations of inequality and middle-aged workers are no longer as unequal as when we do not have an employment restriction. The constant term has decreased from 0.364 in the entire sample to 0.314 in the sample with only employed individuals, which reflects that inequality is partially driven by inequality between the employed and the unemployed.

In column 4, I limit the sample to only full-time workers (those working above 35 hours
per week). The regular weekly hours are calculated as the sum of hours worked at first and second jobs including family work and overtime. It is interesting to note that in the full-time sample, it is men that are more unequal than women and inequality in hours worked is partially responsible for the high inequality among women. Workers of age 45-64 years old seem to constitute the most unequal groups.

Table 1.4: Cross Cohort Inequality Dynamic, Other measures and Gini coefficient of employed and full-time workers

<table>
<thead>
<tr>
<th></th>
<th>(1) Theil</th>
<th>(2) P90/P10</th>
<th>(3) Gini (Emp.)</th>
<th>(4) Gini (Full-time)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender Female</td>
<td>0.0386***</td>
<td>8.7153***</td>
<td>0.0045*</td>
<td>-0.0198***</td>
</tr>
<tr>
<td>Age 25-29</td>
<td>-0.0527***</td>
<td>-0.2082</td>
<td>-0.0455***</td>
<td>-0.0250***</td>
</tr>
<tr>
<td>30-34</td>
<td>-0.0344**</td>
<td>1.9630</td>
<td>-0.0335***</td>
<td>-0.0110</td>
</tr>
<tr>
<td>35-39</td>
<td>-0.0058</td>
<td>2.4440</td>
<td>-0.0138**</td>
<td>0.0073</td>
</tr>
<tr>
<td>40-44</td>
<td>-0.0026</td>
<td>0.2898</td>
<td>-0.0083</td>
<td>0.0130</td>
</tr>
<tr>
<td>45-49</td>
<td>0.0200</td>
<td>1.1385</td>
<td>-0.0011</td>
<td>0.0230***</td>
</tr>
<tr>
<td>50-54</td>
<td>0.0282**</td>
<td>1.7253</td>
<td>0.0024</td>
<td>0.0239***</td>
</tr>
<tr>
<td>55-59</td>
<td>0.0500***</td>
<td>2.5312</td>
<td>0.0074</td>
<td>0.0252***</td>
</tr>
<tr>
<td>60-64</td>
<td>0.0391***</td>
<td>-1.5992</td>
<td>0.0072</td>
<td>0.0213***</td>
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<tr>
<td>65-69</td>
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<td>-5.7385**</td>
<td>0.0094</td>
<td>0.0126*</td>
</tr>
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<td>70-74</td>
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<td>-6.5138***</td>
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<td>75-79</td>
<td>-0.0464***</td>
<td>-7.0225***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race White</td>
<td>0.0453***</td>
<td>6.6004***</td>
<td>0.0305***</td>
<td>0.0279***</td>
</tr>
<tr>
<td>Hispanic</td>
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<td>0.0197***</td>
<td>0.0173***</td>
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<tr>
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<td>0.3095***</td>
<td>0.2789***</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Obs.</td>
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<td>720</td>
<td>600</td>
<td>600</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.285</td>
<td>0.253</td>
<td>0.404</td>
<td>0.371</td>
</tr>
</tbody>
</table>

*p < 0.1, **p < 0.05, ***p < 0.01

In what follows, I review other factors that I believe can explain cross-cohort variations in inequality in the United States.
1.4.3 Other factors

Female labor supply, marriage, and birth rate

Inequality in terms of income among individuals regardless of their labor force or employment status is largely affected by their labor supply decisions. This is particularly important among women who traditionally have a more elastic labor supply. Factors such as cultural changes, and changes in divorce rate and household technology 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. It is important to note that the expansion in female labor supply has been mainly driven by changes that have occurred in job market decisions of married women, more specifically white married 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.\footnote{See Juhn and Potter (2006).}

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 et al. (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 among workers. Most of the impact of marriage rate 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.

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 1.12 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 1.13 represent 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 correlated with the decline
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 in 2012 women with children work around 24 percent fewer hours per week than women without children. 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 (Sigle-Rushton and Waldfogel, 2007). 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 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 mothers (Lundberg and Rose, 2000).

My calculations show that inequality in terms of number of children among married workers has decreased by about 8 percent 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. I 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.

**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 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 the consequences of this job polarization for wage inequality 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. It was possible to recruit a large number of idle women into the labor force because female labor supply is 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.

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

Lastly, the high rate of substitution between routine jobs and computerization means lower wages for those working in the related sectors. Figure 1.14 shows the employment shares of occupational categories for both men and women. I have added two more categories: (1) cognitive routine jobs, which are routine jobs that require more cognitive skills, include sales and office occupations, and (2) manual routine jobs, which are routine jobs that require physical skills more than cognitive skills, include construction, transportation, production and repair occupations. As Figure 1.14 shows, women have reduced their employment in manual routine jobs at a higher rate than men (30 versus 15 percentage points between 1979 and 2014).

\[\text{In fact, it seems that the rise in the demand for skilled labor is positively correlated with automation and computerization. Weinberg (2000) finds evidence for a positive correlation between computer investment at the industry level and demand for female labor.}\]
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Figure 1.14: Changes in occupational distribution for major occupational groups by gender between 1979-2014

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 decrease in inequality among women between 1979 and 2013. Note that the share of women in abstract jobs has increased over the period. Also it is important to notice that for men the changes in employment shares are quite negligible. Figure 1.15 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.
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1.4.4 Regression with More Variables

Equation 1.2 shows the relationship between WGI and the factors discussed above controlling for gender, race, and age. I add another factor measuring the share of cohort with college or graduate degrees. Occupations are grouped into four exhaustive and mutually exclusive categories: (1) abstract, (2) manual, (3) cognitive routine, and (4) manual routine. The manual-routine group is the omitted category in the regression.

\[
WGI_{it} = \beta_0 + \beta X_{it} + \gamma_1 \text{ShareMarr}_{it} + \gamma_2 \text{VarChild}_{it} + \gamma_3 \text{ShareHiEd}_{it} + \gamma_4 \text{ShareForeign}_{it} + \gamma_5 \text{ShareAbstract}_{it} + \gamma_6 \text{ShareManual}_{it} + \gamma_7 \text{ShareCogRoutine}_{it} + v_t + \epsilon_{it}
\] (1.2)

where \(WGI_{it}\) is inequality within cohort defined by age, race, and gender, \(X_{it}\) represents \(Age\), \(Female\), and \(Race\) dummy variables for cohort \(i\) at time \(t\). \(\text{ShareMarr}_{it}\) is the share of married individuals in the cohort, \(\text{VarChild}_{it}\) is the variance of number of children in each cohort, \(\text{ShareHiEd}_{it}\) is the share of individuals with college degrees or above, \(\text{ShareForeign}_{it}\) is the share of cohort that is foreign born, and \(\text{ShareAbstract}_{it}\), \(\text{ShareManual}_{it}\), and \(\text{ShareCogRoutine}_{it}\)
are the share of those in abstract, manual, and cognitive-routine jobs, respectively. Share of workers in manual routine jobs is the base category and is omitted from the regression. All the explanatory variables are measured at cohort level where cohorts are defined by age, race, and gender.

Table 1.5 shows the regression results. After adding the variables, females remain to be more unequal. Looking at the Gini coefficient for all individuals in the sample, women are more unequal by almost 3.3 Gini points based on Model (3). Again, this gap in terms of within-cohrot inequality between men and women vanishes when we only consider only employed and full-time workers. The inequality among the youngest cohort (20- to 24-year olds) is the highest followed by 55- to 64-year olds. Inequality among cohorts with higher share of individuals with college degree and above is slightly lower. A 10-percentage point increase in share of highly educated individuals is associated with a 1.4 point decrease in in the Gini coefficient. The share of abstract workers does not seem to affect inequality much. Only in model (5), a 10-percentage point increase in the share of abstract workers increases the Gini coefficient by about 2.6 points. For every 1-point increase in the variance of number of children, inequality can decrease by 1.2 points in model (3).

1.5 Concluding Remarks

In this essay, I have analyzed the evolution of income inequality in American society 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. I pursue this by decomposing the inequality into different sub-groups using a Gini decomposition method introduced by Pyatt et al. (1976). I advocate decomposing inequality into smaller age and gender groups for the following reasons: (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 across space and time 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.

I find 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 proportion 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 I used in this study. As a point of reference, the within-

<table>
<thead>
<tr>
<th>Gender</th>
<th>Theil Index</th>
<th>P90/P10</th>
<th>Gini</th>
<th>Gini (Emp.)</th>
<th>Gini (Full-time)</th>
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</thead>
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<tr>
<td>Female</td>
<td>0.0532***</td>
<td>5.1818***</td>
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<td>0.0044</td>
<td>-0.0420***</td>
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<td>Age</td>
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<td></td>
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</tr>
<tr>
<td>25-29</td>
<td>-0.1055***</td>
<td>-4.0609***</td>
<td>-0.0767***</td>
<td>-0.0748***</td>
<td>-0.0583***</td>
</tr>
<tr>
<td>30-34</td>
<td>-0.1193***</td>
<td>-4.4250***</td>
<td>-0.0868***</td>
<td>-0.0773***</td>
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<td>White</td>
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<td>Share Married</td>
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<td>0.0007**</td>
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<tr>
<td>Var(No. of Children)</td>
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<td>-7.3536***</td>
<td>-0.0125</td>
<td>-0.0101</td>
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</tr>
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<td>Share High Ed.</td>
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<td>-0.0016**</td>
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<td>0.0353</td>
<td>0.0006**</td>
<td>0.0013**</td>
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<td>-0.0000</td>
<td>0.0005</td>
<td>0.0005</td>
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<td>Share in Cog-Routine</td>
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<td>0.0489*</td>
<td>-0.0001</td>
<td>-0.0012**</td>
<td>-0.0003</td>
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<tr>
<td>Share Foreign-Born</td>
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<td>0.0345</td>
<td>0.0006*</td>
<td>0.0009**</td>
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<td>0.458</td>
<td>0.390</td>
<td>0.433</td>
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</table>

*p < 0.1, ** p < 0.05, *** p < 0.01
CHAPTER 1. ANATOMY OF INCOME INEQUALITY

cohort share of inequality in the United 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. This is mainly due to three facts: (1) a relatively stable age-income profile, (2) the Permanent Income Hypothesis combined with demographic changes in the American society and the aging of the baby boomers. I also find that about 17 percent of the increase in inequality during this period is due to between age-cohort inequality and the rest is due to the rise in inequality within age cohorts.

I further break-down income inequality into gender and racial groups in addition to age and find cross-group differences in WGI and change in WGI. I find that there are significant differences in terms of WGI across groups. For instance, while inequality among middle-aged Americans has remained the same or has changed little, it has increased by 9 and 5 percent respectively among 20- to 24-year olds and 25- to 29-year olds. Another finding is that men are the primary contributor to the increase in overall inequality. To investigate what factors determine these cross-group differences in inequality, I employ a regression model. The regression results are interesting. I find that whites are more equal compared to blacks and Hispanics. Moreover, men tend to be more equal than women but the difference fades out over the period. Middle-aged Americans of age range 55-64 are less equal than their younger and older counterparts. Other factors such as share of abstract workers, share of people with post-secondary degrees, share of married individuals, and variance of number of children can explain the cross-group WGI.

Of course, the analysis in this essay is not yet the complete picture. There are other factors to consider across time and groups. The decrease in the real value of minimum wage is coupled with a sharp decline in the share of female workers who earn at or below the wage floor and a relatively stable share for male workers. This can lead to a decline in inequality among women and a rise in inequality among men. One can also argue that the combination of the larger decline in unionization among men than women and arguably the larger negative
impact of deunionization on wage inequality for men than women can explain differences in WGI between men and women. The dynamic of education policy during the period 1979-2013, too, can explain why some groups are more equal than others especially across age and time. Educational opportunities and inequality of income are two sides of the same coin. The gap in financial resources provided to children and youth and differences in the capacities of families to invest in their children has widened in recent decades. This trend has been coupled with a period of constant increase in the return to education and college premium. Therefore, unless offset by public policies that lessen such effects, the lower equality of opportunity and mobility rates get translated to higher degrees of inequality. Other factors such as the increase in Social Security’s full retirement age, reduction in participation in retirement benefits, a transition from defined benefit plans to defined contribution plans, a fall in the share of employers that offer retiree health benefits, and an increase in average total out-of-pocket spending on services and premiums by Medicare beneficiaries could all be suspects in the rise in inequality among the American elderly in the past few decades.

All in all, I believe studying the evolution of income inequality in the United States, or any other country requires a 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.
Chapter 2

Misperceptions and Mismeasurements: An Analysis of Subjective Economic Inequality

2.1 Introduction

There are many reasons why we should care about people’s perceptions of inequality. First, public support for redistribution has been linked to the way people think about inequality and interpret their relative positions in society. Engelhardt and Wagener (2014) use survey results and find that a subjective distribution of income based on their respondents’ perceived location in the income distribution greatly explains the respondent’s demand for redistribution. Niehues (2014) shows that while the Gini coefficient has no statistically significant effect on support for redistribution, perceived inequality is positively correlated and highly significant.

Perceptions of inequality are not only relevant in public finance models; they may also have psychological and behavioral implications. Traditionally, the link between inequality
and happiness has been studied by looking at the link between average happiness and aggregated, statistical measures of inequality (Wilkinson and Pickett, 2010). However, more recent studies have shown that it is the perception of differences rather than objective differences in circumstances that have negative effects on happiness (Diener et al., 1993; Ferrer-i Carbonell, 2005; Clark et al., 2003).

Most studies that look at perceived inequality have found inconsistencies between perceived inequality and officially reported statistical measures of inequality. For instance, research by Norton and Ariely (2011) finds that in most surveys in the United States, respondents systematically underestimate the inequality of wealth. In contrast, Chambers et al. (2014) find that Americans tend to overestimate the gap between the top 20 percent and the bottom 20 percent of wealth earners in the United States. Gimpelson and Treisman (2015) find that people in most countries do only slightly better than chance at guessing the shape of the distribution of income in their country. In only 5 of the 40 countries where their survey was administered were a majority of respondents able to correctly state the level of income inequality in their country. According to Gimpelson and Treisman, “it requires a great leap of faith to suppose that ordinary people can guess the level of inequality more accurately than expert statisticians—with all the censuses, surveys, and sophisticated statistical techniques at their disposal.”

The inconsistencies between perceived inequality and objective measures of inequality are thus typically attributed to errors on the part of everyday individuals. Ordinary individuals are said to be “wrong” about the level of inequality in their country, and their biases are frequently referred to as misperceptions. Yet, despite these characterizations, it seems reasonable to consider whether part of the observed discrepancy between perceptions and official inequality statistics can be attributable to errors and biases on the part of those who measure inequality rather than those who perceive it. Given some of the divergent results in the perceptions literature, given the many difficulties associated with capturing and inter-
preting subjective, and often tacit, pieces of information, and given the specific construction of our “objective” inequality measures, it is likely that the discrepancies between objective and subjective measures of inequality are not simply the result of misperception, but also the result of some mismeasurement.

Surveys that ask ordinary individuals about inequality are the fountainhead of many potential errors. Questions framed too broadly or too technically on a survey can easily be misinterpreted. For instance, if not specified, survey respondents may easily confuse wealth inequality with income inequality, household income with individual income, and before-tax income with after-tax income. More technical questions, on the other hand, many also lead to confusion. Many survey questions ask respondents to describe their perception of inequality in terms of probability distributions using quantiles, moments, or points of the distribution – all of which may be challenging concepts for anybody who is not accustomed to thinking about inequality in terms of probability and statistics.

This has been shown in the contrast between the work of Norton and Ariely (2011) and Eriksson and Simpson (2012). In their study, Norton and Ariely (2011) ask respondents what percent of wealth is owned by each of the five quintiles in the United States. They find that Americans drastically underestimate the level of wealth inequality and conclude that individuals are unaware of the true gaps that exist. However, in a replication of this study conducted by Eriksson and Simpson (2012), respondents, rather than being asked about the relative wealth shares of each quintile, were asked to indicate the average wealth of individual households within a given quintile. This line of questioning resulted in dramatically higher answers than what Norton and Ariely found. When the question was asked about the percentage of wealth owned by each quintile the ratio of the wealth of the top to bottom quintile was perceived to be 1:21. However, when the question was asked about the average wealth of each quintile in the United States, respondents estimated the same ratio to be 1:1,500. Eriksson and Simpson’s replication demonstrates that simply rephrasing survey
questions can lead to dramatically different answers. Similarly, Amiel and Cowell (1999) find that respondents to their questionnaires, answered differently to verbal and numerical questions that were aimed at asking similar things.

These studies among many others demonstrate the wide range of choices researchers face when trying to extract information about perceptions. In another study, Chambers et al. (2014) use multiple choice questions and ask individuals to guess the cut-off points of income quintiles in the United States. Respondents were asked, for example, whether the cut-off point for the top 1% was at $380,354 (the actual value) or $681,649 (an extremely high value). In their survey, they found that most participants (76%) selected the wrong answer. Cruces et al. (2013) who conducted their study in Argentina find that providing supplementary information to respondents alters results. They show that if participants are asked to estimate the average income of different income groups without any further information, their answer would be different than the case in which they are given some basic information about, for instance, the average income of the bottom 20% of the income distribution. Cruces et al. (2013) also attempted to eliminate the notion of percentage shares from some of their questions. For example, they ask their respondents the following question: “There are 10 million households in Argentina. How many have incomes lower than yours?” They use this question as a proxy for individuals’ perception of their own position in the income ladder. Finally, a nationwide survey of 3,000 Canadians demonstrates contradictory results. When asked what the ideal distribution of wealth should be across each quintile of the population, individuals in the sample, on average, responded that while the wealthiest quintile should own 30.3% of the total wealth, the rest of the quintiles should own 20.4%, 23.7%, 14.1%, and 11.5%, respectively (Broadbent-Institute, 2014). The second quintile was given a lower share of wealth than the third quintile, demonstrating there was some confusion regarding the question.

Given these issues, I question some of the conclusions drawn from previous studies. Are
respondents really misperceiving inequality or do our measures of subjective inequality depend just as much on how researchers frame questions and interpret survey results? Using the same survey data used by Gimpelson and Treisman (2015), but using a different interpretive approach, I am able to draw conclusions that are somewhat contrary to Gimpelson and Treisman’s findings. One of the questions in the International Social Survey Programme (ISSP) asks individuals to guess the shape of the income distribution in their country. The advantage of this question over others is the relative simplicity and clarity of the question. Respondents are shown five diagrams depicting five different types of distributions and are asked which diagram “best describes” the county they live in. Using personal-level micro data from the Luxembourg Income Study (LIS), I find the shape of the income distribution for each country represented in the survey, and using the Bhattacharyya coefficient, I compare each respondent’s answer to the distribution I derive for their country. In doing so, I am able to show that the perceptions of many of the respondents are well aligned with the actual distributions.

Respondents of the survey are shown to do a better job at guessing the income distribution when their answers are compared to the actual distribution rather than compared to synthetic measures of inequality like the Gini coefficient such as they are in Gimpelson and Treisman (2015) and Niehues (2014). Given these exceptions, I investigate some factors that could explain variations in perceived inequality across countries, and find that income and education are important factors that can explain differences in how accurately individuals perceive inequality across countries.

Moreover, I investigate the role of “reference groups” in shaping perceptions of inequality. I look at whether subjective and objective inequality levels will be closer if one readjusts the income distribution based on more refined reference groups. This is based on the hypothesis that people’s perception of inequality and where they stand in the income distribution is to a large extent based on their reference groups, which can be formed on the basis of educational
and demographic factors.

Unfortunately, economists who study inequality tend to ignore reference groups, often pointing to the arbitrariness of defining reference groups and arguing *de gustibus non est disputandum*. However, in this project, taking advantage of the richness of the LIS dataset, I attempt to calculate the distribution of income within a variety of reference groups and see whether respondent’s perceptions of inequality are closer to any of these distributions than they are to the overall distribution of income in their country. I define reference groups based on education, age, and gender. The importance of each of these reference groups varies from country to country.

While the inconsistencies between subjective and objective levels of inequality are important, it is imperative that researchers do not entirely write these inconsistencies off as misperceptions. It is important to fully recognize that despite being armed with “censuses, surveys, and sophisticated statistical techniques,” researchers can still be prone to misinterpretation, mismeasurement, and biases of their own. Thus, any consideration of misperceived inequality needs to be considered with scrutiny for how the perceptions were observed. This essay sheds more light on perceptions of income inequality especially through the lens of reference groups.

The structure of the paper is as follows. Section 2.2 summarizes the data sources used in this study. In Section 2.3, I introduce my methodology and show the results of comparing objective inequality measures and perceived inequality. In Section 2.4, I consider the role of reference groups in shaping perceptions of inequality. Sections 2.5 and 2.6 discuss the limitations of my analysis and conclude the paper.
2.2 Data

There is only a limited number of cross-national surveys on perception of inequality. While most of these surveys include questions about individuals’ relative position in the income scale (information that is then used in order to find the perceived income distribution), only a few of them ask respondents what they think is the existing level of inequality in their country, and only one, the International Social Survey Programme (ISSP), asks individuals to guess the shape of inequality in their country.

ISSP is a collaboration of international organizations and universities surveying individuals from more than 50 countries covering topics for social science research. The data set contains information on around 1000 individuals from each participating country resulting in a large overall sample. The themes of the survey change from year to year, but in 2009, the survey focused on the topic of social inequality and included questions ranging from attitudes toward inequality, discrimination, corruption, and merit; perceptions of inequality; sources of inequality; and government policies to reduce inequality. The survey also includes demographic, educational, occupational, social, and cultural variables corresponding to each participant.

Question 14 on the ISSP survey, which is the main question I consider, asks respondents to guess the shape of distribution in their country, but does not make any reference to wealth or income. The exact prompt of the question is shown in Figure 2.1. As a result the same criticism about such confusion applies to this data set as well. However, as Gimpelson and Treisman (2015) suggest, since the previous question on the survey (Question 13) asks directly about "pay" and "earnings," it is safe to assume most respondents interpreted the question as referring to income and not wealth.\(^1\)

While I use the ISSP data to get insights into perception of inequality across countries, I

\(^1\)Question 13 asks "Is your pay just? We are not asking about how much you would like to earn - but what you feel is just given your skills and effort. If you are not working now, please tell about your last job."
use Luxembourg Income Study (LIS) micro data in order to construct objective distributions of income for each country included in the ISSP survey. The LIS Database is one of the largest available income databases of microdata collected from multiple countries over a period of decades. These data are harmonized for cross-country comparisons, and the data set contains income (among many other variables) at both the individual and household level. 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 these discrepancies and harmonizes the surveys. In this study, I will choose individuals, rather than households, as the consumption unit due to the fact that I rely on individual characteristics such as age and occupation that are impossible to define for a households.\(^2\)

I use individual characteristics such as age, education, and occupation to define types or reference groups. I then find the objective income distribution within each of those groups. For instance, I find the income distribution of highly-educated individuals or those of age 20-29. Calculating the objective income distributions based on types allows me to have a better understanding of how individuals perceive income inequality and how they make inferences about the overall income distribution.

Lastly, since the ISSP survey was done in 2009, there are limits to the number of countries that show up in both LIS data and the survey in or around 2009.\(^3\) The number of countries that appear in both data sets is 21 countries.

### 2.3 Perception of Inequality Across Countries

The main question from the survey I use in this study is a question about the shape of the income distribution. In the question, shown in Figure 2.1, individuals are asked to

\(^2\)Other researchers have, nonetheless, used the age of the head of the household, which seems irrelevant.

\(^3\)For some countries, I use LIS data for 2010 instead of 2009 because data was not available for them in 2009.
choose one of five distributional shapes (each accompanied by a brief explanation), which best represents their country. The five diagrams range from a more unequal society to more equal one. The diagram labeled “Type A,” for instance, represents a society with a large percentage of people at the bottom of the distribution, a small middle class, and a relatively large group at the very top end of the distribution. The figure labeled, Type D represents a large middle class with a small and equal share of the population at the top and bottom end of the distribution.

Responses to the question are shown in Table C1 in Appendix C and are categorized by country. The table clearly shows that there is a large variations in the responses within each country. For instance, in countries such as Austria, the United States, Great Britain, the Philippines, Slovenia, and Germany answers are divided among distributions A to D. In the United States, while a majority of respondents chose distribution B (38.9%), the rest of the population was divided between distributions A, C, and D (17.1%, 15.0%, and 26.0%, respectively). Across countries, too, answers are surprisingly at odds with each other. While in countries such as Croatia, Lithuania, Russia, Ukraine, South Africa, and Argentina a majority of individuals chose distribution A, most Scandinavians chose distribution D. In
most western European countries, the United States, and China, distribution B was the most popular choice. Austria was the only country where the majority of individuals chose distribution C, and in New Zealand, the majority of answers were split between B and D.

There are large variations in answers if we group individuals based on their education, income, or their political affinity. I show this for the United States in Tables C2, C3, and C4 in Appendix C. Those with graduate degrees in the U.S. are more likely than any other group to have chosen distribution C. The same group is the least likely group to have chosen distribution A, which represents a more dramatic income distribution with a large portion of the population at the bottom and a very small middle and upper class. Among income groups, those with incomes higher than $80,000 were less likely to choose distribution A. Distribution B was the most popular choice for the low income group, while the high income group tended to choose D. Across the political spectrum, too, the answers varied. Table C4 shows the answers for different political groups in the United States with the groups ranging from those who strongly identify as Democrats to those who strongly identify as Republicans. Note that strong Democrats are twice as likely to choose distribution C than strong Republicans.

This pattern is different across countries, i.e. the percentage of respondents from each educational and income group that selected different distributions varies from country to country.\footnote{For the sake of space I have not provided the statistic here} Taking advantage of this large data set of nearly 55,000 individuals across the world, how can we compare the perception of inequality in each country to their corresponding objective measures? As I mentioned before, one approach used by researchers\footnote{See Niehues (2014) and Gimpelson and Treisman (2015).} has been to compare the respondents answers to a single metric such as the Gini coefficient. For instance, Gimpelson and Treisman (2015) use the corrected Gini calculation method offered by Van Ourti and Clarke (2011) to calculate a Gini coefficient for each of the five diagrams rep-
resented in the question. They assume that each of the seven bars constituting one diagram represents a distinct income class. One issue with this method is that the conversion of each diagram into a single number, i.e. the Gini coefficient, expunges some of the fundamental differences of the diagrams. For instance, while diagrams D and E represent fundamentally different societies, the Gini coefficients calculated in Gimpelson and Treisman are almost the same (0.20 versus 0.21 respectively). A similar approach is used in Niehues (2014). Furthermore, the method used in the paper is only suitable only when the group sizes belonging to each bin are equal. Lastly, there is a problem of arbitrary choice of average income within each group. Gimpelson and Treisman (2015) assumed that the income gaps between each two consecutive bars were the same and that the scaled average income in the bottom bar is 1 and in the top bar is 7. This is a strong assumption and an alternative assumption will give different Gini coefficients for the distributional shapes. The combination of these problems will make it hard to rely on the comparisons of subjective and objective inequality measures as suggested in these papers.

To overcome such shortcomings, I use a method of closeness of distributions in order to compare subjective and objective income distributions without the need for calculating an index such as the Gini coefficient. I find the shape of the income distribution in each country using LIS data. To have an income distribution comparable to the diagrams in the ISSP survey, I divide the income distribution into 7 equal-width bins and calculate the share of population in each category.\(^6\) Since extremely high and low income will result in

\(^6\)Niehues (2014) takes a different albeit arbitrary approach in grouping the income distribution into bins. She chooses bin 1 to include everyone whose income is below 60\% of the median income in the country (to represent a measure of poor household), bin 3 to be between 80\% to 110\% of the median income, bin 4 to include those with income between 110\% to 150\% of the median income (therefore, bin 3 and bin 4 together constitute the middle class), and bin 7 to include those with income higher than 250\% of the median income representing the very rich. Since the share of each country's population who fall into each group highly depends on the choice of the numbers in grouping, this could be a bigger problem as those definitions such as the poor, the middle class, the rich, etc. ranges significantly across countries. For instance, while in most Western European countries poverty is a relative concept and is linked to the median income, in the United States and a majority of the rest of the world the definition is absolute.
very few people in the very bottom and very top bins, I need to "trim" the distribution by "winsorizing" the top 5% of the income distribution, an exercise that is common in calculations of inequality.\footnote{For more on winsorizing see Daniels (2008); White (2015).} Figure 2.2 shows the objective income distributions in all the 21 countries. As is apparent, there is large variations in the shape of income distributions among the sample of countries depicted in the figure.

In what follows, I use the Bhattacharyya Coefficient (BC) in order to compare the shape of the income distribution in each country to the shape of distributions presented to respondents in the ISSP survey. Using the coefficient, I can find a \textit{closeness} index between perceived and actual distributions.

### 2.3.1 Bhattacharyya coefficient

For each diagram, I measure the size of each bin as a share of the addition of all the bins in each diagram.\footnote{Simply by using a ruler.} For instance, the relative size of the first bin in diagram A of the questionnaire relative to the overall size of all the bins is 49.07. Table C5 in Appendix C shows the frequency of the bins 1 to 7 in each distributional diagram in the questionnaire.

I now use BC to compare the amount of overlap between the subjective distribution $S$ and the objective distribution $O$ as follows

$$BC(S, O) = \sum_{i=1}^{7} \sqrt{S_i O_i}$$

where $S_i$ is the size of the $i$-th bin of distribution $S$, and $O_i$ is the size of the $i$-th bin of distribution $O$ (Bhattachayya, 1943). BC is equal to 0 if there is no overlap at all due to the multiplication by zero in every partition and equal to 100 if there is perfect correspondence between $S$ and $O$. BC is widely used in research of feature extraction and selection, image processing, and other statistical purposes.
Figure 2.2: Income distribution in the countries in the sample
Table 2.1: Normalized Bhattacharyya coefficient for the closeness of objective distributions in each country to different distributional diagrams from ISSP

<table>
<thead>
<tr>
<th>Country</th>
<th>Diagram A</th>
<th>Diagram B</th>
<th>Diagram C</th>
<th>Diagram D</th>
<th>Diagram E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>56.64</td>
<td>100</td>
<td>95.8</td>
<td>30.33</td>
<td>0</td>
</tr>
<tr>
<td>Taiwan</td>
<td>0</td>
<td>72.93</td>
<td>100</td>
<td>74.39</td>
<td>45.93</td>
</tr>
<tr>
<td>Czech Republic</td>
<td>0</td>
<td>72.1</td>
<td>100</td>
<td>79.35</td>
<td>52.44</td>
</tr>
<tr>
<td>Denmark</td>
<td>0</td>
<td>71.9</td>
<td>96.11</td>
<td>100</td>
<td>69.64</td>
</tr>
<tr>
<td>Estonia</td>
<td>46.63</td>
<td>97.72</td>
<td>100</td>
<td>31.38</td>
<td>0</td>
</tr>
<tr>
<td>Finland</td>
<td>0</td>
<td>80.56</td>
<td>100</td>
<td>56.38</td>
<td>12.28</td>
</tr>
<tr>
<td>France</td>
<td>33.37</td>
<td>100</td>
<td>99.31</td>
<td>48.05</td>
<td>0</td>
</tr>
<tr>
<td>Germany</td>
<td>57.86</td>
<td>100</td>
<td>94.52</td>
<td>30.83</td>
<td>0</td>
</tr>
<tr>
<td>Hungary</td>
<td>0</td>
<td>79.42</td>
<td>100</td>
<td>96.22</td>
<td>57.26</td>
</tr>
<tr>
<td>Iceland</td>
<td>0</td>
<td>82.93</td>
<td>100</td>
<td>48.8</td>
<td>5.33</td>
</tr>
<tr>
<td>Italy</td>
<td>3.67</td>
<td>85.63</td>
<td>100</td>
<td>60.55</td>
<td>0</td>
</tr>
<tr>
<td>Japan</td>
<td>65.85</td>
<td>100</td>
<td>87.19</td>
<td>22.52</td>
<td>0</td>
</tr>
<tr>
<td>Norway</td>
<td>0</td>
<td>77.62</td>
<td>100</td>
<td>91.24</td>
<td>47.85</td>
</tr>
<tr>
<td>Poland</td>
<td>0</td>
<td>73.75</td>
<td>100</td>
<td>74.75</td>
<td>41.23</td>
</tr>
<tr>
<td>Russia</td>
<td>16.48</td>
<td>84.88</td>
<td>100</td>
<td>35.94</td>
<td>0</td>
</tr>
<tr>
<td>Slovak Republic</td>
<td>0</td>
<td>76.6</td>
<td>100</td>
<td>97.31</td>
<td>70.45</td>
</tr>
<tr>
<td>Slovenia</td>
<td>0</td>
<td>82.56</td>
<td>100</td>
<td>99.33</td>
<td>69.85</td>
</tr>
<tr>
<td>South Africa</td>
<td>100</td>
<td>81.81</td>
<td>56</td>
<td>3.59</td>
<td>0</td>
</tr>
<tr>
<td>Spain</td>
<td>6.23</td>
<td>87.31</td>
<td>100</td>
<td>40.14</td>
<td>0</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>56.05</td>
<td>100</td>
<td>97.02</td>
<td>30.75</td>
<td>0</td>
</tr>
<tr>
<td>United States</td>
<td>72.26</td>
<td>100</td>
<td>90.75</td>
<td>25.15</td>
<td>0</td>
</tr>
</tbody>
</table>

As an example, we can calculate BC for the United States. The size of the bins as a share of the overall distribution in the United States, shown in Figure 2.2, are 28.3 (in the bottom bin), 25.0, 18.0, 11.0, 6.0, 3.5, and 8.0 (in the top bin). Therefore, the closeness of diagram A to the income distribution in the United States is calculated as

\[
BC(S, O) = \sum_{i=1}^{7} \sqrt{S_i O_i} = \sqrt{49.07 \times 28.3} + \sqrt{12.42 \times 25.0} + \sqrt{6.52 \times 18.0} + \sqrt{6.52 \times 11.0} + \sqrt{6.52 \times 6.0} + \sqrt{6.52 \times 3.5} + \sqrt{12.42 \times 8.0} = 95.27
\]

After this calculations, I normalize he BC scores such that the highest score is set to 100 and the lowest is set to 0. Table 2.1 presents this normalized BC measure for the closeness of the different distributional diagrams in the ISSP survey to the objective income distribution in each country.

It is worth mentioning that there are other methods that are used in calculating the
closeness of two distributions such as the chi-square measure and the Kullback-Leibler divergence measure. However, BC has the advantage of avoiding singularities when empty bins are compared. When empty bins are compared the denominator of the chi-square measure will be zero; in contrast, BC is insensitive to zero denominators. It is important to note that all these measures are ordinally equivalent. Since the relative closeness of distributions and not the absolute values are the main subject of this study I find that both chi-square and BC measures give the same rank ordering for the closeness of distributions, i.e., for instance, if the chi-square measure finds the diagram C to be the closest (among other diagrams) to the actual income distribution in the U.S., BC, too, will rank diagram C as the closest to the actual income distribution.

2.3.2 Are perceptions different?

Based on Table 2.1, distributions B and C are the closest to the objective distribution in most countries with the exception of Denmark (where the closest distribution is D) and South Africa (where the closest distribution is A). While South Africa is the only country where the distribution of income is closest to diagram A, there is virtually no country where the income distribution mimics diagram E. To answer the question of whether perceptions are different from measured inequality we can simply look at what percentage of respondents have chosen each of the distributions in the questionnaire. For instance, 58.7% of Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, Danish, 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CHAPTER 2. Misperceptions and Mismeasurements

53.6% of French, 35.4% of Germans, 38.5% of Japanese, 50.8% of South Africans, 41.9% of the British, and 38.9% of Americans, which constituted the majority in their countries, chose the closest distribution to the actual income distribution in their country. However, for countries such as Hungary, Poland, and Slovak Republic, 56.6%, 37.1%, and 43.6% of respondents, respectively, (again majorities in their countries) chose the least similar shape to the shape of income distribution in their countries. Only 6% of Hungarians selected the correct shape.

Since the BC measure gives us a non-binary closeness index, I can calculate an aggregate closeness index for each country by multiplying the share who selected each diagram by the normalized BC measure for each diagram. Figure 2.3 shows the score for the countries in our sample. The average closeness across all countries is 66.7%, a number smaller than the closeness score in the United States and the United Kingdom. The aggregate closeness seems to be highest in two Scandinavian countries, Denmark and Norway, and lowest among Eastern European countries.

In what follows I try to answer whether BC is different across individuals with different
In the first exercise, I divide individuals into three educational groups: low education, medium education, and high education.\footnote{Low education are those with no formal education, with lowest formal qualification, or above lowest qualification. Medium education are those with higher secondary completed or those above higher secondary level. High education are those with university degree completed or with graduate studies.} As shown in Figure 2.4, and not very surprisingly, respondents with higher education are better at guessing the correct income distribution. The gap in terms of BC between a highly educated person and someone with low levels of education is, on average, 14.5 points. After testing age as another explanatory factor, I find practically no difference in terms of normalized BC across different age groups.

In order to study other factors that can help explain the variations in answers across all countries, I employ regression analysis with country fixed effects. I first use normalized BC as the dependent variables as shown in the first two columns of Table 2.2. On the right hand side of the regression, I use factors such as gender, self-identified income decile, education, and age as well as country fixed effects. This is shown in model (1). I find that those with high levels of education and at the top deciles of the income distribution are the most likely to correctly guess the shape of the income distribution in their country. In model (2)
I add factors such as political affinity, occupational groups, and whether the person lives in urban area as explanatory variables.\footnote{The indication of whether the individual is politically on the left, center, or right is done by surveyors based on individuals’ party memberships.} My intuition is that individual’s political affinity may affect their perception of the income distribution. Additionally, their perception of inequality is likely affected by people around them, so it seems important to study factors such as occupational group or geography.\footnote{Unfortunately, I do not have more specific geodata beyond a dummy variable indicating whether the person lives in rural or urban areas.} I find that those on the left are slightly better than those in the center or right in guessing the shape of the income distribution. I do not find any significant differences across the occupational spectrum, except for those in professional occupations. Moreover, location does not seem to be an important variable.

Regression (3) uses a binary variable for whether the person guessed the correct distributional diagram in their country. Therefore, in the United States, it is equal to 1 for a person who chose distribution B and 0 for everyone else. The coefficients on education categories are the opposite of the ones in Regressions (1) and (2). This may be due to the heterogeneity in choosing diagrams other than the one that is the closest to the shape of the income distribution in a country. The dependent variable in Regression (3) does not distinguish between getting a \textit{wrong} answer and a \textit{very wrong} answer. The results in this column are similar to the binary approach used in Gimpelson and Treisman (2015). Note that Regressions (1) and (2) fit the data better compared to Regression (3). In all three regressions, I control for country fixed effects.

One possible reason for why characteristics such as income and education are important determinants of correctness in choosing the shape of income distribution is the notion of reference groups. The socio-economic or demographic group an individual belongs to may indeed shape their perception of inequality. In the next section, I explore the role of reference groups by defining reference groups based on education, age, and gender.
### Table 2.2: Regression of BC and a binary score for closeness of objective and subjective distributions on individuals’ characteristics

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>BC</td>
<td>BC</td>
<td>Binary Score</td>
</tr>
<tr>
<td>Female</td>
<td>0.0978</td>
<td>-0.2346</td>
<td>-0.0078</td>
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<td>Education</td>
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<td></td>
<td></td>
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<tr>
<td>Medium</td>
<td>1.9497***</td>
<td>1.4237**</td>
<td>-0.0127</td>
</tr>
<tr>
<td>High</td>
<td>3.2849***</td>
<td>1.9975**</td>
<td>-0.0399***</td>
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<td>Income Decile</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>2nd</td>
<td>8.0994***</td>
<td>9.9872***</td>
<td>0.0535*</td>
</tr>
<tr>
<td>3rd</td>
<td>6.4969***</td>
<td>6.3877***</td>
<td>-0.0180</td>
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<tr>
<td>4th</td>
<td>9.4803***</td>
<td>8.4556***</td>
<td>-0.0032</td>
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<tr>
<td>5th</td>
<td>12.9066***</td>
<td>11.6019***</td>
<td>0.0189</td>
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<tr>
<td>6th</td>
<td>11.5352***</td>
<td>10.3949***</td>
<td>0.0046</td>
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<tr>
<td>7th</td>
<td>12.3421***</td>
<td>11.5086***</td>
<td>0.0027</td>
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<td>8th</td>
<td>12.4439***</td>
<td>12.2454***</td>
<td>0.0005</td>
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<td>9th</td>
<td>7.8354***</td>
<td>6.1418**</td>
<td>-0.0369</td>
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<tr>
<td>10th</td>
<td>9.0288**</td>
<td>5.1720</td>
<td>-0.0517</td>
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<td>Age</td>
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<td>30- to 39-year olds</td>
<td>0.5682</td>
<td>1.7409*</td>
<td>0.0051</td>
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<tr>
<td>40- to 49-year olds</td>
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<td>-0.0352</td>
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<tr>
<td>50- to 59-year olds</td>
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<td>-0.6259</td>
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<td>60- to 69-year olds</td>
<td>0.2543</td>
<td>1.3519</td>
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<td>Political Affinity</td>
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<tr>
<td>Left</td>
<td>1.8662**</td>
<td>0.0097</td>
<td></td>
</tr>
<tr>
<td>Right</td>
<td>-1.2064*</td>
<td>-0.0086</td>
<td></td>
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<td>Occupation Groups</td>
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<tr>
<td>Professionals</td>
<td>3.2088***</td>
<td>0.0266*</td>
<td></td>
</tr>
<tr>
<td>Technicians &amp; Associate Professionals</td>
<td>1.9448*</td>
<td>0.0219</td>
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<td>Clerical Support Workers</td>
<td>1.5669</td>
<td>0.0169</td>
<td></td>
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<tr>
<td>Service &amp; Sales Workers</td>
<td>0.5961</td>
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<td></td>
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<tr>
<td>Agricultural, forestry &amp; Fishery Workers</td>
<td>-0.3895</td>
<td>-0.0214</td>
<td></td>
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<td>Crafts &amp; Related Trades Workers</td>
<td>-0.4209</td>
<td>-0.0233</td>
<td></td>
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<tr>
<td>Operators &amp; Assemblers</td>
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<td>-0.0007</td>
<td></td>
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<td>Elementary Occupations</td>
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<td></td>
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<td>Armed Forces</td>
<td>-2.1983</td>
<td>0.0773</td>
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<tr>
<td>Lives in Urban Areas</td>
<td>-0.6428</td>
<td>-0.0053</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<td>52.5935***</td>
<td>0.2862***</td>
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<td>Observations</td>
<td>19840</td>
<td>13964</td>
<td>14680</td>
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<td>Adjusted $R^2$</td>
<td>0.175</td>
<td>0.146</td>
<td>0.117</td>
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</table>

*Note:* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each regression model contains country fixed effects. Reference groups are male, those with low levels of education, age group 20- to 29-year olds, those at the center of the political spectrum, those in managerial jobs, and those living in rural areas. BC is normalized. The binary score is a score that is 1 if the individual guessed the closest diagram to the income distribution in her country and 0 if she selected any other diagram.
2.4 Comparative Reference Groups and Perceptions of Inequality

Individuals’ perception of inequality are significantly correlated with their relative position within their reference groups. The term “reference group” is defined as the group of individuals to which one compares oneself to for the purpose of self-appraisal. Roper (1940) was probably the first to introduce the idea of reference group. He argued that two people of equal income living in different areas may have different relative statuses depending on the incomes of their associates. He attempted to classify respondents by economic status. Hyman (1942) was first to delve into the empirics of reference groups in his seminal work, *The Psychology of Status*.

The concept of reference groups is crucial for studies of inequality. Milanovic (2007) notes that “there is no point in studying inequality between two groups that do not interact or that ignore each other’s existence.” Sen (2000) also argues that the focus of inequality studies is “on the utilities of the individuals only in that group [the reference group], without any direct note being taken of the utilities of others not in the group.” Cruces et al. (2013) point out that the perceptions of where individuals stand in the distribution of income are significantly correlated with their relative position within their reference groups. Surveys that ask whose income the respondents are most likely to compare their own income with suggest that colleagues, friends, and family members are the most important reference groups. Reference groups are usually defined on the basis of geographical, education, and demographic groups or even friends and family. An individual’s reference group could also be one’s own status in the future.

So what is the role of reference groups in perceptions of inequality? According to Kahneman and Tversky (1972), subjective assessments are statistical inference problems in the

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12 See for instance Clark and Senik (2010).
presence of limited information. In other words, individuals observe the income of others in their reference group, which is a sub-sample of the overall population, and then infer the income distribution in the overall population. Cruces et al. (2013) claim that agents will still be able to arrive at consistent estimates of the entire distribution "by factoring in the selection process of the non-representative sample of incomes that they observe." Based on their model, an agent $i$ can infer information about the distribution of income in the society, $f(.)$, or some statistic of the distribution such as the mean, median, or agents own ranking, using information about observed incomes. An individual with income $x_i$ estimates the distribution of income in his or her reference group through the following identity

$$f(x_i | i \in S_j) = \frac{Pr(i \in S_j | x_i) f(x_i)}{P_{S_j}}$$

where $Pr(i \in S_j | x_i)$ is the probability that individual $i$ belongs to the reference group $S_j$, given that his or her income is $x_i$; $f(x_i)$ is the income distribution for the entire population; and $P_{S_j}$ represents the population share of group $S_j$, which may also be written as $Pr(i \in S_j)$.

Based on the Bayes rule, individuals’ inference of the income distribution is then

$$f(x_i) = f(x_i | i \in S_j) \frac{P_{S_j}}{Pr(i \in S_j | x_i)}$$

In other words, the inference about the income distribution of the population requires knowledge about the relative size of the reference group, knowledge about the selection process leading to the formation of the reference group, and the ability to make probability judgments. Imperfection in any of this information will result in biased perceptions about how income is distributed among the general population. An implication of this discussion is that individuals perceive inequality in the overall population by virtue of observing inequality in their reference group.

What determines who individuals compare themselves to? D’Ambrosio and Clark (2015) argue that one of the most important drawbacks in the literature on well-being and inequality
is that the reference groups are usually defined on the basis of conjecture and that there have not been thorough studies attempting to identify what the most likely reference group is. Other than a few experiments, we can only rely on surveys to understand what reference groups individuals are more likely to compare themselves to. In most studies, reference group definitions are imposed by the researcher (Clark and Senik, 2010). Senik (2009), Knight et al. (2009), and Clark and Senik (2010) use surveys in which people are explicitly asked about their reference groups. People in the same locality, colleagues, former schoolmates, and family members constitute most respondents’ reference groups.

In this essay, I take an analytic approach to studying reference groups. Having defined a way of finding the degree of similarity between perceived distributions and the objective distribution in each country, I can replicate the analysis by finding an objective distribution for specific reference group. For instance, I can divide the population into three education groups and look at how similar a respondent’s answer is to the distribution of income within her education-based reference group. I do this analysis using three different types of reference groups: education, age, and gender. A better approach would be to find reference groups based on interactions of the three types mentioned above. However, due to the small sample size in each group, the statistical power of the results will be severely diminished.

It is also important to note that reference groups are likely to be endogenous and to depend on respondent’s age, gender, education level, marital status, labor market status, etc. (Clark and Senik, 2010). Even the concept of reference group for an individual is dynamic: our reference group might change as we age, earn a higher income, migrate, get married, etc. Hyman (1942) suggests that reference groups “are chosen by virtue of similarity to the subject, proximity to him in life situation, or as the result of subjective facts which facilitate such comparisons” and uses the term “affinity” for such similarities. Note that reference groups can also be chosen by virtue of “contrast” as opposed to affinity.\footnote{It might be that individuals in the contrast group are so different from the person himself that they}
and Knell (2004) suggest that the disparity in reference groups across the population reflects diverse coping strategies such as self enhancement and self improvement.

2.4.1 Education-Related Reference Groups

In both LIS and ISSP data I categorize education into three groups: low, medium, and high education.\(^{14}\) I first find the income distribution within each education group for each country. Studies have shown that inequality varies across different demographic and socio-economic groups.\(^{15}\) Education is not an exception and the distribution of income is different depending on the education group, at least in most countries. Figure B1 in Appendix B shows the distribution of income for education groups defined above across a selected sample of countries. These distributions are quite different across education groups (see Iceland, France, and South Africa).

I then find the Bhattacharyya coefficient that measures the distance between respondent’s chosen diagram and the income distribution in their education group. The first question is whether education is a relevant reference point. The second question is who is more likely to compare themselves to their education-related group. To answer these questions, I first compare the overall BC and the education BC. The cross-country variations in the difference between education-related BC and overall BC is shown in Figure 2.5. Note that the larger the number, the more important education is as a reference group. Not surprisingly, there are variations both at the individual and country levels. In Iceland and Finland, respondents’ answers tend to be better aligned with the distribution of their education reference than

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14 The group denoted as low education included individuals with less than secondary education completed (never attended, no completed education or education completed at the ISCED levels 0, 1 or 2). The group denoted as medium education includes those with secondary education completed (completed ISCED levels 3 or 4). Finally the group with high education consists of those with tertiary education completed (completed ISCED levels 5 or 6).

15 For a comprehensive analysis of inequality across cohorts in the United States see the first chapter of this dissertation.
they are with the overall distribution. For South Africa and France, answers are closer to the overall income distribution. One way to interpret these results is to assume that in countries with a higher BC for education-related reference groups such as Iceland and Finland, education-related reference groups are more important. It is interesting that in the United States and the United Kingdom, respondents’ perceptions are equally similar to both education-related and overall distributions.

One might argue that in countries with more access to higher education individuals may compare their income only to those in their education group. One explanation is that in countries with higher (more equal) access to education individuals may feel more responsible for their education (lack of education) and, therefore, are more likely to compare themselves to others in their education-related reference group as opposed to the whole population. To test this hypothesis, I compute the correlation between access rate of higher education\textsuperscript{16} and the difference between education-related BC and overall BC. The correlation equals 0.39 and is statistically significantly positive at 0.10 significance level ($z = 1.64$). Figure 2.6 show a

\textsuperscript{16}Data on access rate by country come from the \textit{Education Indicators in Focus} report by OECD. February 2012. \url{http://www.oecd.org/education/skills-beyond-school/49729932.pdf}.
Figure 2.6: The relationship between the importance of education-related reference groups and access to higher education

scatter plot representing this correlation.

Let us now investigate the differences among individuals, i.e., who is more likely to guess the distribution of income in their education-related reference group. I argue that those who are more likely to compare themselves to others in their education group are also likely to think that everyone has equal access to education and if there is any gap in education it is just. In the ISSP questionnaire, there are three statements related to this in which the respondent is asked to indicate to what extent he/she agrees or disagrees with the following statements: (i) [your country] only students from the best secondary schools have a good chance to obtain a university education, (ii) in [your country] only the rich can afford the costs of attending university, (iii) in [your country] people have the same chances to enter university, regardless of their gender, ethnicity, or social background. For the first and second statements, across roughly 20,000 respondents in 21 countries, those who agree or strongly agree that there is no equal access to post-secondary education in their country are more likely to accurately perceive the overall income distribution and those who disagree or strongly disagree are more likely to have their perception based on their education group.
CHAPTER 2. Misperceptions and Mismeasurements

Table 2.3: The difference between education-related BC and overall BC versus beliefs about educational opportunities

<table>
<thead>
<tr>
<th>Statement</th>
<th>Strongly Agree or Agree</th>
<th>Neither Agree nor Disagree</th>
<th>Strongly Disagree or Disagree</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>In [your country] only students from the best secondary schools have a good chance to obtain a university education</td>
<td>-7.1</td>
<td>-3.5</td>
<td>-0.5</td>
<td>0.000</td>
</tr>
<tr>
<td>In [your country] only the rich can afford the costs of attending university</td>
<td>-7.2</td>
<td>-3.1</td>
<td>0.2</td>
<td>0.000</td>
</tr>
<tr>
<td>In [your country] people have the same chances to enter university, regardless of their gender, ethnicity or social background</td>
<td>-1.9</td>
<td>-3.6</td>
<td>-4.9</td>
<td>0.000</td>
</tr>
</tbody>
</table>

This is evident in the third statement as well, where the same question is framed positively rather than negatively. The results are shown in Table 2.3.

The findings in Table 2.3 are tied to an equality of opportunity approach to inequality. If individuals are likely to think of differences in access to education as just and mainly due to effort, then they are less likely to compare themselves to groups with higher levels of education. In countries where individuals feel there is equality of opportunity, there may be more feeling of responsibility for lack of education. In this regard, education may only be individuals’ normative reference group\(^\text{17}\) and not their comparative reference group.

Given the regression results shown earlier in Table 2.2, it may be expected that political affinity is correlated with the likelihood that a respondent identifies more with the overall distribution than the education-related distribution. Indeed, I find that, as shown in Figure 2.7, across the political spectrum, perception of those on the left are more likely to be based on the overall distribution than on the education-related distribution. The difference between the left and the right is 8.2 points on the normalized BC scale.

\(^{17}\)A normative reference group according to Kelley (1952) is a reference group that an individual does not necessarily use for the purpose of self-appraisal but rather a group that the individual aspires to be a member of. An individual is not necessarily a member of her normative reference group.
2.4.2 Age-Related Reference Groups

Rawls’s theory of original position behind the veil of ignorance (Rawls, 1971) can be useful in characterizing just and unjust inequalities. The advantage of the veil of ignorance is to force us to think about the problem of social justice through an impartial lens, minimizing our reliance on subjective morals and instead rely solely on rational self-interest. From the Rawlsian perspective, income inequality due to differences in experience, typically measured in terms of age, can be justified since individuals typically expect to receive higher incomes as they age. This is contrary to inequalities due to gender and race, characteristics that are not subject to change during a person’s lifetime. Stigler (1960) states that “if the men in an occupation were of identical ability and worked equal periods and with equal intensity, the present value of their lifetime earnings would be equal (chance factors aside), but their earnings in any one year... would display substantial dispersion.”

There have been few attempts to find the impact of age distribution on inequality (Paglin et al., 1977; Osberg, 2003). All these studies show that objective measures of inequality such

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18However, inequality due to differences in age would be unwanted or unjust in highly immobile societies.
Figure 2.8: Cross-country differences between age-related BC and overall BC

as the Gini coefficient or the Theil index would be smaller if we disregard income differences due to age. Individuals’ perception of inequality can also be influenced by their age and the distribution of income within their age cohorts.\footnote{The definition of age cohort varies from study to study. While some consider individuals of the same exact age as a cohorts, others consider 2-, 5-, or 10-year intervals as a cohort.} One could argue, therefore, that since younger individuals typically expect to receive higher wages as they age, their reference group may be limited to individuals in their own age cohort.

To study whether age-related reference groups are important in an individual’s perception, I examine the distribution of income in the individual’s age cohort using LIS data and compare it to their choice of distribution in the ISSP data. I define age cohorts as individuals in 10-year intervals. The shape of distributions based on age groups are shown in Figure B2 in Appendix B for a sample of four countries. Inequality within age cohorts varies based on the age of the cohort across most countries. Similar to education-related reference groups, it is interesting examine at where age-related reference groups are important. Figure 2.8 shows that this measure varies across countries from its lowest value in Slovenia (-13.8) to its highest value in Iceland (16.4).
In his infamous book, *The Study of Man*, Linton (1936) suggests that societies with a high rate of social mobility (in his terminology high rate of change) exhibit little difference between individuals’ objective and subjective standing. If societies function smoothly and younger individuals may well expect to earn higher incomes as they age, one would expect age-related reference groups to have an important impact on shaping individuals’ perception. I examine this by finding the relationship between the importance of age-related reference groups and mobility. The mobility data come from Corak (2016) who calculates the ”intergenerational earnings elasticity,” which is the association between the percentage difference in earnings in a child’s generation and the percentage difference in their parent’s generation. A more mobile society has a lower earnings elasticity. Figure 2.9 shows the association between the importance of age-related reference groups and mobility across a sample of countries (where mobility data was available). The correlation coefficient is equal to -0.45, and is statistically significantly negative at 0.10 significance level ($z = 1.59$). The interpretation for the negative correlation is that where mobility is higher individuals’ perception of inequality is less likely to be shaped by the inequality in the overall population.
Figure 2.10: The importance of age-related reference groups across age groups

Furthermore, Konrath et al. (2011) find that younger cohorts are more likely to think that they are above the average. This can be attributed to the fact that younger people may compare themselves to narrower age groups. As individuals get older, their reference group expands. For an individual from the age cohort of 40- to 49-year olds, the reference groups may include the individual’s age group and those below. I find evidence of this claim in my data. After calculating the age-related BC, I find that the degree to which age-related reference groups are important is stronger for younger individuals across all countries. This is shown in Figure 2.10. As individuals get older, the likelihood of referencing the overall distribution increases.

2.4.3 Gender-Related Reference Groups

Income comparisons are said to be to those whose income generating attributes are similar (van de Stadt et al., 1985). If this is the case, in addition to education and age, we should
look at gender groups. Although it is merely an assumption that women (men) compare themselves to other women (men), in some developing countries and in countries where gender disparities are more pronounced, it might indeed be the case that gender is a defining factor in shaping perceptions. There is, however, no hard evidence that this is indeed the case. Ferrer-i Carbonell (2005) find that, in the case of Germany, gender is not an important reference group.

I first find the distributional diagrams for each gender group across all countries using LIS data, and similar to before, I calculate the degree of similarity between the subjective and objective distributional diagrams. The shapes of distributions for gender groups are shown for a few selected countries in Figure B3 in Appendix B. Note that in Iceland and South Africa\textsuperscript{20}, there is not much difference between the distribution of wages of men and women. In the United States and France, however, the two distributions are quite different. After finding the BC measures between distributions, I calculate the difference between gender-related BC and overall BC that reflects the importance of gender-related reference groups. Figure 2.11 shows this difference measure for each country.

If the difference between gender-related BC and overall BC shows the importance of gender reference groups, then why is it that it varies notably from country to country? One conjecture is that in countries where gender disparities are more accepted, gender reference groups become a significant predictor of perceived inequality. I use the Gender Inequality Index (GII) by the United Nations Development Programme (UNDP) in order to find whether such disparities are correlated with the importance of gender-related reference groups.\textsuperscript{21}

Using GII, I indeed find a positive correlation between the two measures, however, the correlation is not significantly positive ($z = 1.18$). The scatter plot for a sample of countries

\textsuperscript{20}The country abbreviation for South Africa is ZA.

\textsuperscript{21}GII measures gender inequalities in three different dimensions: reproductive health, empowerment, and economic status. More information about the index can be found here http://hdr.undp.org/en/content/gender-inequality-index-gii
Figure 2.11: Cross-country differences between gender-related BC and overall BC (for which data exist) is shown in Figure 2.12.

2.5 Limitations of the Analysis

First and foremost, similar to most inequality studies that rely on surveys, my analysis suffers from underrepresentation of the top incomes. This is a problem with both data sets that are used in this essay. Chambers et al. (2014) find that most of the distortion in guessing the income distribution comes from the large overestimation of the top 1%. Therefore, one could argue that part of the mismatch between perceptions and objective measures is due to the fact that ISSP respondents’ perception may in fact be shaped by the existence of the 1% or the media attention given to them.

Second, an independent definition of reference groups based on education, age, and gender may not be accurate. One can argue that an individual’s reference groups may be a combination of the factors mentioned above. For instance, it is more accurate to define comparative reference groups as people in one’s education, age, and gender groups. I have ignored such definitions to avoid small sample sizes in each group.
A third, and yet important, caveat is the fact that in ISSP, like most other surveys of subjective inequality, there is no specifying whether the question refers to wealth, before-tax income, or after-tax income. As I discussed in Section 2.1, this can plague the results of any study on the subject. Related to this is the fact that I use personal-level data for reasons mentioned in Section 2.2. It is worth mentioning that a household approach to welfare analysis is preferable to an approach based on personal income since individuals’ perception of inequality and where they stand in the income distribution is likely to be affected by overall family income and transfers (including both monetary and in-kind transfers) minus taxes.

Lastly, there are other types of reference groups to explore that are not considered in this study. One of these is reference groups based on location. Although common sense suggests that reference groups based on individuals’ locations are important, the idea has been picked up by only a few researchers. Luttmer (2005) uses reference groups based on geography to show that, after controlling for own’s income, average income of the local area is negatively correlated with respondents’ life satisfaction. A limitation of the data I use is the absence
of any geodata to calculate income inequality within specific locations.

2.6 Concluding Remarks

In some ways, perceptions of inequality are just as as important as the official statistical measures we use such as the Gini coefficient and income shares. Perceptions are shown to impact happiness, job satisfaction, and support for redistribution. If perceived inequality is important, the next question is whether there are any discrepancies between perceived inequality and objective inequality measures. Numerous studies have argued that the inconsistencies between perceived inequality, usually measured through surveys, and statistical measures of inequality are the result of individuals’ misperception of inequality.

I introduce a new method of deducing individuals’ perception of inequality from survey results from the International Social Survey Programme (ISSP) in which individuals across more than 40 countries are asked about their perception of the shape of income distribution in their society. I introduce a measure of closeness between the distributions and find that although there are inconsistencies between objective and subjective inequalities, in most countries a majority of respondents choose the closest distribution to the income distribution in their society. For instance, 58.7% of Danish, 53.6% of French, 35.4% of Germans, 38.5% of Japanese, 50.8% of South Africans, 41.9% of the British, and 38.9% of Americans, which constituted the majority in their countries, chose the closest distribution to the actual income distribution in their country. However, the difference between subjective and objective measures varies across countries. For instance, only 6% of Hungarians selected the correct shape. I also find that characteristics such as income level and education can be important factors explaining variations in correctness across individuals.

In this essay, I address whether perceptions of inequality are shaped by observing the overall population or only specific subgroups known as reference groups. Reference groups
and an individual’s perception of inequality are intrinsically related. However, the definition of reference groups in the literature has been mostly arbitrary. One can define factors such as age, gender, education, geography, friends, etc. as factors defining reference groups. In this essay, I take a more analytical approach to reference groups. I test whether answers to a question on the ISSP are closer to overall distributions or distributions based on education, age, and gender. I find that perceptions are indeed affected by reference groups. Across countries, I find that education is a more important reference group where access to education (more specifically to higher education) is better. In addition, I find that age-related reference group are more important in societies with higher intergenerational mobility. Lastly, there is some tentative evidence that gender reference groups are more pronounced in countries where gender disparities are more dire and maybe more accepted.
Chapter 3

Educational Aid Policy and Inequality: The Case for Merit- and Need-Based Aid

3.1 Introduction

Student aid in higher education is designed to increase access and, therefore, efficiency. Such aid, administered by the federal government, states, local governments, universities, or other institutions can be awarded on the basis of financial need, academic merit, or a combination of both. The need-based aid targets students with a low ability to pay for their educational expenses measured in terms of Expected Family Contribution (EFC). On the other hand, merit-based aid is designed to benefit students with strong academic backgrounds as demonstrated by factors such as their high school GPA or SAT scores. A closer look at higher education policies in the United States reveals that merit-based aid tends to be favored over need-based aid based and that merit-based policies are frequently favored on the grounds that it increases access for those who are more likely to persist and
succeed in higher education. The stronger emphasis placed on merit-based aid has diverted resources away from students who struggle financially towards those who have greater access to resources.

While most researchers have studied how different aid policies affects schooling decisions, there is a void of research on distributional impacts of different educational aid policies. If government has a fixed amount of resources to distribute, one of the main questions facing policymakers is to choose a policy (or a combination of policies) that minimizes wage disparities. This essay is one of the first attempts to theoretically and empirically analyze how different aid schemes shape the distribution of wages and inequality.

The framework is inspired by a model suggested by Autor et al. (2003) and Acemoglu and Autor (2011), in which the assignment of tasks is determined by labor shares of skill groups, technologies, and task demands. Workers are not endowed with skills but they acquire them based on their endowments. Skills do not produce outputs alone but are used in production when applied to tasks in the economy. Contrary to traditional models such as the one introduced by Tinbergen (1974, 1975), in the model presented in this essay, the assignment of tasks to skills is endogenous rather than exogenous and is based on an individual’s productivity relative to others’.

The advantage of my model is that it allows for a range of skills instead of simply including the efficiency units in human capital models. The model endogenously allocates skills to tasks while changes in education policy change those allocations. In this regard, the distribution of wages is determined through task allocations. The model allows a comparative static analysis of the effect of different educational aid regimes on inequality and productivity under the assumption that financial aid policy changes the labor shares of various groups.

I use National Longitudinal Survey of Youth 1997 (NLSY97) data in order to calibrate the model. I use these data because of the existence of some ability tests in the data set. If the

\[ \text{See Katz and Murphy (1992) and Card and Lemieux (2001) for more on these types of models} \]
distribution of abilities and family resources are known to policy makers, the model provides a framework for an inequality-minimizing solution to educational aid distribution, especially in the context of need-based aid, merit-based aid, or policies based on a combination of both.

Section 3.2 discusses the trends in educational aid policy in recent decades in the United States and reviews the existing literature on comparing different aid regimes. In Section 3.3, I introduce the theoretical model of skills and tasks and a framework for finding the Lorenz curve in a society that consists of individuals with different ability and access to resources. In Section 3.4, I perform a comparative static analysis of the effect of different educational aid regimes on the shape of the wage distribution and I calibrate the model. Sections 3.5 and 3.6 discuss the limitations of my approach and some concluding remarks, respectively.

### 3.2 Background

Among the explanations of the disparities in income among individuals, human capital may receive the most attention. In the early human capital literature, labor economists such as Becker (1964) and Mincer (1958) emphasized the role of primary, secondary, and post-secondary investments in human capital in explaining variation in wages. Across OECD countries, 73 percent of people without an upper secondary education are at or below the median level of earnings compared to only 27 percent of university graduates. Evidence suggests that the ratio of the wage of the median worker with a college degree to the wage of the median worker with a high school diploma has increased from roughly 1.3 in 1979 to 1.8 in 2013 (Figure 3.1). Increasing returns to education during the past decades has made higher education a major determinant of income distribution. Krueger et al. (2002) speculates that measured differences in education (and experience) account for about one third of the wage variability. The college premium is at a historically high level, and if children from low income families face credit constraints with regards to higher education
or have distorted college decisions due to risk aversion, it will have a huge influence on the future distribution of income.

Current research is inconclusive on how much of this inequality in college attainment is associated with credit constraints and the role of family resources.\(^2\) Credit constraints that prevent disadvantaged students from pursuing higher education reinforce inequality in early childhood and adolescence. In the past few decades, published tuition and room and board costs in the United States have increased for students of almost all income backgrounds. This has been compounded with a decline in federal and state government aid in real values and an increase in the share of finances borne by families. A report by the College Board shows that the average tuition and fees has increased by 210 percent in private non-profit four-year colleges and by 305 percent in public four-year colleges between 1980 and 2015.\(^3\) The enrollment gap between different racial and economic groups has been large and steady and it

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\(^2\) For an extensive review of the literature see Heckman et al. (2004).

\(^3\) Tuition and Fees and Room and Board over Time, 1975-1976 to 2015-2016, Selected Years, Table 2A, The College Board, Annual Survey of Colleges; NCES, IPEDS data.
is often argued that the hype in college enrollment during recent decades comes mostly from more advantaged students. In fact, enrollment rates for students with low-income parents has decreased by almost 10 percentage points during 2008-2013. Equal access to higher education makes it easier for people in the lower bottom of the income distribution to climb the income ladder and close the wage gap. Although it is hard to draw any immediate causal inference between access to higher education and inequality, it is easy to observe a positive correlation between the two as shown in Figure 3.2. The figure shows the correlation between out-of-pocket after-tax college expenditures (as a percentage of median income) versus the Gini coefficient for selected OECD countries.\footnote{The educational expenses data are from a 2010 report by Higher Education Strategy Associates (Usher and Medow, 2010).} It is apparent that more equal societies have lower out-of-pocket costs as a percentage of median income.

One can argue that higher demand for colleges, the almost steady number of higher
education institutions\textsuperscript{5}, and the decrease in inflation-adjusted educational aid provided by
the federal government and the state governments are responsible for the substantial run-up
in the out of pocket tuition expenditures in the United States in recent decades. While
tuition has soared for all students regardless of their family background, the increase in
tuition has been mostly borne by those coming from low-income families. McPherson and
Schapiro (1999) report that even between 1986 to 1992, net tuition increased by 163 percent
for low-income students, by 90 percent for students from middle-income families, and by 57
percent for those coming from more affluent families. The increase in net tuition for low
income students has been more dire for public institutions.

With the implementation of massive public programs such as the G.I. Bill in 1944 and Pell
Grants in 1972, higher education, which once used to be limited to the wealthy, became more
accessible and admission was no longer heavily based on family status. Higher education
served low-income students as a way to catch up with the privileged. But since then, it is
hard to argue that higher education continues to be a weapon against inequality. Therefore,
in order to better understand what has changed that has aggravated educational inequality
among youth, we will take a look at the changes in educational policy in the United States
during this period.

Pell grants are probably the most important example of need-based aid. Prior to Pell
grants, the aid was channeled to institutions rather than students. Pell grants were intro-
duced by Senator Claiborne Pell in the early 1970s, and by providing a minimum financial
aid package, they ensured that low-income students. In 1978, the federal government in-
creased the number of students who were awarded Pell grants but they failed to increase the
total funding going to the program resulting in a decrease in the average grant. In 2005,
however, while the average grant increased, stricter conditions were imposed resulting in a

\textsuperscript{5}According to the report by Department of Treasury, in the past two decades, the total number of non-
profit degree-granting institutions has remained steady at about 3,300, equally divided between public and
private institutions.
smaller pool of qualified applicants. Since about the same time, the number of applicants for the grant has been increasing.

In response to the increase in applicants, the federal government has tried to reform the student loan program in order to save more to support the Pell grant program. The purchasing power of Pell grants, which are the foundation of need-based federal aid programs, has plummeted in recent decades. The Pell grants, which once covered 91% of tuition and fees at a public university in 1993-1994 and the entire tuition cost in 2001-2002, covered only 63% of tuition and fees at a public university in 2013-2014. Figure 3.3 shows the trend in purchasing power of the federal Pell grant since 1993. The inflation-adjusted Pell grant started deviating from tuition costs in 2000 and since then it has been far behind costs. The decrease in the real value of Pell grants has been so drastic that as McPherson and Schapiro (1999) suggest, "virtually no student in private higher education and relatively few in public higher education have their full need met by Pell [grants]."

Merit aid on the other hand is awarded contingent upon academic performance. Although most of the educational aid by the federal government is on the basis of need or a combination of need and merit, the main sources of merit aid are states, institutions, and private entities. According to Dynarski (2004a), although the majority of scholarships based on merit still come from institutions, more recently, states have also gotten involved with awarding merit-based aid with a degree of performance thresholds. In general, merit-based aid funded by institutions are more generous in terms of the amount but also more restrictive in terms of eligibility requirements.

While the main objective of merit-based scholarships is to encourage high-performers regardless of their family backgrounds, other programs such as tuition tax credits directly

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6 At a private university, the percentage of tuition and fee covered by Pell grants declined from 21% in 1993-1994 to 19% in 2013-2014. Also, the percentage of tuition, fee, and room and board covered by Pell grants declined from 37% to 31% at public universities and from 15% to 14% at private universities.

7 For example, the Arkansas Promise Scholarship in the state of Arkansas currently only requires a minimum GPA of 3.0.
benefit upper and upper-middle classes. A tuition tax credit is a reduction in the taxes one owes, usually dollar for dollar, for the amount one spends on college tuition. However, since the introduction of tax credits, opponents of the policy have argued that since almost one third of American do not owe taxes, the policy only benefits middle- and high-income families rather than those in need. In order to respond to such criticism, tax credits are changed to refundable ones that will benefit those who do not pay taxes as well. Although there were attempts to expand the educational tax credit to the low income families, such as the American Opportunity Tax Credit in 2009, most critics believe that tax credits were not the best policy to fight inequality in access to higher education. In most cases, the benefit from the tax credit is larger the bigger is the income of the person. Another criticism directed toward tax credits is that they are delayed benefits, i.e. there is no immediate realization of the benefits since families have to wait almost a year in order to see the benefits of the policy. It is also argued that these policies are complicated. Dynarski (2004b) finds that the advantages of the 529 and Coverdell policies (another form of federal educational tax credit)
that were introduced in 1996 and 1997, respectively, rise sharply with income.

All these trends in educational policy remind us that despite attempts initiated in the mid-1960s to help children of lower income families with college access, changes in policies during recent decades have contributed to less equal access to higher education in the United States. Inequality in enrollment is not the only aspect of educational inequality. There are other dimensions to educational inequality in the United States. It stretches from inequality in the quality of access, disparities in terms of graduation and length of study among different socio-economic groups, and different after-graduation employment support. Students from higher income families tend to have access to the best colleges in America, enjoy a richer curriculum, and have access to better teachers, research resources and alumni network. Moreover, expenditure per student such as spending on instruction, research, academic support, student services at private universities is almost twice as much as in public universities which may reflect inequality in quality of higher education.

Most state and institutional aid are based on academic merit. Other forms of scholarships can be on the basis of athletic performance, etc. The third form of financial aid is a combination of need-based and merit-based aid such as the federal Academic Competitiveness Grants (ACG) and National Science and Mathematics Access to Retain Talent (SMART) Grants that were both introduced in 2006 and specify rigorous academic standards for recipients but are only awarded to students from low-income families. ACG and SMART grants that have a merit component are only available to Pell-eligible students, therefore are based on both merit and need.

Richmond et al. (2001) argue that although beginning with the passage of the Higher Education Act of 1965, financial aid has been awarded based on need, since 1980s there has been more attention on merit-based financial aid. They argue that between 1981 and 2000 the proportion of the financial aid that is in the form of merit-based aid has grown from 9
percent to 22 percent.\(^8\) Woo and Choy (2011) use data by National Postsecondary Student Aid Study and find that in 2007-2008 the proportion of merit aid recipients exceeded that of need-based grant recipients in public universities. They also report that the prevalence of merit aid is the highest in “moderately” selective private nonprofit institutions.

According to data from the National Center for Education Statistics,\(^9\) after dividing family economic status into high, high-middle, low-middle, and low income, the shares of merit-based aid going to student from low- and high-income families were the same at 23 percent of all aid in 1995-96 academic year. However, in the academic year 2007-2008 while only 20 percent of the total merit-based aid went to children of low-income parents, the share for their high-income counterparts increased to 28 percent of the total aid. In the same year, while 21 percent of all the need-based aid went to children from high- and high-middle-income families, 57 percent of all the merit-based aid goes to those children. In terms of average amount, too, grant recipients have received larger average amounts in terms of merit-based aid than need-based aid in the past two decades. Student aid can come in the form of federal loans (34 percent of the overall aid amount), institutional grants (22%), federal Pell grants (16%), federal education tax credits and deductions (8%), and other forms of aid.

There is an ongoing debate about whether the focus of educational aid should be on merit-based aid or need-based aid. These debates tend to be on both efficiency and equity grounds. Supporters of merit-based financial aid argue that it increases competition in high school and improves university attendance. Furthermore, it has been argued that those merit aid recipients are more likely to persist in higher education. Lochner and Monge-Naranjo (2011) show that although need-based programs target those who need the funds more, they may lead to inefficient over-investment by lower ability individuals. Backes et al. (2015) show that while earnings of disadvantaged workers can significantly improve through

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\(^8\)For a detailed analysis on this see McPherson and Schapiro (1999)

technical certificate and associate programs, those who end up going to low-selective colleges and studying low-earning fields will hurt their future income. They also find that low-income students more than others choose humanities at the associate and baccalaureate levels and concentrate less than others in technical fields such as engineering and sciences.

However, opponents of merit aid argue that since more talented youth generally come from more affluent families that do not need any stimulus to pursue higher education, merit-based policies may only exacerbate inequality. For instance, Dynarski (2003) finds that the Georgia HOPE Scholarship in fact increases the racial gap in higher education. Supporters of this view claim that merit-based aid is another form of reward to students who have already been granted a disproportionate share of resources, and that any additional help to them does not in any sense improve the social optimum (Cameron and Heckman, 1999).

In addition to the direct distributional effect of merit-based aid, a shift to more aid based on merit has diverted resources from need-based aid. Studies have shown that a greater focus on merit-based aid can crowd out students with financial need from higher education institutions. Ehrenberg et al. (2005) show that an increase in the share of the institutionally funded so-called National Merit Scholarship winners at an institutions first year class means a lower share of Pell Grants recipients.
Although there is a void of research on how different financial aid strategies affect the distribution of income, there have been some attempts in theorizing higher education decisions and the role of credit constraints, tuition, and financial aid policy. Fender and Wang (2003) review an overlapping-generations model of human capital decisions in which individuals are credit-constrained. They argue that, in steady state, credit constraints are associated with a lower aggregate level of education and a greater skilled wage rate than when individuals face no credit constraint. As a result, credit constraints have two effects: distorting educational decisions and widening the gap between the skilled and unskilled workers. There is no discussion on how policy can impact outcomes in their paper.

Caucutt and Kumar (2003) look at the effect on welfare and efficiency of increasing higher education subsidies by developing a dynamic general equilibrium model. They study three policies: a tax and subsidy scheme, a large-scale educational aid, and provision of aid based on a combination of merit and need. They find that the benefits of the first policy are exaggerated since it has little effect on welfare and in fact reduces efficiency.

Using a theoretical model, Hendel et al. (2005) make the case that making education more affordable carries a risk of higher inequality. In their model, differences in educational attainment are a consequence of either ability or financial resources. Individuals who cannot get an education are either low ability or high ability with financial restraint. When education is made more accessible by the government, high-ability constrained individuals leave the pool and this in turn drives the quality of unskilled workers and their wages down. Thus, according to them, a more accessible higher education will reinforce the middle class and make those at the bottom grapple more.

Krueger and Ludwig (2016) quantitatively show that a progressive income tax hinders an individual’s incentives to acquire higher education. Under an assumption of borrowing constraints, they find that the negative effect of the tax can be mitigated by a higher education subsidy. They show that an individual’s decision of whether to go to college depends on the
flat labor income tax rate, the education subsidy rate, college premium, and cost of higher education but is independent of the lump-sum transfer/tax. Therefore, they suggest an increase in college subsidies, if financed by a reduction in the lump-sum transfers or increase in the lump-sum taxes, will have a positive effect on the fraction of households attending college.

Perhaps the most relevant to this essay is the work by Hanushek et al. (2014) which focuses on how various college aid schemes alter inequality and intergenerational mobility using a dynamic general equilibrium framework. Although they find that all schemes including need-based aid, merit-based aid, and income-contingent loans reduce income inequality in the society, need-based aid is more likely to the best combination of aggregate efficiency and a more equal income distribution. What distinguishes my work from theirs is the existence of tasks and skills in the economy that is ignored in their model.

3.3 Model

3.3.1 Model Setup

There is a continuum of tasks, indexed by $s \in [0, 1]$ and each require a set of ability and education.\footnote{Tasks are units of work activity that are used to produce output.} Tasks are sorted based on how human capital intensive they are.\footnote{Equivalently, I could sort tasks based on how ability-intensive they are. This would yield similar results.} Individuals in the economy differ in their ability and their direct cost of getting education beyond compulsory schooling. Therefore, the sources of heterogeneity in the model are ability and the amount of bequest individuals receive from their parents, assuming tuition costs are the same for everyone. Individuals are then grouped based on their endowments into four categories: those who have low ability and make low investments in higher education, those who have low ability but make high investments, those who have high ability but make low investments, those who have high ability but make low investments.
investments, and finally those who have high ability and can highly invest in education, ranked respectively. Table 3.1 shows the grouping of individuals based on their ability and investment in higher education. The nature of this ranking will be explained later.

Table 3.1: Grouping of individuals based on their ability endowments and cost of education

<table>
<thead>
<tr>
<th>Group in Higher Education</th>
<th>Ability Level</th>
<th>Level of Investment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>2</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>3</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>4</td>
<td>High</td>
<td>High</td>
</tr>
</tbody>
</table>

Investment in higher education beyond compulsory schooling is costly and consists of direct costs and indirect costs. The direct costs consist of tuition, room and board and the indirect costs, or effort costs, are inversely related to ability, where higher ability students have lower indirect costs. If the borrowing constraint does not bind, investment in human capital will only be a function of ability. It has to be noted that I am ignoring the opportunity cost of being in school in terms of both the forgone wages and experience in the job market.

The payoff to education is in terms of added productivity, which then gives individuals an advantage over more skilled tasks. Workers are paid based on their productivity factor, which is a function of ability, human capital, and the ability- and human-capital-intensity of the tasks they perform. In this model, productivity advantage is the matching formula for tasks and individuals skills that are based on their productivity. In this regard, skill is defined as an individuals capabilities of performing tasks.

### 3.3.2 Basic Model

Ability and the stock of human capital appear in the productivity factor function in the following manner
\[ \theta_j(s) = \zeta(s)(h_j)^{\alpha_1(s)}(a_j)^{\alpha_2(s)} \] (3.1)

\( a_j \) is the ability of an individual from the \( j \)-th group, \( h_j \) is her stock of human capital, and \( \zeta(s) \) is a scale parameter that depends on each task. Here, \( \alpha_1(s) \) and \( \alpha_2(s) \) are output elasticities of human capital and ability in the productivity function, respectively (or intensity of each task on education and ability). This productivity function tells us that individuals with higher level of human capital or ability are more productive in performing task \( s \), or alternatively, can perform the task at a lower cost. Output of workers in Group \( j \) is given by

\[ y_j(s) = \theta_j(s)l_j(s) \] (3.2)

As a result, the total output of all workers assigned to task \( s \) is given by

\[ y(s) = \sum_{j=1}^{4} y_j(s) \] (3.3)

I assume that workers of the same productivity Group \( j \) are indifferent in performing tasks in range \((S_{j-1}, S_j)\). Therefore, the price difference between any two tasks performed by workers from the same productivity group should offset the productivity differences of workers in the two tasks. In other words, perfect competition among members of a given group across different tasks forces wages across tasks paid to members of the group to be equal. Given this and the assumption that the value placed on the output of a worker in Group \( j \) at task \( s \) equals \( P_j(s) \), we will have the following Mincerian-type wage equation based on productivities

\[ w_j(s) = P(s)\theta_j(s) = P(s)\zeta(s)(h_j)^{\alpha_1(s)}(a_j)^{\alpha_2(s)} \quad j = 1, 2, 3, 4 \] (3.4)

As a result, in equilibrium, we must have \( P_j(s) = w_j/\theta_j(s) \) for each group \( j \) for which
$l_j(s) > 0$. I assume that, in short run, there is a fixed and inelastic supply of workers in each group. If factor markets clear we have

$$\int_0^1 l_j(s) \leq L_j \quad j = 1, 2, 3, 4 \quad (3.5)$$

Higher education decisions follows a modified version of Ben-Porath (1967) model of human capital investment in which the stock of human capital depends on ability and the amount of investment or in other words, the direct cost that includes tuition, room, and board, and the indirect cost that in this case is the same as effort cost.\(^\text{12}\) Taking both monetary and indirect costs into account, I assume individuals in Group 1 will not pursue higher education since they have limited ability and investments. Individuals in Groups 2 and 3 will pursue higher education but with a lower quality since they are either credit-constrained or low abilities. And finally individuals in Group 4 will invest in high-quality education since they do not have any ability or credit constraint.\(^\text{13}\) Table 3.2 summarizes the choices of schooling. In Section 3.4, I provide numerical values for different levels of education shown in Table 3.2 using NLSY97 data.

<table>
<thead>
<tr>
<th>Group</th>
<th>Human capital stock at the end of schooling</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No higher education</td>
</tr>
<tr>
<td>2</td>
<td>Low quality higher education</td>
</tr>
<tr>
<td>3</td>
<td>Low quality higher education</td>
</tr>
<tr>
<td>4</td>
<td>High quality higher education</td>
</tr>
</tbody>
</table>

As in Spence (1973), education is more costly for low-ability students than for high-ability students.\(^\text{14}\) This higher cost can be thought of as a monetary cost by channeling...

\(^\text{12}\)Psychic costs of schooling in estimations of returns to schooling are neglected in the conventional literature. However, they usually tend to be substantial. The psychic costs of education explain why some low-ability students who are financially self-sufficient do not get enough education.

\(^\text{13}\)Another way to formulate the model is to introduce a quality parameter. The quality choice has a large impact on earnings both through the model presented here and empirical evidence. See for instance Black and Smith (2002).

\(^\text{14}\)Alternative models of higher education assume that the cost of education for low-ability individuals is
this cost as more time cost, more tutoring costs, and the need for supplemental materials for the low ability individuals. It is obvious that in this model, unlike in Spence (1976), education enhances productivity\(^{15}\) and the inequality in individuals ability and financial resources determines differences in educational attainment.

As in Acemoglu and Autor (2011), I assume that the unique final good is produced by combining the continuum of tasks \(s_i \in [0, 1]\) through the following technology function

\[
Y = \exp\left[ \int_0^1 \ln y(s) ds \right] \quad (3.6)
\]

which implies that \(y_1(s), y_2(s), y_3(s),\) and \(y_4(s)\) are perfectly substitutable. According to Acemoglu and Autor (2011), this implies that

\[
P_j(s)y_j(s) = P_j(s')y_j(s') \quad \text{for all } s \text{ and } s' \text{ for which } l_j(s) > 0 \quad (3.7)
\]

\[
P_j(s)y_j(s) = P_j'(s)y_j'(s) \quad \text{for all } s \text{ for which } l_j(s) > 0 \text{ and } l_j'(s) > 0 \quad (3.8)
\]

\[
P_j(s)y_j(s) = P_j'(s')y_j'(s') \quad \text{for all } j \neq j', s \neq s' \quad (3.9)
\]

Equations 3.7 and 3.8 imply

\[
P_j(s)\theta_j(s)l_j(s) = P_j(s')\theta_j(s')l_j(s') \quad \text{for all } s, s' \text{ for which } l_j(s) > 0 \text{ and } l_j(s') > 0 \quad (3.10)
\]

or

\(^{15}\)As opposed to the signaling role of education.
This is due to the fact that wages for workers in Group $j$ do not depend on the task performed. This implies

$$l_j(s) = l_j(s') = l_j$$ for all $s, s'$ for which $l_j(s) > 0$ and $l_j(s') > 0$ \hspace{1cm} (3.12)

On the other hand, Equation 3.9 implies

$$P_{j'}(s') = P_j(s) \frac{\theta_j(s)}{\theta_{j'}(s')} \frac{l_j}{l_{j'}}$$ \hspace{1cm} (3.13)

The perfect substitutability from the production function in Equation 3.6 means that the firm could get one unit of $y(s)$ from group $j$ for the price $P_j(s)$ and one unit from group $j'$ for the price $P_{j'}(s)$, which means that the equilibrium requires that $P_j(s) = P_{j'}(s)$.

Now, suppose task range is divided among the groups with thresholds $S_0 = 0 < S_1 < S_2 < S_3 < 1 = S_4$ and workers in group $j$ perform tasks in the range $(S_{j-1}, S_j)$. We need to see how these thresholds are assigned. The firm will need to determine $S_1$, $S_2$, and $S_3$ by maximizing profits. Following Equation 3.12, that requires workers in Group $j$ supply the same amount of labor in performing tasks $S_{j-1} < s, s' < S_j$, I find that

$$l_j(s) = \frac{L_j}{S_j - S_{j-1}} \quad j = 1, 2, 3, 4$$ \hspace{1cm} (3.14)

This is the firm’s signal of how and where to use workers in Group $j$. If the interval $(S_{j-1}, S_j)$ is wider, the number of workers on task $s$ diminishes and $y_j(s) = y(s)$ decreases. Now, let us find the task thresholds $S_j$ for $j = 1, 2, 3$.

**Proposition 1** Given a perfectly competitive environment, profit maximization for the firm
(each firm) gives us the task threshold $S_j$ for $j = 1, 2, 3$.

**Proof:** Firm’s profit is given by

\[
\Pi = P_y Y - \sum_{j=1}^{4} w_j L_j = 0 \tag{3.15}
\]

The firm must choose $S_1$, $S_2$, and $S_3$ so as to maximize $\Pi$. Since in the short run $w_j$ and $L_j$ are given, the problem boils down to maximizing $Y$ or $\ln Y$. We know

\[
\ln Y = \int_0^1 \ln y(s)ds = \sum_{j=1}^{4} \left[ \int_{S_{j-1}}^{S_j} \ln y_j(s)ds \right] = \sum_{j=1}^{4} \left[ \int_{S_{j-1}}^{S_j} \ln(\theta_j(s) L_j)ds \right] \tag{3.16}
\]

First-order conditions imply that $\partial \ln Y / \partial S_j = 0$. Therefore, we have

\[
\frac{\partial \ln Y}{\partial S_1} = \ln \theta_1(S_1) - \ln \theta_2(S_1) + \ln L_1 - \ln L_2 + \ln (S_2 - S_1) - \ln S_1 = 0 \tag{3.17}
\]

in other words,

\[
\frac{\theta_1(S_1)L_1}{S_1} = \frac{\theta_2(S_1)L_2}{(S_2 - S_1)} \tag{3.18}
\]

In general, first-order conditions for $j = 1, 2, 3$ leads to the following terminal conditions for finding $S_j$

\[
\frac{\theta_j(S_j)L_j}{(S_j - S_{j-1})} = \frac{\theta_{j+1}(S_j)L_{j+1}}{(S_{j+1} - S_j)} \tag{3.19}
\]

which then determines the sequence $\{S_j\}_0^4$ with $S_0 = 1$ and $S_4 = 1$. The sequence $\{S_j\}_0^4$ is endogenous and will change in response to changes in productivity differences and labor.
Note that the terminal conditions in Equation 3.19 means, for instance, that between Groups 1 and 2, \( y_1(S_1) = y_2(S_1) \), i.e. the firm is indifferent whether a worker of Group 1 or Group 2 performs task \( S_1 \). Equation 3.7 implies that \( P_1(s)\theta_1(s)l_1 = P_1(0)\theta_1(0)l_1 \). Therefore,

\[
P_1(s)\theta_1(s)l_1 = P_1(0)\theta_1(0)l_1
\]  

(3.20)

which then leads to

\[
\begin{cases}
P_1(s) = \frac{\theta_1(0)}{\theta_1(s)}P_1(0) \\
P_2(s) = \frac{\theta_2(S_1)}{\theta_2(s)}P_2(S_1) \\
P_3(s) = \frac{\theta_3(S_2)}{\theta_3(s)}P_3(S_2) \\
P_4(s) = \frac{\theta_4(S_3)}{\theta_4(s)}P_4(S_3)
\end{cases}
\]

for \( S_{j-1} < s < S_j \)  

(3.21)

Also from Equation 3.9, we know

\[
P_j(s)\theta_j(s)\frac{L_j}{(S_j - S_{j-1})} = P_{j'}(s')\theta_{j'}(s')\frac{L_{j'}}{(S_{j'} - S_{j'-1})}
\]

(3.22)

which implies

\[
P_2(S_1)\theta_2(S_1)L_2/(S_2 - S_1) = P_3(S_2)\theta_3(S_2)L_3/(S_3 - S_2)
\]

\[
= P_4(S_3)\theta_4(S_3)L_4/(1 - S_3) = P_1(0)\theta_1(0)L_1/S_1
\]  

(3.23)

Thus, once \( P_1(0) \) if determined, every price path is given. This in turn determines wages since we saw in Equation 3.4 that perfect competition in the labor market dictates \( w_j \) as the
value of marginal product of workers in Group \( j \), and thus

\[ w_j = P_j(s)\theta_j(s) \quad (3.24) \]

Moreover, based on Equation 3.15 we have

\[ P_y Y - \sum_{j=1}^{4} P_j(S_{j-1})\theta_j(S_{j-1})L_j = 0 \quad (3.25) \]

This together with Equation 3.23 gives us

\[ P_y Y = P_1(0)\theta_1(0)\frac{L_1}{S_1} \quad (3.26) \]

Therefore, given \( P_Y \) and once the equilibrium settles (we know the \( S_j \) and \( P \) sequences), Equation 3.26 gives us the total output. The next question is how we find inequality across all groups in equilibrium.

### 3.3.3 Productivity Differences and the Lorenz Curve

The following Proposition discusses the relationship between task thresholds and wage inequality among individuals across all groups.

**Proposition 2** Given equations 3.19 and 3.23, the Lorenz curve, defined as the percentage of total wages for each group, is given by \( \phi^j(j/J) = S_j \) where \( \phi^j : [0, 1] \rightarrow [0, 1] \) shown in Figure 3.5.

**Proof:** Appendix D provides the proof.

My approach in finding the Lorenz curve based on share of tasks is similar to Matsuyama (2013) where he applies the method to trade among countries. Note that the Lorenz curve
defined above shows the inequality between the four groups and not within group inequality. It is easy to see that the Gini coefficient associated with the Lorenz curve in Figure 3.5 is equal to

\[
Gini = 1 - [S_1L_2 + (S_1 + S_2)L_2 + (S_2 + S_3)L_3 + (S_3 + 1)L_4]
\] (3.27)

A conclusion of the Gini formulation above is that the inequality analysis does not depend on neither output \( Y \) nor on the prices. In order to calculate the Gini coefficient it is sufficient to find \( S_1, S_2, S_3 \).

### 3.4 The Effect of Merit- Versus Need-Based Aid on Inequality

In order to empirically solve the model, we need to find the solution to Equation 3.19. Let us rewrite the equation substituting for productivities. Since we already know \( S_0 = 0 \) and \( S_4 = 1 \), we will only need to solve for \( S_1, S_2, \) and \( S_3 \).
Financial aid in education can enter the model in two ways. Financial aid can affect the average schooling of each group and hence the schooling ratios $h_{\text{min}}/h_{\text{low}}$ and $h_{\text{low}}/h_{\text{high}}$ in the model. The limitation of this approach is in the fact that the average schooling of the groups shown in Table 3.2 changes insignificantly over a short span of time. A better way of analyzing aid policies is through the dynamic of labor shares. Before I explain how different aid policies change the labor shares in each group, we must find the system of equations solving for labor shares. We can rewrite Equation 3.28 as

$$
\begin{align*}
\alpha_1(S_1) \ln \left( \frac{h_{\text{min}}}{h_{\text{low}}} \right) &= \ln \left( \frac{S_1}{S_2 S_1 L_1} \right) \\
\alpha_2(S_2) \ln \left( \frac{a_{\text{low}}}{a_{\text{high}}} \right) &= \ln \left( \frac{S_2 - S_1}{S_3 - S_2 L_2} \right) \\
\alpha_1(S_3) \ln \left( \frac{h_{\text{low}}}{h_{\text{high}}} \right) &= \ln \left( \frac{S_3 - S_2 L_4}{1 - S_3 L_3} \right)
\end{align*}
$$

(3.28)

where

$$
\gamma_1 = \ln \left( \frac{h_{\text{min}}}{h_{\text{low}}} \right), \quad \gamma_2 = \ln \left( \frac{a_{\text{low}}}{a_{\text{high}}} \right), \quad \gamma_3 = \ln \left( \frac{h_{\text{low}}}{h_{\text{high}}} \right)
$$

(3.30)

Taking derivatives of the set of equations 3.29 we have
As I discussed above, educational aid can impact the labor shares in each group. Therefore, the optimal education policy can be found by examining how equal changes in labor shares of different groups change the Gini coefficient. In this regard, I can assume a functional form for the relationship between changes in labor share and the amount of aid to each group, 

$$\frac{dL_i}{m_iR} = f_i(m_iR) \text{ for } i = 1, 2, 3, 4,$$

where $m_i$ is the share of resources given to individuals in Group $i$ and $R$ is the total amount of resources and is exogenous. The total amount of resources available is assumed to be fixed under different aid regimes. I assume that the change in a group’s labor share is a linear function of resources weighted with the price elasticity of demand for higher education for that group. Therefore, $f_i(m_i) = \mu_i m_i R$.

There is a whole body of literature on the price elasticity of demand for higher education and how changes in price (tuition minus financial aid) affects demand. These studies are mostly done through cross-sectional regression or panel regression analysis controlling for other factors. Most studies, however, find student demand for college to be very inelastic. Leslie and Brinkman (1987) use a meta-analysis of studies between 1967 and 1982 and find that a $100 increase in tuition decreases college enrollment by 0.6 to 0.8 percentage points depending on the study.\(^{16}\) For a survey of literature on tuition elasticity of demand for higher education and how changes in price (tuition minus financial aid) affects demand. These studies are mostly done through cross-sectional regression or panel regression analysis controlling for other factors. Most studies, however, find student demand for college to be very inelastic. Leslie and Brinkman (1987) use a meta-analysis of studies between 1967 and 1982 and find that a $100 increase in tuition decreases college enrollment by 0.6 to 0.8 percentage points depending on the study.\(^{16}\)

\(^{16}\)The studies in their meta-analysis use tuition data between 1960-1980.
higher education see Hemelt et al. (2008). Note that most of these studies focus on tuition prices and not necessarily on the effect of grants and subsidies. John (1990) shows that a $100 increase in the size of grants had an impact on enrollment decisions twice as big as the impact of a reduction of the same size in tuition for low-income students. I will consider a $1 increase in tuition price as equivalent to a $1 decrease in financial aid. In spite of the attention to finding the elasticity of demand for higher education, unfortunately, I could not find any research on the elasticity of demand for different ability or income subgroups of the population.

Turning back to the model, educational aid moves individuals from one group to another. Consider the first group including individuals with low ability and low resources. Assuming that educational aid does not change abilities significantly, any aid to this group leads to a decline in the labor share of Group 1 and an increase in labor share of Group 2. With the same logic, aid to Group 3 will move individuals from this group to Group 4, and hence leads to a decline in the labor share of Group 3 and a rise in labor share of Group 4. It is easy to see that since ability is assumed to be innate, any aid to Groups 2 and 4 does not have any major impact on the shares of individuals in these groups.17 Table 3.3 summarizes the discussion. The last column of this table is critical to my analysis of different aid regimes.

Table 3.3: The effect of different aid policies on labor shares of different groups

<table>
<thead>
<tr>
<th>Type of Policy</th>
<th>Impacted Groups</th>
<th>Changes in Labor Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td>Need-based</td>
<td>1, 3</td>
<td>( dL_1 = -dL_2 = -\mu_1 mR, ) ( dL_3 = -dL_4 = -\mu_3 (1 - m) R )</td>
</tr>
<tr>
<td>Merit-based</td>
<td>3, 4</td>
<td>( dL_1 = dL_2 = 0, ) ( dL_3 = -dL_4 = -\mu_3 m' R )</td>
</tr>
<tr>
<td>Need- &amp; Merit-based</td>
<td>3</td>
<td>( dL_1 = dL_2 = 0, ) ( dL_3 = -dL_4 = -\mu_3 R )</td>
</tr>
</tbody>
</table>

Note that \( m \) in need-based policy is the share of resources that is spent on Group 1

---

17 An implication of this argument is that an aid policy directed towards Groups 2 and 4 will not have any impact on the distribution of income. For instance, a merit-based aid to Group 4 only affect the overall distribution of wages by reducing the amount of aid that can potentially go to Group 3.
(therefore $1 - m$ is spent on Group 3) and $m'$ in merit-based policy is the share of resources that is spent on Group 3 (therefore $1 - m'$ is spent on Group 4). In the combination policy, all resources are spent on one group (Group 3). Therefore, resources decrease (increase) the labor share of Group 3 (Group 4) by $-\mu_3 R$ amount. Given that the change in inequality can be calculated as

$$d\text{Gini} = -[S_1(dL_1 + dL_2) + (L_1 + L_2)dS_1 + S_2(dL_2 + dL_3) + (L_2 + L_3)dS_2 +$$

$$S_3(dL_3 + dL_4) + (L_3 + L_4)dS_3 + dL_4]$$ (3.32)

testing whether a policy, A, lowers inequality more than another policy, B, (or equivalently does not increase inequality as much as B) boils down to checking whether $d\text{Gini}_A < d\text{Gini}_B$.

For instance, a policy based on a combination of need and merit is considered better in terms of inequality than a need-based policy if and only if $d\text{Gini}_{\text{merit \\& need}} < d\text{Gini}_{\text{need}}$

### 3.4.1 Empirical Analysis

In order to calibrate the model, I will first calculate the labor shares in each of the four groups as well as the relative ability and schooling among groups. For this, I use the National Longitudinal Survey of Youth (NLSY97). The main reason for using this data set is the existence of ability scores. During the first round of the study, participants were asked to take a computerized form of the Armed Services Vocational Aptitude Battery (CAT-ASVAB) test. A total of 7,127 NLSY97 respondents completed this test. In addition to ability scores, the data includes demographic and socio-economic information about the respondents.

I categorize groups using the average ability and average resources (parental income) in each group as thresholds, therefore, the cutoff points for ability is score 48295 and for parental education is $\$21,603$. As a result, I create four groups according to Table 3.1 and
calculate the labor share and average schooling and ability for each group. The following table reports the parameters used in the model.

Table 3.4: Calibrated Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{\text{low}}$</td>
<td>24113</td>
<td>$L_1$</td>
<td>0.340</td>
</tr>
<tr>
<td>$a_{\text{high}}$</td>
<td>73405</td>
<td>$L_2$</td>
<td>0.165</td>
</tr>
<tr>
<td>$h_{\text{min}}$</td>
<td>12.48</td>
<td>$L_3$</td>
<td>0.245</td>
</tr>
<tr>
<td>$h_{\text{low}}$</td>
<td>14.24</td>
<td>$L_4$</td>
<td>0.250</td>
</tr>
<tr>
<td>$h_{\text{high}}$</td>
<td>15.43</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We first need to specify the functional form of $\alpha(s)$. To fix ideas, let us assume that $\alpha_1(s) = 1 - \alpha_2(s) = s$. Given the parameters reported in Table 3.4, the nonlinear set of equations shown in Equation 3.28 can be solved using numerical analysis.\(^{18}\) Column 1 in Table 3.5 reports task cutoff points and the Gini coefficient associated with the above functional form for $\alpha(s)$. The Gini coefficient is calculated using Equation 3.27. While in column 2 I assume $\alpha_1(s) = s^2$ and $\alpha_2(s) = 1 - s^2$, in column 3-5 I use a truncated Pareto functional form $\alpha_1(s) = 1 - \alpha_2(s) = \ln[1 + (e^\theta - 1)s]^{1/\theta}$ for different values of $\theta$. Note that column 1 is a special case of this functional form when $\theta \to 0$.

Table 3.5: Task cutoff points and the Gini coefficient for different functional forms of $\alpha(s)$

<table>
<thead>
<tr>
<th></th>
<th>(1) $\alpha_1(s) = s$</th>
<th>(2) $\alpha_1(s) = s^2$</th>
<th>(3) $\alpha_1(s) = 1 - \alpha_2(s) = \ln[1 + (e^\theta - 1)s]^{1/\theta}$</th>
<th>(4) $\theta = 0.1$</th>
<th>(5) $\theta = 0.5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>0.198</td>
<td>0.200</td>
<td>0.195</td>
<td>0.195</td>
<td>0.177</td>
</tr>
<tr>
<td>$S_2$</td>
<td>0.294</td>
<td>0.297</td>
<td>0.310</td>
<td>0.310</td>
<td>0.330</td>
</tr>
<tr>
<td>$S_3$</td>
<td>0.638</td>
<td>0.639</td>
<td>0.646</td>
<td>0.646</td>
<td>0.655</td>
</tr>
<tr>
<td>Gini</td>
<td>0.211</td>
<td>0.208</td>
<td>0.195</td>
<td>0.195</td>
<td>0.177</td>
</tr>
</tbody>
</table>

3.4.2 Special Case: Linear Output Elasticities of Human Capital and Ability

In order to solve the system of equations in 3.31, we must assume a functional form for elasticities of human capital and ability, \( \alpha_1(s) \) and \( \alpha_2(s) \). A simple case is a linear form in which elasticities increase linearly as tasks become more human-capital intensive \((s)\). As a result, we have the functional form \( \alpha_1(s) = 1 - \alpha_2(s) = s \). A matrix representation of the system of equations can be written as

\[
\begin{bmatrix}
L_1 e^{\gamma_1 S_1} [-1 + (S_2 - S_1)\gamma_1] - L_2 \\
L_3 \\
0
\end{bmatrix}
\begin{bmatrix}
dS_1 \\
dS_2 \\
dS_3
\end{bmatrix}
= 
\begin{bmatrix}
L_1 e^{\gamma_1 S_1} \\
L_2 e^{\gamma_2 (1-S_2)} [-1 - (S_3 - S_2)\gamma_2] - L_3 \\
L_4 \\
L_3 e^{\gamma_3 S_3} [-1 + (1 - S_3)\gamma_3] - L_4
\end{bmatrix}
\begin{bmatrix}
dL_1 \\
dL_2 \\
dL_3
\end{bmatrix}
\] (3.33)

If we find the solution to \( dS_1 \), \( dS_2 \), and \( dS_3 \), substitute the parameters in Table 3.4 in Equation 3.33, and after matrix inversion, we will have

\[
\begin{bmatrix}
dS_1 \\
dS_2 \\
dS_3
\end{bmatrix}
= 
\begin{bmatrix}
-5.808 & -7.510 & -1.057 \\
-5.668 & -11.232 & -1.581 \\
-2.866 & -5.679 & -2.822
\end{bmatrix}
\begin{bmatrix}
0.569dL_1 + 0.008dL_3 \\
-0.028dL_1 + 0.012dL_3 \\
-0.014dL_1 + 1.397dL_3
\end{bmatrix}
\] (3.34)

We find the relationship between change in the Gini coefficient and the labor shares as

\[
d \text{Gini} = 0.027dL_1 - 0.001dL_3
\] (3.35)

It is now easy to see how different aid regimes change the Gini coefficient. Table 3.6 shows...
how Gini coefficient changes under different aid regimes. Given a fixed total amount of resources under all regimes, we can rank policies based on their equalizing effects.

Table 3.6: Aid regimes and the dynamic of inequality

<table>
<thead>
<tr>
<th>Type of Policy</th>
<th>Change in Gini coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Need-based</td>
<td>$dGini = -0.027\mu_1mR + 0.001\mu_3(1 - m)R$</td>
</tr>
<tr>
<td>Merit-based</td>
<td>$dGini = 0.001\mu_3m'R$</td>
</tr>
<tr>
<td>Need- &amp; Merit-based</td>
<td>$dGini = 0.001\mu_3R$</td>
</tr>
</tbody>
</table>

Let us start comparing need-based policies and policies that are based on a combination of need and merit. For the need-based policy to lower inequality more than the combination policy, we should have $dGini_{need-based} < dGini_{combination}$. Using Table 3.6 we can see that this only happens when

\[-0.027\mu_1 < 0.001\mu_3\] (3.36)

Since $\mu_1$ and $\mu_2$ are both positive numbers, the equation above always hold and a need-based policy always leads to a larger reduction in inequality compared to a combination policy. The comparison between need-based policies and merit-based policies is also straightforward. A need-based policy is advantageous (in terms of inequality) to a merit-based policy if and only if

\[-0.027\mu_1m < -0.001\mu_3(1 - m - m')\] (3.37)

Note that the inequality above is unlikely to be violated, therefore, it is safe to assume that a need-based policy is preferred to a merit-based policy when it comes to inequality. Finally, comparison of merit-based policy and a combination policy boils down to the following inequality

\[0.001\mu_3m' < 0.001\mu_3\] (3.38)
CHAPTER 3. EDUCATIONAL AID POLICY AND INEQUALITY

This by definition is always true and hence, we can conclude that a merit-based policy reduces inequality more than a combination policy.

3.4.3 Other functional forms of Elasticities of Human Capital and Ability

How are the results presented in this model sensitive to the choice of elasticity functions? To see this, I perform the analysis by substituting a different functional form for \( \alpha_1(s) \) and \( \alpha_2(s) \) in Equation 3.31. For the Pareto functional form, the parameter \( c \) depends on the parameter \( \theta \). The value of parameter \( c \) under different functional forms of elasticities are reported in Table 3.7. The conclusion from the table is that under all functional forms a policy based on a combination of both merit and need does not reduce inequality as much as a policy based on only merit or need. Furthermore, note that under the functional forms of columns 2-4, a need-based policy is very likely to be better than a merit-based policy when it comes to inequality. In this regard the results here are, to a large extent, aligned with the results found in Hanushek et al. (2014).

Table 3.7: Educational aid and inequality under different functional forms of \( \alpha(s) \)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_1(s) = s^2 )</td>
<td>( \alpha_1(s) = 1 - \alpha_2(s) = \ln[1 + (e^\theta - 1)s]^{1/\theta} )</td>
<td>( \theta = 0.1 )</td>
<td>( \theta = 0.5 )</td>
<td>( \theta = 1 )</td>
</tr>
<tr>
<td>( \alpha_2(s) = 1 - s^2 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( c = 14.5 )</td>
<td>( c = 4.5 )</td>
<td>( c = 3.1 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Need &gt; Combination (If 4( \mu_1 &gt; \mu_3 ))</td>
<td>Need &gt; Combination (Always)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Need &gt; Merit (If (-0.25\mu_1m &lt; \mu_3(1 - m - m')))</td>
<td>Need &gt; Merit (If ( c\mu_1m &gt; \mu_3(1 - m - m') ))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Merit &gt; Combination (Always)</td>
<td>Merit &gt; Combination (Always)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3.5 Limitations of the Analysis

One the main limitations of my framework is that I leave out any welfare analysis. A welfare analysis is needed in order to compare different policy schemes. Adding the welfare analysis is, however, not an impossible task. Since wages are known in my model, one can look at the overall wages in the economy given the prices of tasks.

A second caveat of the analysis is the assumption of exogenous labor supplies. In my defense, I assume labor supplies to be exogenous for simplicity but also because the framework is used to analyze policies in a specific time frame where the policy maker has limited resources and is deciding among different educational aid alternatives with equality as an objective. I do not claim that the model provides a dynamic general equilibrium answer to such questions. As a result, the assumption of exogenous labor shares of groups is not too unrealistic.

Lastly, I assume that resources directed toward students are exogenous. A more realistic framework would be one in which resources are funded through taxation. In this regard, one can assume resources, $R$, are funded through taxation of the high-income group, mainly Group 4. As a result wages in this group will be $w_4^* = w_4(1 - t)$ where $t$ is the tax rate. As a result, overall amount of resources devoted for educational aid is equal to $L_4Ntw_4$ where $N$ is the size of the population.

3.6 Conclusion

My paper sheds light on the distributional effects of educational policy. Using a model of productivity, I find the range of tasks that individuals with different skills (combination of human capital and ability) can do and find their wages. I categorize individuals into four ability and family income groups and find the associated Lorenz curve based on task cutoff points and the share of individuals in each group. After finding the relevant Gini coefficient,
I study the effect of educational policy on the distribution of wages.

There are multiple advantages to this approach. First, in my framework, tasks are not uniform but require different skill sets. This can be helpful in analyzing the impact of technological change on wage distribution as well. Second, skills do not produce outputs but are used in production when applied to tasks in the economy. Therefore, there is an endogenous task allocation in the economy that is based on skills (human capital and ability). Third, the model allows for a comparative static analysis of the effect of educational intervention (more specifically through aid) on the shape of wage distribution. For this, I assume that educational aid changes the labor shares of each group based on the elasticity of demand for higher education for each group.

I analyze the effect of three types of educational aid: aid based on need, merit, or a combination of both. Each of these policies apply to one or two specific groups. After calibrating the model using NLSY97 data, I find the share of each ability/human-capital group in the United States and find that a policy based on both merit and need is the least favorable in terms of reducing inequality. Furthermore, a need-based policy is very likely to be better than a merit-based policy in terms of reducing inequality under different model parameters and functional forms. Therefore, if the distribution of ability and family resources are known to the policy, and given the educational aid design parameters (the share that goes to each group), the policy makers can find the the best policy that minimizes inequality.

There are a few points worth mentioning. Although, the model is based on four ability/family resources groups, the framework is easily extendable to more groups. Therefore, the model not only can take into account the inequality between different education groups that is mostly the scope of research on higher education premium, but also within those education groups in terms of their ability.

Furthermore, for the purpose of simplicity, technology is assumed to be constant over time in the model. However, this assumption can be removed easily which allows for studying the
effect of technological progress\textsuperscript{19} on the distribution of income.

Lastly, although studying schooling decisions and intergenerational mobility requires dynamic models, analyzing immediate distributional impacts of different policies can be done in a static partial-equilibrium model such as the one presented in this essay.

\textsuperscript{19}Or skill-bias technological change
Appendices

A  Pyatt’s Decomposition Method

To understand Pyatt’s method, first note that the inequality among a set of numbers $x_1, x_2, x_3, ..., x_n$ can be expressed, in terms of the Gini coefficient, as

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

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

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

Now, 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.\(^{20}\) 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.\(^{21}\)

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 \(j\)

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 \(\Pr(i \rightarrow j) = \frac{p_i}{p_j}\) where \(p_i\) and \(p_j\) are population shares of groups \(i\) and \(j\), respectively. Gini coefficient in matrix form can be written as

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

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,

\(^{20}\)For a more detailed discussion on deprivation see Runciman (1966).

\(^{21}\)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 \( E^* = \hat{s}^{-1} E \). 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.\(^{22}\)

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.\(^{23}\) 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 et al., 1977). Based on this approach the within-cohort Gini can be calculated as follows

\[ \text{Within-Gini} = \pi' E^*_1 p \]

\(^{22}\)A detailed explanation of the matrices can be found in Pyatt et al. (1976).
\(^{23}\)This is what Nelson (1977) suggests.
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.
Figure B1: Income Distribution Within Educational Groups in Selected Countries, Source: LIS Data, 2008–2010
Figure B2: Income Distribution Within Age Groups in Selected Countries, *Source: LIS Data, 2008–2010*
Figure B3: Income Distribution Within Gender Groups in Selected Countries, \textit{Source: LIS Data, 2008–2010}
### Table C1: Share of people in each country who chose different diagrams

<table>
<thead>
<tr>
<th>Country</th>
<th>Type A</th>
<th>Type B</th>
<th>Type C</th>
<th>Type D</th>
<th>Type E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td>45.6</td>
<td>36.1</td>
<td>9.4</td>
<td>7</td>
<td>1.9</td>
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<tr>
<td>Austria</td>
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<td>31</td>
<td>22.6</td>
<td>2.5</td>
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<tr>
<td>Australia</td>
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<td>29.5</td>
<td>21.7</td>
<td>40.7</td>
<td>2.1</td>
</tr>
<tr>
<td>Belgium</td>
<td>6.8</td>
<td>34.5</td>
<td>23.5</td>
<td>32.1</td>
<td>3</td>
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<tr>
<td>Bulgaria</td>
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<td>5.5</td>
<td>3.3</td>
<td>0.5</td>
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<td>25</td>
<td>39.8</td>
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<td>48</td>
<td>13.1</td>
<td>11.7</td>
<td>2.9</td>
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<tr>
<td>China</td>
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<td>51.4</td>
<td>12.2</td>
<td>12.2</td>
<td>2.2</td>
</tr>
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<td>Croatia</td>
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<td>6.4</td>
<td>5.5</td>
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</tr>
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<td>13.5</td>
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</tr>
<tr>
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<td>35.4</td>
<td>23</td>
<td>18.6</td>
<td>4.2</td>
</tr>
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<td>58.7</td>
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<td>46.6</td>
<td>9.6</td>
<td>9.8</td>
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<td>41.2</td>
<td>21.5</td>
<td>17</td>
<td>3.5</td>
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<tr>
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<td>20</td>
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<td>Sweden</td>
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Table C2: Choice of Distribution Based on Education Level in the United States

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<th>Junior college</th>
<th>Bachelor</th>
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<td>A</td>
<td>17%</td>
<td>18%</td>
<td>24%</td>
<td>16%</td>
<td>9%</td>
<td>17%</td>
</tr>
<tr>
<td>B</td>
<td>35%</td>
<td>42%</td>
<td>33%</td>
<td>35%</td>
<td>39%</td>
<td>39%</td>
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<tr>
<td>C</td>
<td>14%</td>
<td>13%</td>
<td>15%</td>
<td>16%</td>
<td>24%</td>
<td>15%</td>
</tr>
<tr>
<td>D</td>
<td>27%</td>
<td>24%</td>
<td>22%</td>
<td>33%</td>
<td>28%</td>
<td>26%</td>
</tr>
<tr>
<td>E</td>
<td>8%</td>
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<td>5%</td>
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<td>0%</td>
<td>3%</td>
</tr>
<tr>
<td>Total</td>
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<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table C3: Choice of Distribution Based on Income Level in the United States

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<th>40k-60k</th>
<th>60k-80k</th>
<th>80k-100k</th>
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<th>120k-140k</th>
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<td>22%</td>
<td>17%</td>
<td>12%</td>
<td>11%</td>
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<td>0%</td>
<td>16%</td>
<td>17%</td>
</tr>
<tr>
<td>B</td>
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<td>40%</td>
<td>40%</td>
<td>34%</td>
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Table C4: Choice of Distribution Based on Politics in the United States

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Table C5: Size of bins in the subjective income distributions in the ISSP survey

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<td>29.17</td>
<td>19.87</td>
<td>15.03</td>
<td>12.61</td>
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<td>7.77</td>
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D Proof of Proposition 2

Proof of Proposition 2: The cumulative percentage of wages for each quartile on the vertical axis of the Lorenz curve is as follows. From Equation 3.24 we have $w_1 = P_1(0)\theta_1(0)$. Moreover, from Equation 3.26 we know

$$P_1(0) = \frac{P_Y Y}{\theta_1(0)L_1/S_1} \quad (39)$$

I use the price of output $Y$ as numeraire. This together with the Equation above leads to

$$w_1 = \frac{S_1}{L_1} Y \quad (40)$$

Similarly, $P_2(S_1)$ can be calculated as

$$P_2(S_1) = \frac{P_1(0)\theta_1(0)L_1(S_2 - S_1)}{\theta_2(S_1)L_2S_1} \quad (41)$$

which then leads to

$$w_2 = \frac{S_1}{L_1} L_1(S_2 - S_1) \frac{Y}{L_2S_1} = \frac{(S_2 - S_1)}{L_2} Y \quad (42)$$

Similar calculations finds $w_j$ as follows

$$w_j = \frac{(S_j - S_{j-1})}{L_j} Y, \quad \text{for } j = 1, 2, 3, 4 \quad (43)$$

Let us now find the cumulative wages. The first cumulative share for the bottom group is given as
We can similarly find the rest of the cumulative shares as

\[
\frac{L_1 w_1}{L_1 w_1 + L_2 w_2 + L_3 w_3 + L_4 w_4} = \frac{S_1 Y}{S_1 Y + (S_2 - S_1) Y + (S_3 - S_2) Y + (1 - S_3) Y} = S_1 \tag{44}
\]

and

\[
\frac{L_1 w_1 + L_2 w_2}{L_1 w_1 + L_2 w_2 + L_3 w_3 + L_4 w_4} = S_2 \tag{45}
\]

and

\[
\frac{L_1 w_1 + L_2 w_2 + L_3 w_3}{L_1 w_1 + L_2 w_2 + L_3 w_3 + L_4 w_4} = S_3 \tag{46}
\]
Bibliography


A. B. Krueger et al. *Inequality, too much of a good thing*. Industrial Relations Section, Princeton University, 2002.


