Economic Inequality: Traditional and Computational Perspectives

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Abstract

In recent decades, there has been worsening economic inequality among nations. Research on inequality is again gaining traction in the academia. This article reviews the literature on income and wealth inequality from both economic and sociological perspectives in order to understand the factors behind such rising disparities. Standard methods of measuring inequality, such as Gini coefficients and income percentiles, are also illustrated. More importantly, we review research papers that use computational methods to analyze inequality to gain insights on how computational social science is making changes to the field of inequality research.

1 Introduction

Across the world, income and wealth inequality has been growing steadily over the past three decades to an astonishing level (Piketty and Saez 2014). In China, the income inequality since 2005 has reached very high levels, with the Gini coefficient in the range of 0.53–0.55 (Xie and Zhou 2014). In the United States, one of the richest countries in the world, the top 10 percent of the population now average nearly nine times as much income as the bottom 90 percent[†]. In India, a low-or-middle-income country (LMIC), the richest 1% population owned over half of the total wealth of the country in 2016. A recent OECD report stated that traditionally low-inequality countries such as Denmark, Germany, and Sweden also experienced significant increases in income inequality during the 2000s[‡].

Inequality is important for a number of reasons. Inequality could slow down economic growth in a country by impeding the accumulation of human capital (Deininger and Squire 1998). High income inequality may stress aggregate demand because poor people are more likely to spend their marginal earnings than high-

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[†] See Income inequality in the United States. https://inequality. org/facts/income-inequality/.
[‡] See https://www.oecd.org/els/soc/49499779.pdf

income groups (Jappelli and Pistaferri 2014), thereby damaging the health of the whole system. Regional inequality also makes it difficult to match workers and jobs (Ioannides and Loury 2004), reducing the efficiency of the whole economy. Politically, inequality is at the heart of almost all significant policy discussions, either in democracies (Moffitt, Ribar, and Wilhelm 1998), or in authoritarian regimes (Gallagher and Hanson 2009). High inequality is also found to be associated with polarization (Payne 2017), which is becoming painfully obvious in the United States at the time of this writing.

Research on income distribution and inequality was a subject of central importance to classical economists (Atkinson 1997). In recent years, the field has seen a revival in the wake of the 2008 financial crisis and the subsequent economic distress. A dense economics monograph devoted to inequality became an unlikely international bestseller (Piketty 2014), showcasing the popular attention to the issue. Meanwhile, the rise of computational social science also blows a tailwind to the endeavor of better understanding inequality. In this literature review we first survey the traditional methods and theories regarding economic inequality, and then introduced some recent research on the topic using novel data sources and computational methods.

2 The Tradition of Inequality Research

The study of income and wealth inequality is twofold: the severity of inequality, and its economic, social, and political origins. Using administrative or private-sector data, economists and sociologists have long been trying to ascertain the distributions of income and wealth in different societies and to examine different factors and mechanisms behind these often highly unequal distributions.

2.1 The Measurement of Inequality

The first and foremost question of studying inequality concerns its measurement. Although questions about inequality are diverse, the indicators used by researchers are quite similar. Mean GDP, GDP per capita and individual consumption have long been regarded as most popular measurements. But due to the difference between currencies, data of income and consumption from different countries are only comparable after being adjusted using the Global Exchange Rate or Parity Purchasing Power Index. Anand and Segal (2008) compared results of choosing different indices and concluded that the statistics as well as other indices calculated through GDP can be quite different if researchers use different indices to adjust the original data.

Income and wealth percentiles, as well as the share of different income/wealth groups are also intuitive indicators. One advantage of using these indicators is that, when combined with other time series data, they can easily picture the inequality dynamics as well as within-or-across differences. In Piketty, Yang, and Zucman (2019) the national wealth among different types (domestic capital, land and foreign assets) and holders (government and private) and income share of different groups (top 10%, middle 40% bottom 50%) are presented in a time years sequence, making it easy for readers to capture the overall income increase in total, and the dynamics of income and wealth share in different groups. Combining the income percentile with real income change, Lakner and Milanovic (2013) gave an excellent visualization of the growth difference among different income groups. Their "elephant curve" shows a great increase of wealth among the poorest and the richest, and a stagnant middle-class, suggesting the middle group's financial situation has remained stable over the past few decades.

Using basic data like GDP or income percentile, researchers have put forward some calculated estimators to measure inequality, and a group of inequality research have been using and developing these measures. Examples include Gini Coefficient (Chotikapanich, Valenzuela, and Prasada Rao 1997; Dikhanov et al. 2002; McNicoll 2003) , Theil T (Bourguignon and Morrisson 2002), Theil L (Milanovic 1999) and also the variance of log-income (Sala-i-Martin 2006; Schultz 1998).

Different measures are believed to capture different facades of the issue. Both Theil T and Theil L belong to the Theil index family. Theil index uses the log of income as major data input, the difference is that Theil L uses population as weight. Considering the majority of population comes from the lower-class, the Theil L is more sensitive to the income change from lower level, however the Theil T is more indicative of high-class income change. The Gini index, on the other hand, takes the order into consideration and is commonly believed to better capture the income of the middle-class.

Different datasets are used for constructing these indexes. Some use the existing dataset from older literature and make some adjustments (Dowrick and Akmal 2005); others start from the beginning and create their own dataset (McNicoll 2003). The nature of inequality itself attracts the researchers to use official data for their research. Bourguignon used GDP per capita in 33 countries from 1820 to 1992. Though borrowing quintile share data from Squire (1996), Sala-i-Martín (2006) mainly uses GDP per capita data, which add him to the official data camp. uses two different official datasets: the GDP per capita to measure income inequality, and the national account to calculate consumption inequality. There are also others who prefer private sector data. uses two years household survey data from 216 countries. In his later work, he expands the sample to include 345 countries.

In constructing datasets and measuring inequality, at least two problems should be concerned. First, simply using official data, which suffers from problems such as under-reporting of high-income groups and the tendency of excluding extreme poor groups, can sometimes lead to great bias. Combination of both official and private data can help correct the flaws (Piketty et al. 2019). Second, though abundant in amount, researchers should be careful in choosing the measurement. McGregor, Smith, and Wills (2019) believes it is indeed challenging for researchers to have to decide on "the variable, population and distributional characteristics" because the decisions researchers made can affect their conclusions. The measurement, therefore, should be closely connected with the potential research purpose.

2.2 Economic Explanations

The nature of inequality as well as its origins have long fascinated economists. According to Roemer and Trannoy (2016), inequality is merely a problem of opportunity. To be equal can be simply understood as to let individuals have equal amounts or "resources". The total amount of resources is partially determined by geological (nature resource) and social environment (network resource), but the opportunity to access resources can be quite different for each person, probably because of his/her individual characteristics. With different amounts of resources obtained by different groups, and under the impact of self-reinforcing (once privileged groups are more capable of maintaining their superiority), inequality appears and sustains.

Explaining the origin of income inequality can be an even tougher mission, economists of different genres give their own speculation. Some macroeconomics believe in the effect of production, suggesting the difference of development among countries is the result of difference in productivity, with labor, capital and human resource being the major contributors (Solow 1956). Kalleberg, Wallace, and Althauser (1981) blame it on the economic segmentation. They believe the segmentation of the economy as a result of multiple social, political and economic changes. The segment of economy and the difference of labor workers lead to an uneven payment. Employers with more resources may tend to pay more to their employees, and workers with higher ability are easier to get handsomely paid.

A comprehensive explanation comes from Piketty (2014). He goes even further and disentangled the relationship between development and distribution. His study separates the income from labor and that from capital and emphasizes the importance of capital. The accumulation of capital is an inevitable result of economic development. However, the distribution of wealth is not equal, often a small percent of the group holding the majority of overall capital. The income from capital and labor can be quite different for some social and technical reasons, and when revenue from capital exceeds that from labor, the majority of the social revenue will go to the capital and enrich those capital-holders. This process benefits those who have higher capital assets, and leads to an unfair distribution of income, that is, inequality.

Study of other economic contributors of inequality and development is rather abundant. Inborn features like ethnicity (Fox 2004) and gender (Jacobs 1996) can be important. Geographical features of one's habitant are proved to have influence (Assouad, Chancel, and Morgan 2018) as well as social context: the community you live in (Chetty et al. 2014) and the history and institutional system of an area may also have effect (Acemoglu, Johnson, and Robinson 2001, 2002; Assouad et al. 2018)

2.3 Sociological Explanations

Some classical sociologists believed that the rising income inequality could be caused by social inequality, which defines the degree of unequal distribution of resources and rewards among different individuals, groups and societies (Lupton 1992). In other words, some parties would gain more earnings because they stand on the higher hierarchy in the community that allows them a higher chance to access income. When discussing the issue of income inequality, it is essential to review the theoretical approaches to how sociologists comprehend the problem. Guidetti and Rehbein (2014) demonstrated that Marx theory and Weber approach were the two primary theoretical explanations concerning the sociology of income.

Marx illustrated that the social inequality such as income disparities would be intensified because of the apparent distinction regarding social class in which separates people into two major classes: capitalists those own means of production and workers those do not own means of production (Wolff and Zacharias 2013). Under a capitalist economy, workers have to sell their labor power to the capitalists in order to earn a wage and have no control over the actual laboring process. For instance, they are not knowing in advance what specific tasks they are required to do. As a result, Marx argued in his Das Kapital that capitalists have a constant tendency to lower the cost of labor as much as possible by exploiting workers such as surplus value in order to maximize their profits. In other words, the income gap between capitalists and workers would greatly be wider due to the intention of capitalists in accumulating capitals. According to research conducted by Wolff and Zacharias (2013), they found that the median income of capitalist households are much higher than that of all households in the United States in 2000 compared to 1989. This shows that the income gap between two classes was actually widened over the time. Class stratification, suggested by Marx, could be a determinant to explain the origin of income inequality.

Although class and income are highly related, using class theory by Marx to explain the phenomena of income disparities is not comprehensive enough (Robinson and Kelley 1979). Some sociologists criticized that old Marx theory overlooks intra-class inequalities by only focusing on two extreme classes and does not fully explain the issue of income inequality in the modern societies. For instance, in recent decades, the income still varied among different occupations in the same class such as doctors would receive higher income than nurses. Weber further modified Marx's analysis by placing more emphasis than Marx on division within the propertyless class (Bendix 1974). Weber argued that class position depends on an individual's market power such as possession of skills and knowledge. Even in the same class, occupational labor market would determine individual's market power and provide various incomes to workers. Therefore, the income gap within the same class still exists. (Morris and Western 1999) demonstrated that the disparities of education level are more strongly involved in the growth in income inequality than either age and sex groups. By interpreting Weber's view, educated workers have higher skills and knowledge (higher market power in societies), they have higher bargain power to negotiate wages and therefore receive higher incomes. On the other hands, uneducated workers have lower power in wage negotiation because of inadequate skills and eventually they get less paid.

To sum up, Marx and Weber approaches could be used to explain the issue of income inequality by considering the social class of individuals.

3 Computational Social Science in Inequality Research

The unprecedented abundance of data in our digital age has given rise to computational social science (Lazer et al. 2009), which is generally associated with big data and the various means to analyze it such as machine learning, text analysis, and network analysis. We observe that computational social science has found its applications in both fronts of inequality research: empirical and theoretical. These applications illustrate the advantages of computational social science in certain contexts as well as its limitations.

3.1 Observation with Big Data

As mentioned in the previous section, measurement is the first step in studying inequality. Since measurement always concerns data, it naturally lends itself to computational social science in contexts rife with big data. It should be noted that our focus here is empirical studies that combine big data and computational methods. A lot of studies that are conventional in its design and methods may employ data with formidable size and scope. The historical tax data used by Piketty (2014), for example, is of massive volume and was created by governments for purposes other than research, therefore qualifies as ready-made "big data" (Salganik 2018). Piketty's work, however, is clearly not an example of computational social science.

Studies that do meet the requirements usually assemble datasets from novel data sources and convert them into measures of income and wealth with computational tools, thereby providing measures of inequality. One well-known data source is the night-time light, which has been found to be a good predictor of regional wealth (Weidmann and Schutte 2017). Lessmann and Seidel (2017) went further to construct regional Gini coefficients by combining night light data and spatial population data. Such measures are especially valuable for some developing countries where statistical offices are not well-established and disaggregate economic data are often unavailable. However, this technique only works well for measuring regional inequality and performs poorly for individual inequality. Elvidge et al.

(2012) tried to construct Gini coefficients at the level of individuals only to find a week correlation with the traditional Gini coefficients. Researchers have also used high-resolution daytime satellite image data for similar purposes (Jean et al. 2016). A convolutional neural network was used to extract features from these images and predict the regional wealth level with the help of existing survey-based data. It was found that such predictions outperformed the nigh light predictions and did well in out-of-sample testing, therefore held great promise for wider application.

Apart from image data, machine learning also enables the use of mobile phone metadata. Blumenstock, Cadamuro, and On (2015) exemplifies this line of research by showing that the data on phone interactions in Rwanda's largest mobile phone network can be used to predict subscribers' wealth. The trained model ended up explaining 91.7 percent of the regional variation in the traditional survey data, with much lower cost than surveys.

Another branch of studies under this rubric is concerned not with after-the-fact measurement but with real-time monitoring. Due to the nature of such real-time data, monitoring has long been conducted behind the walls of private companies and government agencies (Lazer et al. 2009). Although new tools and initiatives have produced a burgeoning "nowcasting" literature (Lazer and Radford 2017), there are still relatively few such studies on the topic of inequality. Fortunately, Chetty et al. (2020) did a timely and exemplary study in this line of research that is of great value to inequality research. The authors did not set out to study inequality per se but aimed to build a real-time economic tracker against the backdrop of the current coronavirus pandemic. They partnered with several private companies such as credit card processors and payroll firms that have access to real-time economic data and constructed economic statistics from these data. Because they grouped the statistics by county, industry, and (pre-crisis) income level, many of their findings yield great insights into the making of inequality in the pandemic. For example, they found that high income workers recovered their jobs quickly after the initial shock thanks to the possibility of working from home, whereas low income workers were trapped in protracted unemployment. Such "K-shaped recovery" clearly has implications for medium-term inequality among different income groups.

Perhaps more importantly, Chetty et al. pioneered the kind of academic-private partnership that could bring out the real potential of computational social science. If we could expand the coverage of such economic trackers and institutionalize them like we did for GDP, then our understanding and policy response to inequality are likely to be much improved.

3.2 Theory with Network and Simulation

The theoretical part of inequality research mainly concerns the mechanisms that lead to different income and wealth distributions, and computational social science provides new insights and tools for this endeavor through network analysis and simulation.

If we regard network analysis as one of the defining features of computational social science, as did the early formulation of the concept (Lazer et al. 2009), then the effort to include networks in the explanation can be traced to long before the current wave of "computational social science". Early research on this issue mostly focused on the role of social contacts in the hiring process (Granovetter 1974). Subsequent work also showed that certain properties of the network structure can have an impact on income distribution. For example, higher density of social ties or greater stratification by ability could result in greater wage inequality (Montgomery 1991). Such models, however, were still quite deterministic and did not account for the complex dynamics that produce economic inequality in real life, therefore falling short of our notion of "computational social science" today.

What makes this line of research more "computational" is the combination of network effects and simulation, especially agent-based modelling (ABM). DiMaggio and Garip (2011) extended the relationship between social ties and inequality to any good or practice exhibiting network externaliy, i.e. becoming more valuable as the network of adopters gets larger. Using an agent-based model of internet adoption as an example, the authors showed that network externalities increase inter-group inequality under the condition of homophily, i.e. advantaged adopters are socially linked to each other. Using a similar approach, Zhao and Garip (2019) showed that the link between homophily and inequality further depends on network consolidation, i.e. the correlation between traits in the population. As these examples showed, ABM allows researchers to experiment with various network settings with much greater flexibility, thereby helping generate new theoretical insights.

One important caveat is that the bulk of this literature only has indirect bearing to income and wealth inequality, which is our specific focus. In our reading we have found few ABM studies that tackle income and wealth inequality directly. The one exception to this pattern (Dawid and Gemkow 2014) was essentially a follow-up study that explored finer structures of an established mechanism without generating major new insights. This probably reflects the question choice of the research community as well as the limitations of the tool. Agent-based modelling is useful for generating interesting patterns, but it could be much harder to construct coherent narratives around black-box simulation results. Nonetheless, we believe there are still ample opportunities for applying ABM in inequality research.

4 Conclusion

The world has witnessed a surge of overall inequality in the past several decades, during which the study of inequality has also evolved. In this paper we review important measurements and theories in in the literature of economic inequality. We discuss different data resources used by researchers, believing that the use of big data as well as machine learning techniques can help generate new, fascinating data. We also suggest that the computational social science technique can help produce new theories, for which agent-based modelling provides several examples.

The study of income and wealth inequality itself is, for now, not the main topic in computational social science. And the computational methods are themselves criticized for lacking explanatory power. However, we are still confident about the power of computational methods. We believe the combination of traditional and computational methods can help generate new, fascinating discussions in the study of economic inequality.

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