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The Political Economy of Inequality in Rich Democracies

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Abstract

Rich democracies have experienced a large increase in income inequality starting around 1980, coinciding with a rise in international trade and information technology. The leading theories used to explain changes in the income distribution—skill-biased technological change and globalization—have not been called upon to explain why the United States has been more unequal than other democracies even before the recent rise, suggesting other forces are at work. I set out to investigate those forces. First, I clarify the trends in income within the United States. The key rise occurred from 1980 to 2000 in labor income and benefited not just the top 0.1% or even the top 1% but the top 10%. Then, I explore the international correlations using both survey and tax-based sources. Greater exposure to innovation and trade does not predict higher inequality in levels of changes across rich democracies. Political economy relationships are much more successful in explaining the variation, though traditional measures of bias toward capital have mixed results. The strongest predictors of inequality are two variables: an index of excess earnings accruing to elite professionals and racial diversity. Simple regressions confirm this evidence. Digging deeper, I show that the top 1% by income or wealth are disproportionately found in domestic sectors that are not particularly innovative or affected by globalization. This is especially true for the most unequal countries. In the United States, financial sector workers, doctors, and lawyers play a large role in income inequality and are notable for their high levels of sector and occupation-specific regulations. The origins of racial inequality in the United States are well known and reviewed here. I conclude that political economy considerations must be brought into any comprehensive theory of the income distribution in the early 21st century democracies.

I. Introduction

It is well established that income inequality has been rising across developed democracies in recent decades. The United States stands out for experiencing an extraordinarily sharp rise during the last four decades and exhibiting much higher levels of inequality both before and after the recent upswing (Piketty, Saez, and Zucman, 2018).

The rise in inequality has been much discussed and debated in the economics literature; yet, no theoretical or empirical work explains both the high level of inequality in the United States and why it has increased in some countries but not others. The goal of this paper is to combine survey and administrative data sources to assemble a comprehensive international database of income inequality and its potential determinants in rich countries, so as to test the leading theoretical ideas and advance understanding of the above patterns.

The leading theory explaining rising inequality in the United States and other rich countries is skill-biased technological change. The idea is that both the supply of skilled workers and the demand for skilled workers has increased, but demand has outpaced supply as a result of technological change that has favored professional workers or those with a college degree (and are hence considered skilled).

In a notable summary paper focused on the bottom 99% of the distribution, Autor (2015) makes a compelling case for the skill-biased technological change theory. He points out findings from the literature that the rising income returns to workers with a college education, relative those with a high school education, explains at least half of the rise in "earnings dispersion" from 1980 to 2005 within the United States using household survey data. Workers with higher cognitive ability consistently earn higher incomes across OECD countries, and in the United States and several other countries with similar data, the college premium has increased in recent decades. Recent advances in information technology are identified as a primary cause.

Yet, a few noteworthy problems emerge with this theory.

1) Why has education supply not increased enough to satiate the market and reduce relative wage gains?
2) Why have inflation-adjusted salaries for college workers remained relatively flat, even as relative demand has grown in response to technology?
3) Why have wage and salary gains disproportionately accrued to top income earners rather than a broader swath of skilled workers?
4) Why are some technologically advanced countries not experiencing rising income inequality?
5) Across decades and even before the 1980s, why was inequality so much higher in the United States than other industrialized countries? In other words, how does information technology account for persistent differences in the level of inequality?

Autor (2015) notes several other explanations for rising inequality that partly address these criticisms. First, he notes that technology has not only increased demand for college workers, it has decreased demand for workers performing routine tasks, such as production workers in assembly plants as well as administrative and clerical workers in office settings. Second, the global integration of trading markets has put downward pressure on manufacturing workers in rich countries who increasingly compete with Chinese workers and those in other developing countries. Finally and perhaps as a result of the first two, private-sector unionization has weakened the bargaining power of noncollege workers.

These explanations produce testable hypotheses that so far have not been addressed in the literature: Do technological innovation, global integration, and de-unionization predict trends in inequality across rich countries?

Autor (2015) makes clear that he is focused on inequality among the bottom 99%, though his review is relevant to trends in top-earning as well. Two alternative theories are especially pertinent to explaining the rise in top-incomes, as famously documented by Piketty and Saez (2003) in seminal work.

The explanation favored by Piketty (2015) is that the return to capital income has outpaced the return to labor income, driving up the wealth and income of the very rich. This theory, however, fails to match the international patterns, in that the rate of return on capital is not higher in more unequal countries compared to the return to labor (Acemoglu and Robinson, 2015).

An alternative explanation for the growing concentration of income at the top of the distribution is that superstar performers are increasingly able to tap into global markets (Rosen, 1981). In a variant of this theory, Mankiw (2013) suggests that heritable natural ability plays a large role in extreme compensation. Setting aside the origins of stardom, one would expect to see the 1% emerge primarily from occupations and industries that reward global success.

The logic is simple. Assume highly talented people are able to control some percent (p) of the domestic market (m_d) for revenue of p_d*m_d, and they also control some inevitably smaller share (p_g) of the global market (m_g). In the period before widespread globalization, both p_g and m_g are small. After globalization—conceived of here as the total reduction of trade costs for goods and services as a result of both technology and policy, the m_g increases dramatically for would-be exporters of both goods and services. Even if p_g stays very small—suggesting a competitive market with many small players—inequality could still increase because revenue for exporters would increase faster than revenue for domestic-market businesses and workers. "Winner-take-all" superstar effects—which could be brought about through advertising or sheer talent in this story—may lead p_g to also increase. This is relevant not just for professional entertainers and athletes, but also writers, CEOs and top-performers at multinational corporations. On the other hand, we would expect p_g to be zero for people working in domestic industries such as healthcare, legal services, and accounting. One way to examine the effects of globalization on inequality is to measure the share of revenue from exports for a given industry or economy. I consider this below.

Another strand of the superstar literature argues that star-firms are largely responsible for reducing the labor share of value-added, exacerbating inequality, since the rich disproportionately control capital income (Autor et al, 2017).

Firm-level studies that explicitly study inequality cast doubt on the importance of firm-specific characteristics in explaining the level and rise in inequality. The importance of firm-fixed effects in explaining earnings variation has declined from 1981 to 2013, a period of otherwise rising inequality (Song et al, 2018). Indeed, the percentage of top 1% income earners who are the top-earning individual in their firm fell from 18% in 1981 to 11% in 2013—among all firms with at least 20 employees. Even more striking, the share of 1% earnings going to people who are in the top 1% of their firm has also fallen from 55% to 50% (Song et al, 2018). To a greater extent than in the recent past, workers in the top 1% are less likely to be top executives or top-performers in the United States.[1]

The major finding coming from firm-level evidence is that high-paying firms increasingly hire people who were top-earners before joining the firm and continue to pay them high salaries. Thus, the firm itself does not explain the high pay for top-earners, rather one has to look at the attributes the workers take with them across firms (Song et al, 2018). These could be valuable skills, but they could also be licensing or regulatory advantages that are transferable across firms.

Another gap in the literature relates to a lack of comparative work on the level of inequality.

One potential explanation for why the United States stands out is its racial and ethnic diversity, originating in its colonization by American Indians and then Northern Europeans, followed by its recent history of African slavery and high levels of immigration from the rest of Europe, Asia, and Latin America. The United Kingdom, South Africa, and Brazil are other countries that fit the same pattern of having high levels of diversity and income inequality, whereas Scandinavia, South Korea, and Japan tend to be low on both measures. Consistent with these anecdotes, Putterman and Weil (2010) find a strong correlation between contemporary income inequality and racial diversity. Assouad, Chancel, and Morgan (2018) likewise identify historic social segregation and modern institutions and policies as explaining extreme inequality in the countries they survey.

Racial differences in earnings have been studied in detail, and the most recent and comprehensive evidence shows a persistent gap. Intergenerational evidence shows that black males—but not females—have especially low levels of absolute mobility in terms of income gains relative to their parents and are at much higher risk for incarceration even when parental incomes are similar (Chetty et al, 2018). The median U.S. black man is at the 27th percentile of the white male earnings distribution (Bayer and Kerwin, 2018). In fact, when one studies all men, not just all working men, the black-white earnings gap has grown since 1970 and stands as high as it was in 1950 (ibid). In this sense, racial diversity may help explain both the level and trend in overall inequality in the United States.

Racial diversity can plausibly result in persistent inequality if political oppression of racial or ethnic minorities hinders access to the most productive occupations, and limits investment in education and skill development, as has been the case in the United States (Rothwell, 2019). In fact, the negative effects of racial diversity can extend to the majority or white population. Evidence from both political science and economics literatures suggests that hostile views toward minorities predict less support for public services—including education—that would otherwise benefit children from lower-income families and reduce inequality (Alesina and Glaeser, 2001; Kinder and Sanders, 1996).

Aside from race-differences in political power, another potential explanation for both the level and change in inequality is that elite income earners have won political favors that redistribute earnings upward.

[1] See “Table A.2 – Percentage Who Are Top-Paid Person at Firm” and “Table A.1 – Percentage of Top 1% Earnings in the Economy Going to Those at the Top of Their Firms.”

This theory has roots in classical political economy. Adam Smith (1776) described many examples of guilds and business organizations conspiring to distort markets, raise prices, and otherwise gain at the expense of the public.

Modern variants of this theory include the work of Mancur Olson (2008), who attributed slowing productivity growth in rich countries to the rise of organized interest groups, and Anne O. Krueger (1974), who developed the theory of rent-seeking, where economic resources are re-allocated, at least in part, based on political influence rather than productivity considerations. More recently, President Obama's Council on Economic Advisors discussed potential links between rent-seeking behavior and inequality (Furman, 2016).

A handful of empirical studies delve into who comprises top income earners as a means of evaluating the aforementioned theories.

Evidence for the United States comes from Bakija, Cole, and Heim (2012), in that they analyze the occupations and industries of top-earners using tax records from 1979 to 2005. Financial sector workers, physicians, lawyers, and real estate professionals saw their share of top 1% earners increase from 33% in 1979 to 41% in 2005, despite a slight reduction in the share represented by physicians. These professions are heavily regulated and subject to rent-seeking distortions. Meanwhile, top income earners were less likely to be corporate executives outside of finance at the end of the period relative to the start; their share of top-earners fell from 21% in 1979 to 11.3% in 2005. Computer workers, engineers, artists, and entertainers represent small shares of top-earners, suggesting that technology-based theories and superstar based theories are, at most, only modestly useful in explaining the level and trend in U.S. inequality. Likewise, Guvenen, Kaplan, and Song (2014) identify workers in the financial and healthcare sectors as comprising roughly 40% of top income earners in 2012.

In a similar study of Canada, Lemieux and Riddle (2015) find that medical professionals and lawyers are the most overrepresented in the top 1%, but the share of medical professionals has fallen from 14.7% to 10.4% from 1982 to 2011, which they interpret as reflecting the strong role of the Canadian government in setting healthcare pay. The rise in top incomes can be most attributed to the increasing importance of finance and senior-level managers. Moreover, senior-level managers are much more likely to be in the top 1% if they are in industries with large capital requirements and limited competition, such as mining, communications, or finance. Despite the expansion of global trade opportunity, the share of top income earners who are manufacturing executives has fallen sharply, in accordance with the sector's declining overall importance in the workforce; Bakija et al found the same for the United States. Lemieux and Riddle (2015) largely reject technology and market-based explanations for inequality trends in Canada, based on this evidence.

Taken together, these findings suggest a strong role for political and regulatory factors in determining top-income status. If political economy theories are indeed relevant to contemporary patterns in the level and change in income inequality, two other testable hypotheses emerge: One should expect to find evidence that interest groups successfully lobby for political favors that benefit high-earning groups and those who have seen the largest increase in earnings, and international data should suggest that more unequal countries are characterized by overrepresentation of professional elites among top-earners.

In what follows, I attempt to test these theories.

Following this introduction, the paper starts with a summary of the key stylized facts of income inequality in the United States and other OECD countries and an attempt to determine which metrics hold the most validity.

I am particularly concerned with whether the level and trends are robust to several well-known problems with measurement and comparison over time and across countries: 1) How is income top-coding affecting inequality measures? 2) What is the population base? Does it include those who are unemployed or out of the labor force? 3) Which sources of income are included? (e.g., labor income, business income, capital gains, government transfers). To address this, I rely heavily on several major sources of international income inequality data that each have strengths and weaknesses: The United Nations World Income Inequality Database, The World Inequality Database, and the Luxembourg Income Study.

Aside from the source of inequality data, one must also be concerned with the measure. The Gini coefficient satisfies the transfer principle, in that transfers down the income rank reduce inequality, but it is not helpful in identifying where the action is in the income distribution. Top percentile shares are better at doing that. The top one percentile share has gotten the most attention recently, as Piketty and his collaborators have identified the most movement there, and so the Gini Coefficient and top percentile shares are the focus of my empirical work.

Yet, I don't simply assume that one source or one measure is better than another. Instead, I let the data guide me, by validating income inequality measures against alternative measures of welfare, such as health and well-being. My intention is that this section is itself a minor but useful contribution to the literature on income inequality.

The third section uses the summary data to test the theories described above. I examine correlations between the current level of inequality and changes in inequality—over key periods identified in the first section. I also implement simple regression models. There is nothing novel in the methods used here, but these data have never, to my knowledge, been pulled together for this purpose, and as a result, the theoretical discussion described above has not been subjected to even the straightforward examination that I impose upon it here.

In the fourth and final section, I decompose top-earning status into occupations and industries. This allows for more detailed testing of the main ideas and deepens and confirms the suppositions inferred from the aggregated patterns. I also examine country-level data to see if occupational and industrial patterns are consistent with national-level measures of inequality.

Alongside a discussion of the international patterns, I focus on the United States because it stands out as highly unequal in both the level and its rising trend. This allows me to discuss some of the specific historical policies, lobbying positions, and interest group dynamics that have contributed to making the United States especially unequal.

The appendix discusses why international survey data from the LIS and the American Community Survey, specifically, provide reliable tools to decompose the 1%. The income restrictions are broadly irrelevant to identifying who is in the 1% because the reporting thresholds are set above 1% cutoffs. Moreover, I merge IRS data by ZIP code to Census data and find further evidence that self-reported income accurately captures 1% status. Finally, I explore evidence from the U.S. Census and LIS on wealth, finding corroborating evidence that the patterns identified in the previous section also apply to the wealthiest 1%, using net worth instead of income.

The findings that emerge from this study can be summarized as follows: Income inequality is a valid measure of the health and well-being of a population; it cannot be divorced from political economy, including race and ethnic relations, as well as interest group politics; across rich democracies, elite professionals have, with varying levels of success, set themselves apart from the competitive forces that would otherwise check the prices they charge and the returns they garner; similarly, those of European descent have in the United States, and to a lesser degree in other countries, set up obstacles that have inhibited racial and ethnic minorities.

II. Theory

My theory draws heavily upon Hsieh, Hurst, Jones, and Klenow (2013) and Jones (2016) but explicitly adds the consideration of power. National income is a function of capital and labor and a productivity term Z.

$$Y = ZL^{\alpha}K^{1-\alpha}$$

Labor can be thought of in terms of human capital as in H=hL, where H is the stock of human capital and h is average human capital per worker and L is the stock of workers. Output per worker can be shown as:

$$\frac{Y_t}{L_t} = \frac{K_t}{Y_t}^{\frac{\partial}{1-\partial}} h_t Z_t$$

In this framework, growth comes from increase in human capital, other factors that enhance labor productivity captured in Z, and the value of capital relative to aggregate income. Z can be affected by institutions, tax policy, and many other factors. For the purposes of this paper, I focus on misallocation resulting from political inequality.

Labor output can be thought of as the aggregated value of various tasks. For simplicity, consider two tasks, where the omega (ω) term governs their relative productivity.

$$L = {T_1}^{\omega}{T_2}^{1-\omega}$$

The misallocation of labor affects labor output as shown below and is a function of how workers are distributed (s), where "s" is the share of workers who perform task one.

$$Y_L = M(s)L$$

$$M(s) = s^{\omega}(1-s)^{1-\omega}$$

To make this more concrete, consider that a plausible value for ω would be something like 0.55, in which case task one would be approximately 58% more valuable than task two, which is close to the average salary difference between high school workers and those with a bachelor's degree or higher in the United States. In that case, the optimal value of "s" would be 0.55. If "s" is too high or too low, labor is less productive.

Where does misallocation come from? For my purposes, the misallocation of talent can result from inequitable political power, and this, in turn, will result in both slower productivity growth and high-income inequality, as people work in the wrong careers.

To see how the misallocation of talent may arise, imagine that people choose their career in early adulthood in such a way as to maximize their lifetime health and income. To the best of their knowledge, income and health are determined by how productively they can perform the tasks of a given occupation in the economy. When choosing a career, they thus aim to pick the set of tasks that will allow them to work most productively, given what they know about their preferences and talent at young adulthood.

Talent at young adulthood, meanwhile, is determined by genetics, private environmental circumstances (such as neighborhood and familial influences), and public influences, such as environmental security, law enforcement, and education. Aggregate talent of a society (county "c") can be described in the following way, where p refers to an individual's share of aggregate political power; f is a subscript indicating family (or rather private environmental influences) and subscript p stands for public environmental influences; and a, b, and c indicate the relative importance of each influence to a talent index. Each environmental component is influenced by access to political power, though each has a component that does not depend on power, summarized by "u," which can be thought of as the contributions that parents make to their children or societies make to developing even the least powerful residents; genes are not affected by power.

$$Talent_c = \sum {G_i}^a (pE_{f,i} + uE_{f,i})^b (pE_{P,i} + uE_{P,i})^c$$

In a politically egalitarian society, the public environmental contribution is roughly equal and explains approximately zero variation in talent within a political unit (e.g., country or independent city-state). Likewise, the private environmental contribution is more constrained in a politically egalitarian society because neighborhoods are approximately equal in quality and the lowest income families are given support to shore up the development of talent for their children. The genetic contribution to talent explains a non-trivial but small share of the variation, consistent with the latest genome-wide association studies (GWAS) (Lee et al, 2018).

I further assume that genetic basis of talent does not vary across groups (i.e., gender, ethnicity, or race), only individuals within the same group. I develop this argument empirically in Rothwell (2019). In this way, genetics can't cause group inequality in income, only individual inequality. Hsieh, Hurst, Jones, and Klenow (2013) also make this assumption.

In a politically inegalitarian society, private environmental contributions are enlarged because of massive differences in neighborhood conditions, and the public contributions to talent also vary more widely, enlarging the value of "c." To summarize, this model leads to several testable predictions: The "a" term above (related to genetic contributions) should be larger in politically equal societies than in unequal ones. Likewise, the "b" and, especially, "c" terms should shrink in politically egalitarian societies, reflecting lower explanatory importance for public resources as variation in access and quality is limited.

Talent matters because it governs which occupations people choose and how well they perform those occupations, which affect income inequality and national economic growth, respectively.

In addition to affecting the development of talent, power affects the returns to talent or the returns to choosing a specific occupation-industry combination in class "C." The outcome of interest is capital and labor income before taxation.[2] There is compelling empirical evidence that industry-specific effects and occupation-specific effects matter to earnings above and beyond individual talent (Abowd et al, 2012; Kleiner, Marier, Park, and Wing, 2016; Winston, Crandall, and Maheshri, 2011). In this set up, t is like a tax or gratuity that is a function of power. It could be thought of as discrimination based on gender, race, nativity, or religion or a privileged rent resulting from regulatory rules that apply to the specific industry-occupational combination.

$$Y = t(T^a)$$

$$t = f(p)$$

In this way, occupational and specialization decisions are affected by power in both the development of talent needed to perform various occupations and the ultimate value of working in that occupation. Efforts to equate political power in one sphere of life (e.g., adult labor market discrimination) may completely ignore power differences that affect the development of talent and vice versa.

Power is determined by group membership, which is determined by ascribed characteristics "A" (e.g., race, ethnicity, and gender), as well as malleable "class" characteristics "C" (e.g., occupational or industry membership). These factors are multiplied by aggregate power per capita, with parameters that become zero for all people in a completely egalitarian society. By contrast, in a highly racialized society, like the Jim Crow United States, the "A" term is very important in allocating power and "d" is large. In a society heavily influenced by industry or occupational-specific lobbying, the "C" term is important and "e" is large.

$$p_i = \mathrm{A}_{g_i}{}^{d}\mathrm{C}_{o_i}{}^{e}(\mathrm{P/n})$$

To tie this back to growth theory, the optimal share of workers performing a given task (where s=a) arises when genetics determine career choice, with families making complementary investments, and power plays no role. Moreover, all else being equal, faster growing societies are better at developing talent, making it less dependent on power. Since political inequality downplays genetics, it is obvious that a politically unequal society will result in slower economic growth.

As to the distribution of income, political inequality creates a less egalitarian distribution of talent and directly distributes labor market income to the powerful, irrespective of talent. In these two ways, political inequality causes a more unequal distribution of income.

Implementing the theory with limited data

The ideal database to test this theory would have individual microdata across OECD countries that would contain: a valid polygenic score for income (or education, which exists in some data);

[2] Here and throughout, I prioritize pre-tax income as the outcome of interest for income inequality. The reason is that I am interested in studying what people earn through their work and investments, not after the net effects of charitable contributions, inheritance, gifts, or government taxation and transfers. Those channels are subject to very different motivations and forces than earned income. This decision is in no way meant to dismiss those other income sources as irrelevant to welfare, but it strikes me that an individual has a much stronger claim over his or her earned income than income from those other channels, which are much more susceptible to the whims of others and might even disappear as a function of success.

measures of parental investment; neighborhood characteristics; the quality and value of local public goods and services received throughout childhood; income earned; occupational and industry affiliations; regulations pertaining to those industries and occupations; and a measure of talent. These concepts are not impossible to operationalize, but nothing like this is close to existing at present.

What I do have is country-level data on income inequality and many other variables discussed in the literature, and individual-level data on earnings, occupation, and industry in a large group of countries. From this limited basis, I can say which of theories discussed above seem to best fit the data. If the industry and occupational structure of top earners implies that most of them are disproportionately affected by globalization or technology, or access to capital, then those theories—and not the one I laid out above—could be regarded as more plausible. As I argue below, however, my interpretation of the evidence suggests an important role for power.

III. Data and Measurement Issues around Inequality

1) The decennial U.S. census and American Community Survey. These data are accessed through IPUMS USA (Ruggles et al, 2018). The coverage is a random sample of 1% of the U.S. population and contains detailed information on the occupation and industry of respondents, but the income data are top-coded, biasing inequality metrics downward.
2) The United Nations World Income Inequality Database. This has the most comprehensive coverage across countries but relies on household surveys of varying quality with various methods and sources considered.
3) The World Inequality Database (WID). Created by Thomas Piketty and his collaborators. This database offers limited (but growing) cross-country coverage but has many advantages: standardized definitions that are comparable across countries and over long periods of time and are based on the most accurate possible source of income data—government tax records. The data are not top-coded and all sources of income are included. The principal disadvantage is that the database is very limited as to the characteristics of income earners, because that information is not typically included on tax records. To access WID data, I use the STATA program "wid," which allows users to pull WID data into the Stata software package without having to download files.
4) The Luxembourg Income Study. This provides strong cross-country coverage using household surveys from government sources. The main advantage is that the survey data are very high quality and include many demographic characteristics, including standard industry and occupation codes that allow scholars to observe who top earners are across countries. The main disadvantage is that time-series analysis is usually not possible and the data are top-coded and not comprehensive in terms of income sources. I address these concerns below. They are offset, somewhat, by the fact that the Luxembourg Income Study also includes wealth data for many countries.

I also draw upon data from a large number of data sources to analyze the international country-level predictors of income inequality and changes in inequality. These sources are described in the appendix.

A final methodological note is that I classify workers as part of domestic or globally exposed industries using data on the value of export revenue as a share of total revenue (output) using input-output data from the U.S. Bureau of Economic Analysis.

A ranking of large sectors on this measure in 2015 shows those that rely the most heavily on foreign revenue are manufacturing (17.2%) , transportation and warehousing (11%), wholesale trade (10.4%), agriculture (10.3%), and mining (6.9%), all of which have export to output ratios that exceed the U.S. average of 6.4%. The finance, insurance, real estate, and rental sector is generally not reliant on global markets (3.4% of output), mainly because of insurance, but investment banking ("securities, commodity contracts, and investments"), which falls within this sector, does obtain a substantial amount of revenue from exports (13% of output), though, in the United States, it is still overwhelmingly based on domestic markets. Likewise, the information sector is generally domestic, but motion picture and sound recording (with 13% of output from exports) and publishing, including software (14%), are globally oriented. Other professional services, including legal and computer services (4% each) are highly domestic, and healthcare is entirely domestic. Within manufacturing, computer manufacturing (32%) and machinery (28%) are the most globally oriented.

IV Findings

United States inequality level and trends

I begin with a close look at inequality trends in the United States since 1960. Tax record data from the World Inequality Database suggests inequality fell from the 1920s until about the 1960s, which makes it a good starting point for the analysis, especially since the Census Bureau didn't collect income data before 1950.

I start the analysis with Census data covering the working-age population who are employed. By concentrating on workers and the working age population, I make the inequality metrics sensitive to labor market dynamics and minimize changes resulting from the aging population and changes in labor force participation. The top-coding in these data make them problematic for calculating distributional income shares, but I include these so they can later be compared to tax data. The Gini coefficient and Theil index are also biased downward by top-coding, but these are less sensitive. In any case, it is relevant methodologically and otherwise to know if income inequality has increased or not for self-reported income earned at and below the top-codes.

From 1960 to 1970, the Census data show a slight rise in income inequality among workers under 65, using the Gini coefficient and Theil index (with alpha set to one), as well as increasing income shares going to the top 1% and away from the bottom 50%. Yet, from 1970 to 1980, every metric except the Gini coefficient shows a modest fall in inequality. This fall is subsequently reversed. From 1980 to 2000, there is a large and consistent increase in inequality by every measure. Surprisingly, however, the share of income going to the top 1% falls in 2016 from its 2000 peak (from 9.8% to 7.5%), even as the Gini coefficient and Theil index continue to rise. This is likely the result of top-coding. Published tables from the Census Bureau covering 1967 to 2017, which presumably do not suffer from top-coding, show that the top 5% share of household income peaks in 2016 at 22.6%.[3]

My secondary analysis restricts the population to those aged 35 to 45, which corresponds to peak years in labor force participation.[4] This accounts for the shifting demographics of the U.S.

[3] Data from the U.S. Census Bureau, Historical Income Tables: Income Inequality, "Table A-2. Selected Measures of Household Income Dispersion," available at https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-income-inequality.html (accessed July 22, 2019).
[4] https://www.bls.gov/emp/tables/civilian-labor-force-participation-rate.htm

population, which would otherwise bias the analysis toward growing inequality as the largest cohort (the baby boom population) reaches peak earnings capacity. The Gini coefficient and Theil Index and Bottom 50 income share metrics all show inequality reaching its nadir in 1990 before increasing sharply thereafter. The 2010s appear to represent peak inequality using the Gini and Theil, though the top and bottom share metrics are somewhat contradictory on this score.

A third analysis removes the working restriction and analyzes the incomes of all adults. These data also show that the nadir of income inequality was in 1980 using the Gini or 1990 using the Bottom 50 income share. One caveat is that census data did not include social security and welfare income until 1970. In any case, these data confirm that 2000 and 2016 were highly unequal relative to 1980.

[SEE TABLE 1]

Data from the World Inequality Database offer more precise estimates and can help clarify which part of the income distribution has seen the largest changes. I calculate income shares for the bottom half, the 50^{th}-90^{th} percentiles, the 80^{th}-90^{th}, and 90-99, 99-99.9, 99.9 to 100, and 90-100. I present the data as decade averages to facilitate interpretation.

The story that emerges is extremely clear. The 1970s marked the nadir for income inequality. If I had included data going back to 1913, it would be clear that this period registered the lowest income inequality since, but many of the series do not go back that far.

[SEE TABLE 2]

In any case, after 1970, income shares disproportionately go to the top 10%, which has an income threshold of $129,000 in 2015. The top 10% saw income shares increase from 31.4% in 1970 to an astonishingly high 46.8% from 2010-2015. Within the top 10%, each major group benefitted. The top 90^{th}-99^{th} percentile saw their share increase from 24.5% to 28.5%. The top 99^{th}-99.9^{th} saw their share increase from 6.5% to 10.9%, and the top 99.9 percent saw their share go from 2.8% to 10.2%. This runs contrary to a popular narrative that only the top 1% or only the extremely rich have pulled away. In fact, it is a large group of elite earners—10% of the population. This group now takes in almost half of U.S. income, up from a third around the middle of the 20^{th} Century.

Meanwhile, losses in incomes shares are spread between the bottom 50%, which lost 8.8 percentage points from the 1970s to 2015 period, while the top 50-90 saw losses of 6.1 percentage points. The 80^{th}-90^{th} percentile group saw a very slight loss, suggesting most of the losses in this group were among the top 50^{th}-79^{th}, with the 80^{th}-90^{th} group hanging on.

The sources of these income gains are also revealing. The top 10% earns the lion's share of capital income (over 70% in every period), but their share of capital income was actually higher in earlier decades, with most of the losses occurring in the 1960s and 1980s; the drop is -6.3 percentage points since the 1960s to 2010s. Meanwhile, the top 10% saw massive gains in labor income, a 12 percentage point gain since the 1960s, with most of the gains coming since the 1980s. The notable exception is that the very rich—those in the top 0.1 percentile—saw gains in both capital and labor income since the 1980s.

[TABLE 3]

While the World Inequality Database is arguably the best available source for inequality levels and trends, the methods used are not without assumptions, some of which have been questioned recently by Auten and Splinter (2019).

First off, the controversy should not be overstated. Auten and Splinter (2019), the Congressional Budget Office (2018), and Piketty, Saez, and Zucman (2018) all agree that the top 1% share of fiscal income (pre-tax labor and capital income) roughly doubled from 1980 to 2014 from around 10% to over 20%. This is itself an important measure of income inequality, and it includes the money that earned income that recipients can use to purchase goods and services.

Other income concepts are needed to capture national income, and this is where Auten and Splinter (2019) differ from Piketty, Saez, and Zucman (2018). Auten and Splinter argue that just 13.1% of national income goes to the top 1% compared to 20.2% for Piketty, Saez, and Zucman (2018).

The alternative non-fiscal income streams include strange concepts like imputed owner-occupied rent (the value homeowners get from living in their house), which is not actually money that can be used on anything. Other important sources include unreported income, which refers to misreporting on tax records and non-reporting, and unrealized capital gains (versus retained corporate earnings). Auten and Splinter (2019) argue that their method of allocating underreported income is more accurate than Piketty, Saez, and Zucman (2018), by citing tax audit studies. They allocate 32% of underreported income to the top 1% in 1979, but only 11% in 2014. Yet, this contradicts Johns and Slemrod's (2010) tax auditing data, which show that the top 1%'s share of reported income matches their share of true income, after re-ranking. In other words, some people in the top 1% of reported income fall below that threshold when true income is considered and some move up, but the final distribution of the top 1% shares is consistent whether using true income or reported income. The Piketty, Saez, Zucman method preservers this fundamental relationship.

Moreover, the Auten and Splinter allocation is *prima facie* implausible in a way that seemingly biases the income inequality trend downwards. In 1979, they argue that the share of underreported income held by the top 1% was roughly three times larger than fiscal income, but in 2014 only half as large. Auten and Splinter (2019) also replace realized capital gains with retained corporate earnings, lowering the top 1%'s share of that source from 60% to 24%. Across all non-fiscal sources, Auten and Spliter's data suggest a massive drop in the top 1%'s share of non-fiscal pre-tax income (from 10.3% to 3.4%) despite a rise in their fiscal income share from 9.9% to 21.8%. In the end, I agree with Piketty, Saez, and Zucman (2019) that these patterns are hard to believe and not supported by available evidence, including those from sources like the Survey of Consumer Finances (Wolff, 2017). In any case, the CBO (2018), Auten and Splinter (2019), and Piketty, Saez, and Zucman (2019) all show substantial rises in pre-tax income from 1980 to 2014.

To summarize, there is robust evidence across data sources and methods that income inequality in the United States increased considerably since the 1970s and 1980s. The gains have been concentrated among the upper-middle class, not just the top 1% and certainly not just billionaires. In fact, more than half of the total gains going to the top 10% have gone to those below the top 0.1%. Overall, roughly 80% of the massive amount of income held by the top 10% goes to those between the top 90 and top 99.9. As a group, the net gains of the top 10% have been entirely composed of labor income, though the richest 0.1% have seen gains in capital income since the 1980s—from 12% to 20%.

Across data sources, the poor have lost large shares of economic growth since 1980, and so have the middle class—below the 90th percentile. These findings from tax-data are largely consistent in timing and direction with census-based inequality metrics—the Gini coefficient and Theil index, even though they are biased downwards.

Having established a sharp rise in inequality in the United States driven by those in the top 10% starting around the 1980s, I now turn to how the United States compares internationally in both the level and trend in inequality.

International level and trends in inequality

I rely on two sources for international survey data on income inequality: the United Nations World Income Inequality Database (WIID; UNU-WIDER) and the Luxembourg Income Study (LIS).

The WIID includes several quality-related fields that researchers can use to harmonize the database. I include only samples that meet the following criteria:

1) No age restrictions; 2) Complete country coverage (not limited to regions); 3) No population restrictions (not limited to working population); 4) Highest quality rating from the research team at WIID.

This sometimes produced multiple measures for the same country for the same year. I am not interested in annual fluctuations but longer-term trends, so I created 10-year windows and calculated a maximum and minimum value per 10-year period as well as a mean.

LIS also provides pre-calculated inequality statistics on their website.[5] LIS data could be considered a high-quality subset of the UN WIID data, since they are included in it, but harmonization is more straightforward with the LIS data, given the centralized processing of the microdata and the more stringent requirements for inclusion.

Finally, I also use the tax records data from the WID, which we expect to have much more accurate data about top income earners.

Which inequality measure?

Income inequality measures are reliable in the sense that Gini-based measures based on surveys are highly correlated across countries with tax-record-based measures of top income shares. The LIS and WIID Gini coefficients have a correlation of 0.73 and 0.72 with the most recent top 1% income share from the WID, respectively (using 18 and 24 countries), and 0.78 and 0.55 across all countries with observations (25 and 40 respectively).

The question addressed here is whether or not there is evidence that tax-based records are more or less valid than survey measures, which would not be surprising given theoretical issues and measurement problems associated with each data type.

This question is not as obvious as it may seem. The top income shares are highly useful but violate the transfer principle for those within the two binary groups. For example, a top 1% share metric does not decrease even when the top 80th-90th percentiles redistribute more income to the bottom 20th; nor does it increase when the bottom 20 or 50 lose ground to 80th-90th

[5] http://www.lisdatacenter.org/data-access/key-figures/

percentile earners. By ranking individuals (or households), a Gini coefficient explicitly captures this sort of change—but doesn't tell you where the action is within the distribution.

To gain some perspective on the validity of various income inequality measures, I examine cross-country correlations between inequality metrics and healthy life expectancy from the World Health Organization, as well as subjective financial wellbeing using data from the Gallup World Poll. The World Poll collects data from approximately 1,000 respondents per country using very rigorous randomization and collection methods.[6] I focus on a measure of subjective financial wellbeing that asks about the level of difficulty people have getting by on present income.

Both health and financial wellbeing measures are highly correlated with income inequality across countries.

For healthy life expectancy, the correlation with LIS-based measures of inequality in 42 countries is -0.78. It is -0.43 for 103 countries with Gini data from the UN. Within the OECD, however, the Gini performs worse than tax-based measures of top 1 and top 10 income shares, which have correlations of -0.50 and -0.35, respectively.

In explaining subjective financial difficulty, the Gini-based measures generally outperform the income share measures across the broadest range of countries and within the OECD, but the differences are not especially large.

Of course, theses correlations are biased by the fact that poorer countries tend to be more unequal. Regressing either health or financial difficulty on these inequality measures and 2015 income per capital (using World Bank measures that adjust for purchasing-power) reveals that the tax-based measures perform consistently better and top 1% and top 10% shares are significant in the expected negative direction, whereas the Gini measures are not.

Overall, I interpret these findings as suggesting the tax-based measures are preferable in capturing the level of income inequality in OECD countries and top 1% and top 10% shares perform similarly and both much better than bottom 50 shares.

Variation in levels and trends in inequality

Focusing on tax-based data for the sake of comparisons, it's clear that the United States stands out as one of the most unequal countries in the OECD and world.

With 22.6% of U.S. income going to the top 1%, Turkey is the only OECD with higher inequality than the United States, and Chile, with 20.2%, is the only other OECD country even close. The U.K. is fourth with only 13.9% of income going to the top 1%.

Beyond the OECD, only a handful of countries have been added to the WID database, but very few are more unequal than the United States. The monarchical dictatorships of Qatar and the UAE, with their extremely limited legal protections of their non-citizen workforce, are the most unequal with 29% and 26% going to the top 1% (see Marshall and Elzinga-Marshall, 2017).[7] Brazil and Lebanon, with 26% and 23% of income going to the top 1%, are the only democracies that are more unequal than the United States in the WID database. The countries that are

[6] https://www.gallup.com/178667/gallup-world-poll-work.aspx
[7] http://www.systemicpeace.org/polityproject.html

slightly more equal than the United States include Iraq, India, Columbia, Kuwait, Saudi Arabia, and Russia.

The United States also stands out for experiencing the most rapid increase in inequality among OECD countries, with a 10% age point increase in income going to the top 1%. More broadly, only India and Russia have seen a larger percentage-point increase in the share of income going to the top 1% since the mid-1970s.

Across the OECD, Poland, the United Kingdom, Hungary, the Czech Republic, Ireland, and Chile are the only countries to experience a rise in top 1% shares amounting to at least five percentage points. Eleven countries have seen a moderate rise in top 1% shares, including Canada, Sweden, and Germany. Finally, Spain, France, and the Netherlands saw negligible gains in 1% income shares, with Denmark seeing a slight decline.

These changes are highly robust across data sources. The correlation between the rise in top 1% shares is 0.78 with change in Gini coefficients from LIS over the same period for the 10 countries with data from both measures. Using the Gini, the U.K. and Israel—which did not have WID data—experienced a slightly larger increase in inequality from around 1980 to 2015; the survey-based Gini coefficient confirms that Spain, the Netherlands, and Switzerland experienced small increases in inequality, and France saw a decline in survey-based inequality.

Thus, in both the United States and internationally, there is no empirical basis to think that the idiosyncrasies of tax records or issues related to the collection and reporting of survey data imply that measured changes in the income distribution are unreliable.

Explaining variation in the level and change in inequality

Having established that top 1% income trends and levels offer a valid and reliable measure of inequality, I turn to explaining the international patterns.

In explaining variation in inequality across countries, I take two approaches. First, in what I regard as the most intuitive and straightforward approach, I ask: Who comprises the top 1%?

The theories discussed above offer clear predictions about what groups should comprise the top 1%.

Namely, if skill-biased technological change is the explanation, then the top 1% should largely and increasingly consist of highly skilled workers on the cutting edge of technology, such as those working in advanced manufacturing, software development, and information technology. Superstar theories predict those most exposed to global markets should disproportionately comprise the top 1%. This would include manufacturing, large multinational corporations, and entertainment stars. Finally, political economy theory predicts that interest group politics generate excessive returns, suggesting overrepresentation among formalized professional groups like lawyers and physicians, as well as overrepresentation within specific industries that have enjoyed regulatory advantages.

My second empirical approach is to analyze cross-sectional country-level data to understand what correlates with inequality.

The theories mentioned offer related predictions for these outcomes, with a few additional considerations. A Marxist variant of the superstar theory is that countries with weaker unions or more pro-market institutions and tax policies are the ones where giant corporations are most able to extract resources from the global economy and generate top income-earners. Meanwhile, political economy theory predicts that racial diversity will predict higher inequality, because of the political advantages that once accrued—and continue to accrue, in some cases—to Europeans, by virtue of their recent enslavement and colonization of people from other racial groups.

Whatever explains inequality must account for the immense difference in levels and trends between the United States, on the one extreme, and Denmark, the Netherlands, and France, on the other.

Who is in the US 1% and how has it changed?

Examining the 1980 to 2015 period in the United States, which overlaps with the rise of the 1% in tax records, I document the share of employed people aged 18 to 64 in the top 1% by sector using Census data and calculate the absolute change in 1% membership.

I find that 83% of the increase from 1980 to 2015 in U.S. top 1% workers can be attributed to one of three sectors: professional services, finance, and healthcare. The majority of U.S. 1% workers (56% in 2015) earn their incomes from these sectors.

These sectors are less globally oriented than the average U.S. sector, as measured by revenue from foreign transactions; it is worth noting that investment banking (NAICS 523), a subset of finance, is much more reliant on exports than the rest of the financial sector. Removing this industry, I still find that domestic-oriented professional services, finance, and healthcare account for 66% of the increase in top 1% workers. Meanwhile, the most globally oriented sectors—manufacturing, agriculture, wholesale trade and warehousing, and mining—shed 1% workers. Even the information sector, which includes major internet companies like Google, software companies like Microsoft, and Hollywood studies, accounts for just 6% of the increase. In levels, only 3% of the top 1% work in information, and very few (1%) work in arts and entertainment.

Taken together, this is strong evidence against the superstar theory of inequality. Global industry exposure is associated with a reduced probability of being in the 1%. These results are also not easy to reconcile with skill-biased technological change theories of inequality. Professional services, finance, and healthcare rely much less on technology than the information or manufacturing sectors and perform very little research and development. I will return to this point later. Instead, there is reason to think that political economy explanations may be more relevant. Occupational licensing and industrial regulations are particularly important in professional services, finance, and healthcare.

[Table 8]

Just as the industrial basis of top income earners suggests a large role for domestic and highly regulated industries, the occupational distribution confirms that. Physicians and lawyers—perhaps the two most highly regulated occupations in the United States—stand out as accounting for 22% of top-income earners and 30% of the net change since 1980. These occupations are as important to the 1% as executives and miscellaneous managers. Three financial occupations—financial managers, specialists, and sales workers—also account for a large (10.5%) and growing share of workers in the top 1%. Roughly one-third of the increase in 1% workers since 1980 came from these financial occupations. Computer software developers comprise a very small but growing share of top earners, but they are dwarfed by those in highly regulated professions.

[Table 9]

International Data on Sector and Industry of Top-Earners

I rely on data from the LIS to study the composition of the 1% by industry and occupation across a large number of countries.

The first thing to note is that the U.S. pattern in which the majority of top income workers are neither managers nor affiliated with the most globally exposed sectors is consistent across OECD countries. In the average country in this sample, only 17% of top income earners are in manufacturing or mining, and 40% are in managerial occupations. There is also a small and insignificant negative relationship between the share of income going to top earners and the share of top earnings going to manufacturing sector workers or those in managerial occupations.

[Table 10]

As implied in the above, most of the top 1% work in domestic-oriented sectors, with healthcare, public administration and education; finance; and business services being the largest. These three sectors account for over half of top 1% income earners in the average OECD country.

Relative to other OECD countries, the United States stands out as having a higher than average share of top 1% income earners in professional occupations (43% versus 38% average) and a somewhat lower share in managerial roles. Even more sharply, the United States stands out as having a high share of top earners in domestic public-goods-providing sectors of healthcare, education, and government (26.4% versus 19.4% average), as well as business services (28.5% versus 18%). There is a significant positive relationship between the share in public-goods-providing sectors and overall top income shares (0.55). The implication is that countries where top income earners are disproportionately in these highly regulated sectors are more unequal overall.

Surprisingly, countries that have a high share of top earners in the financial sector (like Luxembourg and Switzerland) are no more unequal than those with low shares. Despite having prominent financial sectors in New York City and London, the United States and the United Kingdom do not have a higher share of top earners in finance compared to the average OECD country.

One concern with survey data on income is that they miss capital gains and other business or real estate assets that generate flows of income or buying power. Data on wealth shed light on this. Wolff's (2017) detailed analysis from the U.S. Survey of Consumer Finances shows wealth inequality has been increasing along with income inequality, but wealth is even more unequally distributed. This pattern of more extreme inequality in wealth is also evident in U.S. black-white differences. In fact, while the median white household has $47,000 in financial resources outside of housing; the median black household has virtually nothing—$100 in non-housing wealth (Wolff, 2017).

Concerns about income sources missed through traditional surveys can be addressed by examining data from the Luxembourg Wealth Study, which collects detailed information on net worth. These data are available with the industry of respondents in 11 countries.

The results from the wealth study are consistent with those of the income study. Only a small minority of the wealthiest top 1% of individuals are associated with the manufacturing sector. For the relatively unequal English-speaking democracies of the United States, the United Kingdom, and Australia, manufacturing accounts for less than 10% of the wealthiest top 1%. Meanwhile, in relatively equal countries like Finland and Slovakia, 20% and 26% of the wealthiest are in manufacturing. Meanwhile, in the United Kingdom, 38% of the wealthiest 1% are in finance (13%), healthcare (5%), or professional services (10%). The U.S. data are not disaggregated into single industries, but 63% of the top 1% by wealth work in finance, insurance, real estate, and business services, which includes medical services.

[TABLE 11]

Country-Level Predictors of Inequality

I now turn to investigating the how well various theoretical predictions withstand cross-country empirical scrutiny at the country-level.

To maximize coverage of inequality across OECD countries, I first standardize inequality scores to have a mean of zero and a standard deviation of one. I then combine three measures, using the mean: the top 1% income share, the WIID Gini coefficient and the LIS Gini coefficient, all averaged from 2010 to 2016, except the WIID measure, which uses a 10-year average around the latest year. To calculate the change in inequality, I compare the WIID measure using the latest year to one within 10 years of the oldest measures, with 1970 being the cutoff year. For countries with data from 1970 to 1980, the baseline inequality measure would include the entire decade.

I correlate the levels and changes in inequality across a wide array of theoretical concepts, which can be described as:

a) racial diversity: a diversity index, using continent-of-origin population shares
b) demographic characteristics: the percent of children raised by single mothers, and the working age to retirement age population ratio
c) political economy variables related to occupational and industry patterns and regulations
d) capital versus labor issues related to unionization rates, the labor share of GDP, and the minimum wage
e) globalization measures, including average tariff rates and trade as a share of GFP
f) institutional quality measures of corruption, freedom from government, and political rights
g) skill: higher-education attainment rates and cognitive performance on international exams, and the gap in cognitive performance between the 90th and 50th percentiles of 15-year-olds
h) technology, measured by the number of high-quality patent applications per capita from 2000 to 2016

Altogether, I have 61 variables that fit into these categories.

The item with the largest correlation with inequality is the ratio of income earned by highly paid professionals to the median worker in all occupations. This measures the gap between elite professionals (those at the 90th percentile of professional workers) and everyone else, and this gap is extremely correlated with overall measures of inequality (0.91). There is also a strong correlation between inequality and the gap between elite managers and everyone else (0.73). Yet one key difference is that only the professional gap predicts the change in inequality (with a correlation of 0.32), whereas the manager-gap has no relationship to the change (-0.02).

These facts are consistent with both skill-based and political economy explanations, in that professional work requires formal training and entry is often heavily regulated in OECD countries. Yet, the fact that professional compensation is more predictive of both the level and change in inequality than managerial compensation weakens the skill-based explanation, since managers and professionals have similar education levels, and if anything, managers would be expected to possess greater skill, as top-performing professionals are typically the ones selected for managerial leadership roles, as top lawyers become partners, for example, or top-performing engineers start and manage their own firms after establishing their reputation and experience. Countries that reward managers with very high compensation were no more likely to see inequality grow compared to those that don't, but the same is not true for professionals.

The second most highly correlated variable with inequality is racial diversity. It too predicts both the level (0.78) and change (0.18) in a cross-section of OECD countries. This is most consistent with political economy theories that hold that inequality increases when countries limit minority access to markets and public goods through either direct laws or residential segregation.

Capital versus labor variables show mixed results. On the one hand, union density—which is high in Scandinavia and low in the United States—strongly predicts lower inequality in levels and changes (-0.48 correlation for both). Yet the equilibrium of high unionization has many causes. Changes in unionization—namely the drop in union coverage—are thought to be an important cause of inequality. This drop does not explain the level (-.06) but is correlated with the change (-.36).

In the U.S. context, one theory in this labor versus capital context is that weak unionization explains why the minimum wage is especially low and has not kept pace with inflation. As it happens, countries with a higher minimum wage have higher inequality, contradicting the theoretical prediction. The minimum wage also predicts a greater increase in inequality. One important issue with this analysis is that Scandinavian countries do not have a minimum wage, so I assigned them a value of zero. Excluding them from the analysis does not change the fact that there is a positive—not negative—relationship between the minimum wage and inequality, but it does change the correlation between the change in inequality, which flips from 0.40 to -0.31, if Scandinavian countries are omitted. In general, this provides somewhat weak and contradictory evidence on the importance of the minimum wage.

Other important variables in the capital versus labor theory include: labor protections measured more generally (such as the rules regulating termination and labor contracts), labor share of GDP, top marginal income tax rates, income tax rates more generally, and corporate tax rates. None of these variables are strongly correlated with inequality levels or changes within the OECD.

Globalization theories—which are relevant for superstar theory as well—also perform very poorly. Countries with growing trade deficits are no more or less likely to see an increase in inequality. More protectionist countries (measured by tariff rates) are more unequal, and tariff rates have no relationship to the change in inequality.

Skill-based theories are also not supported by the cross-country correlations. The gap in test scores between the 90th percentile of 15-year-olds and the median predicts lower inequality, which is the opposite of what skill-based theories would predict, though the correlation is very small. Mean test scores are highly predictive of less inequality and have no relationship to the change. Importantly, countries with higher rates of patenting per capita are more equal.

[TABLE 12]

Regressions results

These correlations are modestly informative but also biased by omitted variables. I therefore run a regression of the level measure of inequality on every variable, while controlling for the following baseline characteristics: racial diversity; GDP per capita; high-quality patent applications per capita; higher-educational attainment rate; the share of children raised by single mothers; country population; and trade openness.

Out of 52 variables, only two reach statistical significance: the elite professional income gap, which predicts higher inequality, and the tax share of GDP, which predicts lower inequality. Among the control variables, racial diversity and educational attainment both predict significantly higher inequality in the model. This relationship with education does provide support for the skill-biased technological change theory. This model is only available for the 18 countries with LIS data on occupations. If I replace the inequality index with top 1% shares, there are only 12 countries in the model. The elite professional gap remains significant but not the control variables.

[Table 13]

V Discussion

Economic theory has contributed a great deal to the understanding of what characteristics of countries and people generate income, but economists have made little progress in understanding the fundamental causes of extreme income inequality between people, even those within the same country. The upshot of these efforts is that we have a strong grasp as to how education affects earning for the average degree holder, but very little understanding as to why income differs so much by people with the same level of education and why this might change over time in seemingly democratic countries with well-functioning markets.

This paper limits the discussion to evidence that professional markets may be distorted by political power, but it says little about how the development of talent is affected by power, which is beyond the scope of this paper. In Rothwell (2019), I present detailed discussion of how political power has affected the development of talent since the 19th century in the United States. More generally, I discuss several ways in which political equality has not been achieved in the United States and other democratic countries. I define political equality as the right to participate in choosing political representatives, equal protection under the laws, equal access to public goods and services, and equal access to markets.

First, access to public goods and services is not equal in the United States in several important ways. Most children do not have access to public preschool education, and the quality of educational services appears to be provided in a highly uneven way across races and classes of students (Rothwell, 2019). Because of historic oppression and contemporary segregation, African-American and Hispanic children are the most disadvantaged large racial and ethnic groups in the United States along these lines. Beyond education, important public services like justice and security are not distributed evenly. Criminal behavior is policed and enforced quite differently in African-American and Hispanic neighborhoods than in more affluent white neighborhoods (Rothwell, 2019).

Access to markets is also highly unequal in several crucial ways. Local housing regulations, developed during the Jim Crow era, systematically discriminate against lower-income residents generally and African-Americans in particular, preventing market forces from operating in such a way that would furnish housing supply where willing buyers want it (Rothwell, 2019).

These political inequalities tend to exacerbate racial and class differences, but regulations relating to the buying and selling of professional services also create large gaps in income between certain elite groups and middle-class citizens. In Rothwell (2019), I discuss several of these regulatory biases and show how they benefit the top 1% at the expense of everyone else. Lawyers, dentists, and doctors enjoy privileged status in several important ways: They enjoy a legal monopoly on service provision; it is very difficult to make these workers employees and only under certain conditions; supply-restrictions are onerous and entry barriers are extensive. State laws, which are controlled by the relevant interest groups, have created these conditions over many decades of lobbying and anti-competitive actions described in Rothwell (2019).

A different set of rules privileges hedge fund managers, their employees, and indirectly, large trading banks. Federal laws prohibit independent non-rich Americans from using leveraged financial services or investing in venture capital and private equity funds. As a result, highly profitable intermediaries (like pension funds) essentially cut deals with hedge funds that privilege owners of capital over ordinary investors, who are often workers in public sector unions. By keeping household investors one step removed from sophisticated trading firms, consumer-facing financial service provides are forbidden from creating and marketing more efficient products. As a result, there is a massive gap in the fees charged by hedge funds relative to those charged by consumer-facing mutual funds, and the billions of dollars in gratuitous revenue go to elite financial sector workers, rather than ordinary investors (Rothwell, 2019).

Thus, through the enumerated channels described above, political inequality exacerbates the normal variation in income that would otherwise arise from differences in natural talent, luck, education, and work preferences. In Rothwell (2019), I show that the cognitive and non-cognitive skills of the rich and of people in high-earning occupations and industries aren't nearly high enough to justify their incomes. Instead, political economy factors explain how the top 1% can control just 7.3% of national income in Finland but 20.2% in the United States—two democratic countries with high levels of technology, trade, and education (WID).

This paper aims to pull together various theoretical strands in the political economy and macroeconomic literature to create a new framework for understanding extreme income inequality. The main argument is that the income distribution will converge toward the distribution of talent in politically equal societies, but it will persist at extreme levels of dispersion in politically unequal ones, where gender, race, class, and professional status bring benefits at various points in the life stage, distorting markets along the way.

Assembling and assessing international data on the income distribution, I have shown that several key empirical facts are consistent with this theoretical framework. Racial diversity and gratuitous pay for elite professionals are strong predictors of levels of income inequality and changes over the last three decades. Other factors often identified in the literature show much weaker empirical connections to inequality and are contradicted by an examination of which groups are most heavily represented in the top 10 and top 1%. I conclude that future research on income inequality must confront the political economy of talent development and reward, which cannot be assumed to function equitably, even in rich democracies.

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Appendix: Can survey data measure top-income membership?

One limitation of the American Community Survey is that underlying income sources (wage/salary, investment and business being the most important for the affluent) are top-coded at the 99.5th percentile (the top 0.5%) for each state to make it difficult to identify individuals.

I have concluded this limitation is not a serious problem for identifying membership in the top 1% for several reasons.

First, total income is not top-coded, only the underlying sources, so the only way someone who is really in the 1% can be misclassified is if he or she happens to have top-coded business income or wage income in a state where the top-codes fall below the national 1% threshold (of $315,700) but still does not make it to the 1%, once all other income sources are included.

There are only four states for which the wage/salary income top-code for 2016 falls below the national top-income threshold of $316,000 for the entire period of 2012-2016 (West Virginia, Alaska, Mississippi, and Vermont), but almost everyone with top-coded wage income makes it into the 1% when their salary income is combined with another income source. The business income threshold falls below $316,000 for 36 states in 2016, but again, there are very few people who have top-coded business income and do not reach the 1%.

To be more precise, only 216 respondents out of 12 million with income data are potentially misclassified as not being in the 1% despite having top-coded salaries in the 2012-2016 Census database. Another 1,789 are potentially misclassified because they have top-coded business income data but do not reach the 1%. This is 0.01% of U.S. residents with income. A somewhat higher number (7,447) have top-coded investment income but are not in the 1%. They appear to be mostly retirees living off their investment income, as 81% are out of the labor force and 62% are at least 65 years old.

If you believe that the 1% threshold is best established through fiscal income measures from tax records, then the Census based sources allow nearly everyone to be identified based on salary or business income, at least for recent years. The logic behind this conclusion is based on the World Inequality Database, in which the U.S. national 1% threshold per adult house member for taxable (fiscal) income is only $284,000 for 2014, which is below every 2016 wage and salary top-code in the Census and greater than only three states for 2012 top-codes. The Census threshold is likely somewhat higher because the tax records are often not measured for individuals, but rather for tax returns, which often have multiple adults (e.g., a husband and wife). This is akin to measuring household income per capita, which will tend to be lower than individual income for top earners, since the other adults with whom they share a household will typically earn less.

Among those who are not coded in the top 1% but are top-coded for business or investment income, these individuals are no more likely to be executives than those who are classified as being in the 1%, but they are much more likely to be ranchers or farm managers (9% of total compared to 1% of total). This suggests that if Census top-coding underestimates workers in the top 1% it is likely to be farm owners and ranchers who are self-employed or run small businesses and so do not receive salaries. Yet, the number is too small to meaningfully affect the national estimates.

I conclude that census reporting thresholds are not a serious obstacle to accurate analysis of who is in the 1%.

Another limitation of the American Community Survey is that it does not include income data from the sale or exchange of a “capital asset,” such as a stock or ownership stake in a company. It does, however, include data from business income, including dividends, royalty payments, and rental payments. In effect, this means that the ACS includes only income that flows to individuals as either owners or workers but does not include income from sales of property unless directly tied to a business controlled by the individual. It also does not include employer or government allocations of funds to an individual’s retirement account, the implicit value of owning a home (“owner occupied rent”), the distribution of taxes on business, nor the value of compensation through public or private health insurance plans. Recent work from Piketty, Saez, and Zucman (2018) includes these concepts as part of income (they call it “national income”) and reports that the U.S. top 1% threshold for individual pre-tax income is $470,000 for 2014. The threshold greatly exceeds taxable income because it includes all of these other concepts, which are not like income that one can use to buy products, at least in the present.

The important point is that the sale of assets could be both an important source of income for rich people and be systematically allocated to certain occupations, like executives, in ways that bias my earlier results.

To better understand how different income concepts and sources relate, I combine IRS ZIP code data—which is available to the public—with census data. I use adjusted gross income, which corresponds with what Piketty and co-authors describe as fiscal income. At the ZIP code level, mean census income has a very high correlation of 0.87 with mean IRS adjusted gross income—and a correlation of 0.91 between the share of residents in the top 1% (incomes above $284,000) and mean census income. IRS gross income is also highly correlated with median home values (0.71). IRS data also distinguish income from capital gains and business partnership. Average capital gains income at the ZIP code level has a correlation of 0.58 with mean census income, while income from partnerships has a correlation of 0.72 with mean income. These correlations use ZIP code population as a weight, but the results are similar giving equal weight to all ZIP codes.

Table 1. U.S. inequality in individual total income reported in the decennial census and American Community Survey, 1960-2016

	Top 99-100 income share	Top 80-99 income share	Bottom 50 income share	Gini coefficient	Theil index
			Employed, ages 18-64		
1960	5.5%	39.8%	21.0%	41.3%	30.6%
1970	6.1%	37.5%	20.8%	42.0%	31.5%
1980	5.3%	41.0%	20.1%	42.4%	31.2%
1990	7.6%	42.5%	18.7%	44.8%	36.7%
2000	9.8%	43.4%	18.1%	47.1%	42.8%
2011-2015	8.1%	43.4%	19.1%	48.0%	43.0%
2016	7.5%	42.4%	19.6%	48.3%	44.0%
			Ages 35 to 45		
1960	6.5%	48.8%	8.2%	56.7%	60.3%
1970	7.0%	43.9%	10.4%	54.4%	55.0%
1980	5.7%	45.6%	13.7%	50.7%	46.3%
1990	7.8%	44.8%	15.5%	49.2%	44.9%
2000	10.3%	45.6%	15.2%	51.7%	51.5%
2011-2015	8.7%	46.9%	13.4%	53.9%	54.7%
2016	8.7%	46.1%	15.2%	53.9%	55.0%
			Ages 18 and older		
1960	7.8%	51.0%	6.7%	60.1%	66.6%
1970	8.2%	50.0%	8.6%	58.0%	61.5%
1980	6.9%	48.2%	11.7%	54.1%	52.1%
1990	8.9%	48.0%	12.2%	53.9%	53.3%
2000	11.4%	46.8%	12.0%	55.5%	59.1%
2011-2015	10.2%	49.1%	11.3%	57.4%	62.5%
2016	10.2%	48.6%	11.8%	57.3%	62.6%

Note: There are some important changes in which income sources are included in the income measure here—total personal income. Starting in 1970, social security and welfare payments were included. Starting in 1980, investment income was included.

Table 2. Share of taxable income by place in the income distribution using World Inequality Database, United States 1962-2015

	Bottom 50 (fiscal, equal-split, 20+)	Top 50-90 (fiscal, equal-split, 20+)	Top 80-90 (fiscal, equal-split, 20+)	Top 90-99 (fiscal, tax units, all ages)	Top 99-99.9 (fiscal, tax units, all ages)	Top 99.9-100 (fiscal, tax units, 20+)	Top 90-100 (fiscal, equal-split, 20+)
1960s	19.2%	48.9%	15.7%	23.9%	6.9%	3.5%	31.7%
1970s	18.9%	50.0%	16.4%	24.5%	6.5%	2.8%	31.4%
1980s	15.8%	49.0%	16.6%	25.3%	7.5%	5.1%	36.2%
1990s	13.7%	46.6%	16.2%	26.5%	9.2%	6.9%	41.0%
2000s	12.0%	43.8%	15.6%	27.0%	10.5%	9.7%	44.5%
2010-2015	10.0%	43.9%	16.0%	28.5%	10.9%	10.2%	46.8%
Change 1960s-1970s	-0.4%	1.1%	0.6%	0.5%	-0.5%	-0.7%	-0.3%
Change 1970s-2010s	-8.8%	-6.1%	-0.3%	4.1%	4.4%	7.4%	15.4%

Notes: Fiscal refers to taxable income; tax units are treated as individuals when tax units are indicated, whereas "equal-split" divides income within a filing unit. Ages is either all or 20 and older. The threshold for the top 0.1% is $1,323,837 for 2014 fiscal income on an equally split basis within tax units. It is $2.1 million in 2015 when income is not equally split and allocated to the entire tax unit, and it is $2.0 million for 2014 pre-tax national income equally split. The threshold for the top 1% is $288,742 for fiscal income (equal-split adults 20 and over in 2014), and $477,514 for equal-split pre-tax national income (adults 20 and over), and $456,622 on a tax-unit basis in 2015 for fiscal income. For the top 10%, the equal-split fiscal income threshold is $83,183, but it is $124,070 for 2014 pre-tax national income (equally split), and $128,677 for fiscal income on a tax-unit basis (in 2015).

Table 3. Share of income from labor and capital going to the top 10 and top 0.1 percentiles of income earners in the United States by decade using World Inequality Database

	Top 90% to 100%		Top 99.9% to 100%	
	Labor income	Capital income	Labor income	Capital income
1960s	27.5%	78.2%	1.4%	15.1%
1970s	28.1%	75.8%	1.6%	11.5%
1980s	31.6%	73.2%	2.6%	12.1%
1990s	35.6%	73.2%	3.8%	14.5%
2000s	38.4%	73.8%	5.1%	18.1%
2010-2015	39.8%	71.9%	5.2%	19.8%
Change 1960s-1980s	4.0%	-5.0%	1.3%	-3.0%
Change 1980s-2010s	8.3%	-1.3%	2.6%	7.7%
Change 1960s-2010s	12.3%	-6.3%	3.8%	4.6%

Source: Author analysis of data pulled from WID using Stata Top 90-100 (fiscal, equal-split, 20+); Using WID Stata call, variables are labeled spllin992j and spkkin992j, respectively.

Table 4. The correlation between Healthy Life Expectancy and income inequality, using various sources and measures

	Correlation with Healthy Life Expectancy	Number of countries	Correlation with Healthy Life Expectancy	Number of countries
	Gini coefficient (LIS)		Gini coefficient (UN WIID)	
All countries with data available	-0.78	42	-0.43	103
All OECD countries	-0.09	27	-0.13	34
All countries with non-missing LIS data	-0.78	42	-0.71	42
All countries with non-missing top 1% data from WID	-0.84	25	-0.65	36
	Top 1 percent share, averaged 2010-2016 (WID)		Top 1 percent share, most recent year (WID)	
All countries with data available	-0.65	39	-0.53	44
All OECD countries	-0.48	23	-0.50	24
All countries with non-missing LIS data	-0.69	25	-0.67	25
All countries with non-missing top 1% data from WID	-0.65	39	-0.59	36
	Top 10% share, most recent year (WID)		Bottom 50 share, most recent year (WID)	
All countries with data available	-0.54	43	0.25	21
All OECD countries	-0.35	24	0.11	8
All countries with non-missing LIS data	-0.81	24	0.26	11
All countries with non-missing top 1% data from WID	-0.57	35	0.24	16

Healthy life expectancy is measured in 2015 by the World Health Organization. It is the average equivalent number of years of full health that a newborn could expect to live, if he or she were to pass through life subject to the age-specific death rates and ill-health rates of a given period.

Table 5. The correlation between financial difficulty and income inequality, using various sources and measures

	Correlation with financial difficulty	Number of countries	Correlation with financial difficulty	Number of countries
	Gini coefficient (LIS)		Gini coefficient (UN WIID)	
All countries with data available	0.64	43	0.39	108
All OECD countries	0.37	27	0.29	34
All countries with non-missing LIS data	0.64	43	0.52	43
All countries with non-missing top 1% data from WID	0.68	26	0.45	37
	Top 1 percent share, averaged 2010-2016 (WID)		Top 1 percent share, most recent year (WID)	
All countries with data available	0.42	40	0.29	45
All OECD countries	0.25	23	0.27	24
All countries with non-missing LIS data	0.44	26	0.42	26
All countries with non-missing top 1% data from WID	0.42	40	0.31	37
	Top 10% share, most recent year (WID)		Bottom 50 share, most recent year (WID)	
All countries with data available	0.30	44	-0.01	21
All OECD countries	0.25	24	0.16	8
All countries with non-missing LIS data	0.51	25	-0.09	11
All countries with non-missing top 1% data from WID	0.30	36	0.06	16

Financial difficulty is measured using one item from the Gallup World Poll averaged over 2013-2017: "Which one of these phrases comes closest to your own feelings about your household's income these days: living comfortably on present income, getting by on present income, finding it difficult on present income, or finding it very difficult on present income?" (Item WP2319). The percentage of those responding difficult or very difficult is the metric here.

Table 6. OECD countries ranked by largest top 1% income shares using most recent observation from 2005-2016

Country	Top 1% shares	Top 10% shares	Bottom 50% shares
Turkey	23.4%	53.9%	15.1%
USA	22.6%	51.2%	9.3%
Chile	20.2%	53.7%	
United Kingdom	13.9%	40.0%	14.3%
Canada	13.6%	41.4%	
Poland	13.3%	39.5%	23.2%
Germany	13.2%	40.3%	16.7%
France	12.1%	35.8%	19.2%
Ireland	11.5%	37.2%	
Switzerland	11.3%	34.6%	
Japan	10.4%	41.6%	
Portugal	9.8%	38.3%	
Hungary	9.6%	32.1%	
Czech Republic	9.4%	28.7%	28.4%
Italy	9.4%	33.9%	
Australia	9.1%	31.9%	
Sweden	8.7%	30.6%	
Spain	8.6%	32.0%	
New Zealand	8.1%	31.5%	
Norway	7.8%	28.3%	
Finland	7.5%	32.5%	
Slovenia	7.0%	30.5%	24.6%
Denmark	6.4%	26.9%	
Netherlands	6.3%	30.9%	

Table 7. OECD countries ranked by change in top 1% income shares from 1975-1983 period to most recent observation from 2005-2016

Country	Top 1% shares, 1975-1983	Top 1% shares, 2005-2015	Change in top share from oldest to newest year
USA	12.5%	22.6%	10.0%
Poland	3.6%	13.3%	9.7%
United Kingdom	6.1%	13.9%	7.8%
Hungary	2.7%	9.6%	6.9%
Czech Republic	2.5%	9.4%	6.9%
Ireland	5.0%	11.5%	6.5%
Chile	15.2%	20.2%	5.0%
Canada	8.9%	13.6%	4.7%
Australia	4.9%	9.1%	4.2%
Sweden	5.4%	8.7%	3.3%
Germany	10.3%	13.2%	2.9%
Switzerland	8.5%	11.3%	2.8%
Norway	5.4%	7.8%	2.4%
Italy	7.2%	9.4%	2.1%
Portugal	7.9%	9.8%	1.9%
Finland	5.9%	7.5%	1.5%
New Zealand	6.6%	8.1%	1.5%
Japan	9.0%	10.4%	1.4%
Spain	7.6%	8.6%	0.9%
France	11.2%	12.1%	0.9%
Netherlands	6.1%	6.3%	0.2%
Denmark	6.8%	6.4%	-0.4%

Table 8. Change in number of U.S. income earners in top 1% of national distribution by sector, 1980-2015

	Share of top 1%, 1980	**Share of top 1%, 2015**	**Change in number of 1% members**
Professional, Scientific, and Technical Services	11.1%	19.3%	129,565
Finance and Insurance	8.6%	17.2%	127,674
Healthcare and Social Assistance	17.9%	19.2%	65,410
Information	1.7%	3.3%	23,733
Educational Services	1.8%	2.5%	13,642
Administrative and Support and Waste Management and Remediation Services	1.6%	2.2%	12,441
Arts, Entertainment, and Recreation	0.8%	1.0%	4,836
Utilities	0.4%	0.7%	4,804
Mining, Quarrying, and Oil and Gas Extraction	1.7%	1.7%	4,719
Other Services (except Public Administration)	1.7%	1.6%	3,499
Real Estate and Rental and Leasing	4.1%	3.1%	-159
Public Administration	1.1%	0.8%	-258
Accommodation and Food Services	1.7%	1.2%	-1,233
Wholesale and Retail Trade	6.9%	4.7%	-7,839
Manufacturing	15.7%	11.4%	-8,185
Transportation and Warehousing	4.1%	2.0%	-13,619
Construction	6.2%	3.2%	-18,781
Wholesale Trade	7.8%	4.3%	-20,464
Agriculture, Forestry, Fishing and Hunting	3.4%	0.6%	-23,870

Source: Author analysis of IPUMS-USA 1% samples for 1980 and 2015. Samples is limited to those who are employed and aged 18 to 64.

Table 9. The share of top 1% income earners by occupation for occupations representing at least 1% of top earners in 1980 and 2015

Occupational category	**Share of top 1%, 1980**	**Share of top 1%, 2015**	**Change in number of 1% members**	**Probability of being in the 1%, 1980**	**Probability of being in the 1%, 1980**
Chief executives, public administrators, and managers nec	26.3%	24.9%	57,097	4.7%	15.4%
Physicians	13.5%	14.5%	50,151	31.5%	21.7%
Lawyers	6.5%	7.7%	33,378	12.9%	9.4%
Financial managers	1.0%	4.2%	41,421	2.4%	4.5%
Other financial specialists	1.0%	4.2%	41,068	2.4%	4.8%
Supervisors and proprietors of sales jobs	3.6%	4.1%	17,043	2.3%	1.2%
Salespersons, n.e.c.	4.8%	3.6%	-984	1.1%	1.7%
Managers and specialists in marketing, advertising, and public relations	2.8%	2.8%	8,127	3.4%	3.0%
Accountants and auditors	1.6%	2.2%	11,209	1.6%	1.4%
Financial services sales occupations	1.6%	2.1%	10,510	12.0%	11.1%
Management analysts	0.6%	1.8%	15,625	5.4%	2.9%
Computer software developers	0.1%	1.5%	17,553	0.2%	1.1%
Dentists	2.5%	1.2%	-8,570	20.3%	10.8%
Real estate sales occupations	2.5%	1.2%	-9,534	3.9%	1.8%
Computer systems analysts and computer scientists	0.1%	1.1%	12,330	0.4%	0.6%
Managers of medicine and health occupations	0.3%	1.1%	10,378	2.4%	2.1%

Source: Author analysis of IPUMS-USA 1% samples for 1980 and 2015. Samples are limited to those who are employed and aged 18 to 64. I combine managers NEC with chief executives because the underlying data from 1980 included a separate category for administrators, which seemed to include many executives.

Table 10. Share of top 1% income earners in various sectors and occupational groups by country, using latest available data

Country	Professional occupations, excluding managers	Managerial occupations	Manufacturing and mining sectors	healthcare, education, and public administration sectors	Financial sector	Business services sector
Luxembourg	49.7%	43.6%	3.5%	13.4%	25.4%	39.6%
Poland	49.3%	31.0%	18.3%	20.1%	11.5%	15.0%
Netherlands	48.0%	33.4%	9.8%	29.1%	17.5%	17.0%
Israel	46.3%	34.6%	16.5%	25.6%	14.4%	24.8%
France	44.1%	43.4%	18.6%	18.6%	8.7%	20.8%
United States	42.6%	35.3%	14.1%	26.4%	12.2%	28.5%
Belgium	41.2%	39.6%				
Austria	40.8%	25.0%	32.9%	16.8%	1.8%	9.7%
Ireland	40.3%	53.9%	10.5%	23.4%	22.8%	25.4%
Australia	40.3%	48.2%	16.2%	18.7%	9.6%	28.1%
Greece	40.2%	19.8%	10.3%	16.9%	13.2%	8.0%
Spain	40.1%	28.4%	26.1%	15.4%	17.1%	14.6%
Germany	38.2%	35.5%	23.8%	18.0%	12.5%	22.6%
Hungary	35.2%	16.2%	30.6%	13.9%	15.3%	
Canada	35.0%	48.0%	12.5%	20.9%		
Switzerland	34.3%	48.2%	7.0%	14.1%	29.5%	22.4%
United Kingdom	33.4%	36.6%	14.7%	26.0%	10.2%	17.4%
Denmark	33.2%	47.7%	12.9%	13.3%	12.1%	20.9%
Mexico	33.1%	44.1%	17.0%	29.9%	8.4%	8.7%
Finland	28.2%	52.3%	19.8%	12.8%	11.2%	9.6%
Slovenia	27.1%	54.3%				
Estonia	26.9%	57.5%	16.1%	21.7%	6.0%	12.7%
Iceland	25.6%	42.1%	24.1%	17.8%	8.6%	11.6%
Japan			21.6%	13.5%	5.4%	2.7%
Sweden			21.3%	17.5%		20.3%
Italy			6.6%	33.0%	11.3%	9.1%
Unweighted mean	**38.0%**	**39.9%**	**17.1%**	**19.4%**	**13.0%**	**18.0%**

Source: Author analysis of data from Luxembourg Income Study. Sample limited to those aged 18 to 64 who are employed. Uses latest available data for each country.

Table 11. Share of top 1% by wealth working in various sectors of the economy by country

	Manufacturing	Information	Professional, scientific, and technical services	Healthcare and social work	Finance
Australia	8%	1%	14%	10%	2%
Austria	8%	0%	5%	16%	11%
Finland	20%	2%	13%	18%	4%
Germany	15%	5%	14%	8%	2%
Greece	0%	5%	33%	0%	6%
Italy	15%	0%	2%	22%	4%
Slovakia	26%	0%	0%	0%	0%
Slovenia	12%	0%	0%	11%	1%
Sweden	7%	3%	18%	14%	5%
United Kingdom	9%	3%	10%	5%	13%
United States	8%				

Luxembourg Wealth Study Database for most recent years available. The "Information" sector for Sweden and Germany combines the following: "post and telecommunications," "publishing, printing and reproduction of recorded media," "computers and related." For professional services, Sweden and Germany estimate includes "research and development" and "other business services." The U.S. data combine too many industries together, with the exception of manufacturing. Sixty-three percent of the top 1% by wealth in the Unites States work in finance, insurance, real estate, and business services; another 14% work in transportation, communications, entertainment, and professional services.

Table 12. Correlation of income inequality level and change with range of explanatory variables

Concept	Correlation with level of income inequality	Number of countries for level calculation	Correlation with change in income inequality, 1980-2016 approx.	Number of countries for change calculation
90th percentile of income of professional occupations/Median income of all workers 18-65	0.91	20	0.32	20
Racial diversity of country	0.78	35	0.18	35
Medium income of professional occupations/Median income of all workers 18-65	0.75	20	0.22	20
90th percentile of income of managerial occupations/Median income of all workers 18-65	0.73	21	-0.02	21
Tax revenue as share of GDP	-0.72	35	-0.20	35
Number of people of working age per number of retirement age	0.71	33	-0.12	33
Political Stability and Absence of Violence/Terrorism	-0.69	35	-0.14	35
Number of physicians with income in top 1%/total number of workers in top 1%	0.67	8	0.37	8
Mean test scores, 15-year-olds	-0.67	34	-0.03	34
Medium income of managerial occupations/Median income of all workers 18-65	0.64	21	-0.08	21
Government expenditure as share of GDP	-0.64	35	-0.08	35
Voice and Accountability	-0.63	35	-0.22	35
Number of workers in healthcare, education, and public sectors with income in top 1%/total number of workers in top 1%	0.55	24	0.16	24
Threshold for top tax bracket expressed as multiple of average wage	0.52	35	0.02	35
Rule of Law	-0.48	35	-0.18	35
Union density, average of 2010s	-0.48	35	-0.48	35
Compensation of workers/GDP, 2016	-0.47	33	0.01	33
Minimum wage relative to median wage	0.45	32	0.40	32
Government effectiveness	-0.45	35	-0.20	35
GDP per capita, in purchasing power parity dollars	-0.42	35	-0.20	35
Number of engineers with income in top 1%/total number of workers in top 1%	0.42	18	-0.06	18
Ease of doing business based on 13 subfactors measured by World Bank on starting a business, obtaining a license, closing a business, and getting electricity	-0.41	35	-0.28	35
Control of corruption	-0.41	35	-0.28	35
Average tariff rate on imported goods	0.41	35	-0.16	35

Transparency International's Corruption Perceptions Index	-0.41	35	-0.24	35
This is decreasing with average tariff rates and non-tariff trade barriers, such as import quotas, price restrictions, and government aid to companies	-0.38	35	0.12	35
Related to price stability (low inflation) and lack of price controls	-0.38	35	0.10	35
Trade balance/GDP 2016	-0.37	35	-0.09	35
Combines tax rates on individuals, corporations, and the overall tax burden as a share of GDP	0.37	35	0.20	35
High-quality patent application rate per person	-0.36	35	-0.11	35
Foreign-born population share of total population in 2015 - Foreign-born population share of total population in 1990	-0.34	35	-0.32	35
Regulatory Quality	-0.33	35	-0.12	35
Public expenditure on training as share of GDP	-0.33	30	-0.33	30
Change in trade balance = (Trade balance/GDP 2016) - (Trade balance/GDP 1990)	-0.32	30	0.03	30
Anti-competitive regulations of professional services (engineering, architecture, legal, and accounting)	0.31	35	0.17	35
Percent of children with single parent	0.24	26	0.27	26
Number of workers in technician occupations with income in top 1%/total number of workers in top 1%	-0.24	23	0.25	23
Tertiary educational attainment rate for population 25 and older	-0.24	35	-0.04	35
Foreign-born population share of total population	-0.21	35	0.06	35
Firing difficulty	-0.19	35	-0.25	35
Falls with state intervention in the financial sector and the scope of regulations	-0.18	35	0.07	35
Number of financial sector workers with income in top 1%/total number of workers in top 1%	-0.18	22	-0.24	22
Decreases with regulations that limit or curtail foreign investment or allow government expropriation of assets	-0.18	35	0.02	35
Tax rate on corporate profits	0.17	35	0.04	35
Gap in test scores between 90th percentile and median student, 15-year-olds	-0.16	34	0.24	34
Number of dentists with income in top 1%/total number of workers in top 1%	-0.15	3	0.09	3
Labor protections 2016	-0.15	32	-0.18	32
Income tax rate	-0.13	35	-0.20	35
Top marginal tax rate	-0.12	35	-0.21	35

Number of manufacturing & mining sector workers with income in top 1%/total number of workers in top 1%	-0.12	24	0.23	24
Number of workers in professional occupations with income in top 1%/total number of workers in top 1%	0.11	23	0.43	23
Compensation of workers/GDP	-0.11	24	-0.02	24
Number of workers in business service sector with income in top 1%/total number of workers in top 1%	-0.07	22	0.14	22
Number of workers in managerial occupations with income in top 1%/total number of workers in top 1%	-0.06	23	-0.57	23
Change in union density, 2010 average minus 1990 average	0.06	35	-0.36	35
Healthcare sector revenue share of GDP 2000-2015	-0.06	35	-0.03	35
Number of lawyers with income in top 1%/total number of workers in top 1%	-0.05	16	0.20	16
This is inversely related to the strength of the minimum wage, hiring and firing difficulty, and other regulations; it is increasing with the rate of labor force participation	0.05	35	0.43	35
Number of legal service industry workers with income in top 1%/total number of workers in top 1%	0.04	14	-0.09	14
Index describing rule of law, the size of government, regulatory efficiency, and market openness	-0.04	35	0.05	35
Number of workers outside professional and managerial occupations with income in top 1%/total number of workers in top 1%	-0.01	23	0.31	23

Table 13. Regression of inequality on elite professional premium

	Inequality index	Top 1% share, 2010-2016
	1	2
90th percentile of income of professional occupations/Median income of all workers 18-65	0.913***	0.0777**
	(0.279)	(0.0158)
Racial diversity	3.403**	0.0114
	(1.502)	(0.0787)
Percent of children living with single parents	-0.0350	0.00354
	(0.0235)	(0.00170)
Population	-0.0199	0.0326*
	(0.220)	(0.0134)
Patents per capita	-1.085	0.380*
	(2.109)	(0.146)
Tertiary educational attainment rate	0.0462**	-0.000500
	(0.0168)	(0.000846)
Trade freedom index	0.0473	0.00776*
	(0.0575)	(0.00300)
Ln of GDP per capita, PPP	-0.710	-0.0664
	(0.461)	(0.0307)
Constant	-0.435	-0.310
	(6.402)	(0.346)
Observations	18	12
Adjusted R-squared	0.788	0.883

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 14. Inequality and its corollaries in a cross-section of OECD countries

Country	Inequality index (standardized)	90th percentile of income of professionals/Median	Racial diversity	Thousands of patents per capita
Mexico	2.96	6.00	0.52	0.00
Israel	1.18	4.45	0.46	0.24
United States	1.67	3.54	0.43	0.15
France	-0.23	3.33	0.13	0.10
Germany	-0.10	3.30	0.06	0.20
Spain	0.06	3.18	0.02	0.03
Poland	0.27	3.13	0.01	0.01
Estonia	0.55	3.07	0.02	0.02
United Kingdom	0.46	3.06	0.10	0.10
Luxembourg	-0.59	2.99	0.02	0.10
Ireland	-0.02	2.95	0.00	0.08
Greece	0.46	2.89	0.00	0.01
Austria	-0.56	2.69	0.03	0.14
Hungary	-0.55	2.68	0.07	0.02
Switzerland	-0.27	2.38	0.03	0.27
Slovenia	-1.02	2.29	0.00	0.05
Netherlands	-0.92	2.29	0.08	0.20
Finland	-0.86	2.22	0.00	0.28
Iceland	-1.02	2.10	0.00	0.11
Denmark	-1.11	1.96	0.02	0.20

Classification of variable	Concept	Source of data and year
Racial diversity	Racial diversity of country	Louis Putterman, World Migration Matrix 1500-2000, V1.1; http://www.brown.edu/Departments/Economics/Faculty/Louis_Putterman/world%20migration%20matrix.htm
Demographic structure	Percent of children with single parent	OECD STATS; 2014
Demographic structure	Number of people of working age per number of retirement age	
Technology	High-quality patent application rate per person	OECD STATS, 2000-2016
Skill	Tertiary educational attainment rate for population 25 and older	OECD STATS, latest year available
Level of development	GDP per capita, in purchasing power parity dollars	OECD STATS, 2017
Political economy	Medium income of managerial occupations/Median income of all workers 18-65	Luxembourg Income Survey, author analysis of most recently available data
Political economy	90th percentile of income of managerial occupations/Median income of all workers 18-65	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Medium income of professional occupations/Median income of all workers 18-65	Luxembourg Income Survey, author analysis of most recently available data
Political economy	90th percentile of income of professional occupations/Median income of all workers 18-65	Luxembourg Income Survey, author analysis of most recently available data

Political economy	Number of workers in business service sector with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of dentists with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of physicians with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of engineers with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of financial sector workers with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of workers in healthcare, education, and public sectors with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of lawyers with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of legal service industry workers with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of workers in managerial occupations with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data; IPUMS International 2011 for Canada
Political economy	Number of manufacturing & mining sector workers with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Number of workers outside professional and managerial occupations	Luxembourg Income Survey, author analysis of most recently available data; IPUMS International 2011 for Canada

	with income in top 1%/total number of workers in top 1%	
Political economy	Number of workers in professional occupations with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data; IPUMS International 2011 for Canada
Political economy	Number of workers in technician occupations with income in top 1%/total number of workers in top 1%	Luxembourg Income Survey, author analysis of most recently available data
Political economy	Healthcare sector revenue share of GDP 2015-2000	OECD STATS; 2000-2015
Political economy	Anti-competitive regulations of professional services (engineering, architecture, legal, and accounting)	OECD STATS; 2013
Capital vs labor	Compensation of workers/GDP	OECD STATS; 2016
Capital vs labor	Compensation of workers/GDP, 2016	OECD STATS; 2016
Capital vs labor	Change in union density, 2010 average minus 1990 average	OECD STATS; 2016
Capital vs labor	Union density, average of 2010s	OECD STATS; 2016
Capital vs labor	Minimum wage relative to median wage	OECD STATS; 2016
Capital vs labor	Labor protections 2016	OECD, http://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm
Capital vs labor	Difficulty laying off people on regular contracts	OECD STATS; 2015
Capital vs labor	Public expenditure on training as share of GDP	OECD STATS; 2015
Capital vs labor	Tax rate on corporate profits	Heritage Foundation, Freedom Index 2016

Capital vs labor	Income tax rate	Heritage Foundation, Freedom Index 2016
Capital vs labor	Tax revenue as share of GDP	Heritage Foundation, Freedom Index 2016
Capital vs labor	Top marginal tax rate	OECD STATS; 2016
Capital vs labor	Government expenditure as share of GDP	Heritage Foundation, Freedom Index 2016
Capital vs labor	Threshold for top tax bracket expressed as multiple of average wage	OECD STATS; 2016
Globalization	Foreign-born population share of total population	World Bank
Globalization	Foreign-born population share of total population in 2015 - Foreign-born population share of total population in 1990	World Bank
Globalization	Average tariff rate on imported goods	Heritage Foundation, Freedom Index 2016
Globalization	Trade balance/GDP 2016	OECD STATS; 2016
Globalization	Change in trade balance = (Trade balance/GDP 2016) - (Trade balance/GDP 1990)	OECD STATS; 1990 and 2016
Institutional quality	Control of corruption	World Bank, Worldwide Governance Indicators (2015 data)
Institutional quality	Government effectiveness	World Bank, Worldwide Governance Indicators (2015 data)
Institutional quality	Political Stability and Absence of Violence/Terrorism	World Bank, Worldwide Governance Indicators (2015 data)
Institutional quality	Rule of Law	World Bank, Worldwide Governance Indicators (2015 data)
Institutional quality	Regulatory Quality	World Bank, Worldwide Governance Indicators (2015 data)
Institutional quality	Voice and Accountability	World Bank, Worldwide Governance Indicators (2015 data)
Institutional quality	Index describing rule of law, the size of government, regulatory efficiency, and market openness	Heritage Foundation, Freedom Index 2016
Institutional quality	Transparency International's Corruption Perceptions Index	Heritage Foundation, Freedom Index 2016

Institutional quality	Combines tax rates on individuals, corporations, and the overall tax burden as a share of GDP	Heritage Foundation, Freedom Index 2016
Institutional quality	Ease of doing business based on 13 subfactors measured by World Bank on starting a business, obtaining a license, closing a business, and getting electricity	Heritage Foundation, Freedom Index 2017
Institutional quality	This is inversely related to the strength of the minimum wage, hiring and firing difficulty, and other regulations; it is increasing with the rate of labor force participation	Heritage Foundation, Freedom Index 2018
Institutional quality	Related to price stability (low inflation) and lack of price controls	Heritage Foundation, Freedom Index 2019
Institutional quality	This is decreasing with average tariff rates and non-tariff trade barriers, such as import quotas, price restrictions, and government aid to companies	Heritage Foundation, Freedom Index 2020
Institutional quality	Decreases with regulations that limit or curtail foreign investment or allow government expropriation of assets	Heritage Foundation, Freedom Index 2021
Institutional quality	Falls with state intervention in the financial sector and the scope of regulations	Heritage Foundation, Freedom Index 2022
Skill	Gap in test scores between 90th percentile and median student, 15-year-olds	OECD PISA
Skill	Mean test scores, 15-year-olds	OECD PISA
Inequality	Summary measure of income inequality using three data sources	Author

Inequality	Change in top 1% share from 1980 to 2010s	World Inequality Database
Inequality	Share of annual national total income or taxable income going to top 1% of individuals aged 20 or older, 2010-2016 averaged	World Inequality Database
Inequality	Share of annual national total income or taxable income going to top 1% of individuals aged 20 or older, 1979-1981 averaged	World Inequality Database
Inequality	Gini coefficient for individual and household income; The 10 most recent observations, averaged	United Nations World Income Inequality Database, Version 3.4, January 2017
Inequality	Change in Gini coefficient for individual and household income	United Nations World Income Inequality Database, Version 3.4, January 2017
Inequality	Gini coefficient for individual income	Luxembourg Income Study, http://www.lisdatacenter.org/data-access/key-figures/
Economic dissatisfaction	Financial anxiety	Gallup World Poll
Civic dissatisfaction	Percent of adult population who are confident in the national government	Gallup World Poll
Civic dissatisfaction	Percent of adult population who approve of the national government leader	Gallup World Poll
Civic dissatisfaction	Change from 2006 to 2017 in the percent of adults who are confident	Gallup World Poll

in the national
government