**APPENDIX: A REPUBLIC OF EQUAL: HOW TO CREATE A JUST SOCIETY**

**Organization of Appendix**

This appendix is written for scholars, students, journalists and anyone else interested in the technical details of the data used in the book. Readers should be aware that much of the data used in the book and related replication code (written for STATA software) are available freely for download, and the source and description of each variable accompanies those files. The files include topics that are not addressed here, such as personality, IQ, pre-kindergarten schooling.

The text below discusses the following topics:

Analyzing who is in the top one percent: Methodological challenges with studying top income earners in the United States and around the world, and why I think my analysis is valid.

The validity of income inequality measures: For people skeptical that inequality is a meaningful summary measure or curious about the relationship between different measures of inequality (top 1% shares versus Gini coefficient), I provide a brief discussion and analysis that aims to convince you that inequality can be measured reliably and offers valid insight into living conditions.

The section “Inequality, slow growth, and falling national conference” presents results from a simple regression analysis. The full results are available in an external appendix table.

The section “What explains inequality?” presents results from a historical accounting exercise of which occupations and industries explain the rise in the US one percent. It then turns to an international analysis and discusses correlations and regression results that look at the most robust predictors of inequality across OECD countries. These findings suggest that elite professional power and racial diversity predict higher inequality and government spending (as a share of GDP) and innovation (measured by patenting rates) predict lower inequality.

The evidence is highly consistent with the arguments made in the main text. Remarkably, measures of globalization, the power of business owners as opposed to workers, and gaps in cognitive ability are unrelated to inequality, which is consistent with my fundamental argument: Markets do not inherently lead to mass inequality; mass inequality has been created through racial oppression and isolation—blocking minorities from public services and markets—and the disruption and control of certain markets by elite professionals.

**Analyzing who is in the top one percent**

For trends in top one percent income shares and for analysis of thresholds, I rely on the World Inequality Database (WID), which is assembled by Thomas Piketty and his collaborators using national tax office data. Unfortunately, tax records do not usually record information about the occupation or industry of those who file their taxes, and these data are not available in the WID.

Thus, to analyze top earnings by occupation and industry, I relied on government surveys.

The American Community Survey, with the data packaged and managed by IPUMS USA, was my primary data source for analyzing the U.S. one percent. For international analysis, I relied primarily on the Luxembourg Income Study (LIS).

There are several issues that arise with these sources, which warrant comment and clarification.

*Issue One: Census reporting thresholds for income sources*

One limitation of the American Community Survey is that underlying income sources (wage/salary, investment, 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.

This problem is easy to address, and I have concluded that it is not a significant bias for several reasons.

Total income is not top-coded, only the underlying sources, so the only way someone who is really in the one percent 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 one-percent threshold (of $315,700) but still does not make it to the one percent, 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 one percent 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 one percent.

To be more precise, only 216 respondents out of 12 million with income data are potentially misclassified as not being in the one percent 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 one percent. 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 one percent. 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 one percent 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 reason is that logic behind this conclusion is based on the World Inequality Database, in which the U.S. national one percent 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 (eg 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.

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| **Income thresholds to qualify as a top 1% earner in the United States using World Inequality Database and Census** | |
| **American Community Survey, 2012-2016** | |
| Wage and salary income | $221,616 |
| Total income | $315,700 |
| **World Inequality Database, 2014** | |
| Capital income reported on tax returns per adult on return | $242,775 |
| Labor (or employee) income reported in tax returns per adult on return | $264,286 |
| Total income reported on tax returns per adult on return | $283,749 |
| Total national income (including non-taxable labor and capital income) per adult on return | $469,256 |
| Source: World Inequality Database, accessed via WID STATA program on May 10, 2018. The population is adults aged 20 and over. Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. Integrated Public Use Microdata Series: Version 7.0, 2012-2016 American Community Survey. Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D010.V7.0. | |

Among those who are not coded in the top one percent 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 one percent, 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-one percent 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 effect the national estimates.

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

*Issue 2: Missing capital income in the Census data*

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 Thomas Piketty, Emanuel Saez, and Gabriel Zucman includes these concepts as part of income and reports that the U.S. top one percent threshold for individual pre-tax income is $470,000 for 2014.[[1]](#endnote-1) 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.

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

The IRS publishes data by zip-code (which are neighborhood-like mail distribution units) that includes capital income. I use adjusted-gross-income (which corresponds with what Piketty’s and co-authors describe as fiscal income) at the zip code level to characterize the zip code of people with various incomes in the census data. I match IRS zip code data to Census microdata (from IPUMS USA) using the census concept of ZCTAs, which are like zip codes and be matched to them using the UDS Zip mapper.[[2]](#endnote-2) I allocate census respondents to ZCTAs from their public use micro area, using algorithm published by Missouri Census Data Center.[[3]](#endnote-3)

The results show a high correlation between home values and IRS adjusted gross income levels. The correlation with actual income is lower, but this is not surprising for two reasons: variation within zip codes and variation within households.

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| Correlation with census income among detailed occupational categories | | | | | |
|  | Home value | Average adjusted gross income from IRS in zip code | Percent of residents in zip code with IRS adjusted gross income of $284,000 or higher | Total income, Census | Total family income, Census |
| Home value | 1.00 |  |  |  |  |
| Total income, Census | 0.29 | 1.00 |  |  |  |
| Total family income, Census | 0.43 | 0.64 | 1.00 |  |  |
| Average adjusted gross income from IRS in zip code | 0.51 | 0.26 | 0.33 | 1.00 |  |
| Percent of residents in zip code with IRS adjusted gross income of $284,000 or higher | 0.52 | 0.26 | 0.33 | 0.96 | 1 |
| Source: Correlations based on 1,176,360 individual observations. U.S. Internal Revenue Service, Individual Income Tax Statistics, 2015; Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. Integrated Public Use Microdata Series: Version 7.0, 2012-2016 American Community Survey. Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D010.V7.0. | | | | | |

The high correlation between IRS zip code income data and home values (0.52) implies that home values may be an important proxy measure for the income sources not captured by the American Community Survey (eg capital income). Thus, as a robustness check, I report how occupations vary by home value. At the detailed level, the census data are grouped into 480 occupational categories by IPUMS USA (using “occsoc”). The correlation between the percentage of workers in each occupation that are in the top one percent of income and the percentage who live in a home valued in the top one percent is 0.73. It is likewise high (0.65) between the percentage living in a top home and a top zip-code.

Consistent with my earlier analysis, physicians and surgeons, dentists, lawyers, and securities traders are heavily over-represented among top home owners. While chief executives and other managerial groups are also heavily represented, the additional consideration of home value does not appear to substantially change the analysis. In other words, while it would be desirable to explicitly include capital income in the analysis of which occupations are most over-represented among top earners, doing so probably would have little effect on the actual rankings. Doctors, dentists, lawyers, and finance-related workers are at or near the top any way you measure income.

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| Detailed occupations ranked by share in top one percent of home values, 2012-2016 | | | |
|  | Top1--home value | Top1-zipcode, IRS income | Top1-individual income, Census |
| Physicians and Surgeons | 6.4% | 13.3% | 30.3% |
| Chief Executives | 6.0% | 12.9% | 16.4% |
| Actors | 5.8% | 11.8% | 1.9% |
| Securities, Commodities, and Financial Services Sales Agents | 5.6% | 12.8% | 10.6% |
| Financial Analysts | 5.0% | 14.2% | 6.9% |
| Dentists | 5.0% | 11.8% | 18.4% |
| Lawyers, and judges, magistrates, and other judicial workers | 4.8% | 13.8% | 13.7% |
| Agents and Business Managers of Artists, Performers, and Athletes | 4.1% | 11.4% | 2.6% |
| Producers and Directors | 4.0% | 12.8% | 2.6% |
| Personal Financial Advisors | 3.8% | 12.9% | 11.6% |
| Writers and Authors | 3.6% | 12.6% | 2.1% |
| Property, Real Estate, and Community Association Managers | 3.4% | 9.6% | 3.2% |
| Economists | 3.0% | 14.4% | 6.0% |
| Financial Specialists, All Other | 2.8% | 9.5% | 5.6% |
| Management Analysts | 2.8% | 13.0% | 4.5% |
| Real Estate Brokers and Sales Agents | 2.8% | 10.3% | 3.3% |
| Public Relations Specialists | 2.7% | 12.1% | 2.7% |
| Psychologists | 2.6% | 12.5% | 1.7% |
| Lodging Managers | 2.5% | 8.2% | 1.4% |
| Market Research Analysts and Marketing Specialists | 2.4% | 13.7% | 2.4% |
| Source: Correlations based on 1,176,360 individual observations. U.S. Internal Revenue Service, Individual Income Tax Statistics, 2015; Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. Integrated Public Use Microdata Series: Version 7.0, 2012-2016 American Community Survey. Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D010.V7.0. | | | |

*International estimates*

The same two issues with US Census data apply to census data from other countries, which I access through the Luxembourg Income Study, but I conclude they are not serious obstacles to accurate analysis.

First, maximum income reported in each country in the LIS exceeds national top one percent thresholds in all 12 cases I compared, with income data from 2010 or later. So, reporting restrictions are not an actual problem for describing who is on the one percent outside the United States using these data. It would be a problem, I should note, for calculating how much money goes to the one percent, since it would cut off a large chunk of money flowing to people whose income exceeds the reporting thresholds, but that limitation does not affect the description of who is in the one percent, which is the focus of this book.

As for the capital gains issue, non-labor income is roughly the same share of national income in the United States as in other OECD countries, according to data from the Penn World Table.[[4]](#endnote-4) It is unlikely that including capital income would substantially affect the occupational rankings, since efforts to do so made little difference in the United States.

**The validity of income inequality measures**

Whether measured by the one percent share of taxable income using tax records or the Gini coefficient using household survey data, countries that are more unequal on one measure tend to me more unequal on others. This is true for 26 countries with data from the UN WIID, LIS, and WID. The survey-based UN and LIS measures are highly correlated (0.91), and both are highly correlated with top one percent income shares (0.74 and 0.79). Within the 16 countries in the OECD with data from all three sources, the correlations are similar (0.65 and 0.74) between top one percent shares and UN and LIS Gini coefficients, respectively.

In this sense, the measures used in this book are reliable across data sources and methods.

Inequality measures are also clearly associated with bad outcomes, such as low health and low subjective well-being. In this sense, they are valid.

For example, the Gallup World Poll asks several questions related to financial well-being, including the following:

* Are you satisfied or dissatisfied with your standard of living, all the things you can buy and do?
* 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?

Both of these questions are highly correlated with inequality measured across all three data sources. The most unequal countries in the world—using the UN database—are in Latin American, followed by Sub-Saharan Africa. In these regions, people tend to be dissatisfied with their living standard and many find living difficult. By contrast, in egalitarian Northern and Western Europe, people are highly satisfied with their living standard and few find living difficult. The global correlation (for 101 countries) between income inequality and the percent satisfied with their living standard is -0.27. The correlation between income inequality and difficulty living on income is 0.42.

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| Inequality and subjective financial well-being by world region | | | |
|  | Income inequality, UN database, standardized to mean zero | Percent satisfied with standard of living | Percent finding living difficult with household income |
| Western Europe | -1.11 | 0.87 | 0.17 |
| Northern Europe | -0.97 | 0.74 | 0.20 |
| Eastern Europe | -0.83 | 0.53 | 0.37 |
| Southern Europe | -0.77 | 0.56 | 0.37 |
| Australia and New Zealand | -0.45 | 0.87 | 0.13 |
| Northern America | -0.39 | 0.81 | 0.17 |
| Western Asia | -0.38 | 0.62 | 0.41 |
| Central Asia | -0.31 | 0.78 | 0.22 |
| Southern Asia | -0.28 | 0.67 | 0.42 |
| Northern Africa | -0.18 | 0.67 | 0.41 |
| Eastern Asia | -0.08 | 0.73 | 0.25 |
| South-eastern Asia | 0.26 | 0.77 | 0.30 |
| Sub-Saharan Africa | 0.63 | 0.41 | 0.64 |
| Latin America and the Caribbean | 1.16 | 0.68 | 0.41 |
| Data from the Gallup World Poll are for year 2013-2017, with sample sizes of roughly 1000 per country per year. UN data average the 10 most recent observations up to 2017 and are from the World Income Inequality Database, Version 3.4. | | | |

Among OECD countries, Norway, Sweden, Denmark and Japan have the lowest percentage of people who report difficult living comfortably on their household income, ranging from 10.3% in Japan to 6% in Norway. Meanwhile, in countries with higher income inequality, such as Canada, the United Kingdom, and the United States, 15%, 19.1%, and 19.7% report difficulty. The OECD correlation for 30 countries between income inequality and the percent satisfied with their living standard is -0.37. The correlation between income inequality and difficulty living on income is 0.33. There is also a statistically significant correlation between inequality and healthy life expectancy (-.22) and life evaluation (-.34), within the OECD.[[5]](#endnote-5)

The poor performance of the United States on subjective financial well-being is particularly surprising considering that the United States is richer on a per capita basis than all but five OECD countries but ranks 17th on this measure of subjective financial well-being. The latest World Bank data from 2016 show that only Luxembourg, Singapore, Ireland, Switzerland, and Norway have higher incomes per capita than the United States, after adjusting for purchasing power.[[6]](#endnote-6) High income inequality, presumably, is the chief explanation for why such a high percentage of U.S. residents do not feel comfortable with their living standard, despite living in a rich country.

**Inequality, slow growth, and falling national conference**

To test whether growth and inequality predict political dissatisfaction, I regress the change in national government confidence on income inequality and per capita income growth from 2008 and 2017. There is a strong negative and significant relationship between inequality and rising confidence (t-stat is -3.2), and a strong positive relationship between rising confidence and higher growth (t-stat is 3.3). The r-squared is 0.34 for this model, which uses data from 35 OECD member countries.

**What explains inequality?**

One way to study the factors that relate to rising income inequality is to see how the composition of the 1% has changed over time by sector (the products firms produce) and occupation (the type of work people do for their firm). I focus on 1980 as the starting point because that is when top1% income shares began to rise after a long-term fall, as documented in the World Income Database and by Census Bureau measures of inequality.

The one percent have increasingly consisted of financial sector managers, professional and other business service managers, healthcare professionals and managers, and legal service providers. If you add up the total increase in workers from 1980 to 2015 in these categories you get 98% of the total increase in top1% earners.

Keep in mind that other sectors and occupations also contributed statistically to the rise of the 1% because some sectors had a negative effect. Large reductions in the number of top income earners were found among craft and construction workers in the construction sector, farmers, and retail and wholesale managers.

Overall, this provides more evidence that a fairly narrow group of domestically focused professionals and managers—particularly managers in the financial and healthcare sectors—explain the rise of the 1% in the United States. Any coherent theory of income inequality must focus on why elite healthcare professions, financial sector manager and professionals, and lawyers are so over-represented now and account for such a large share of the increase. This makes the globalization story look rather weak.

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| Accounting for change in number of workers in top1% of U.S. income earners by high level occupation and sector from 1980 to 2015 | | |
| **Broad occupational category** | **High level sector** | **Share of increase in top1 population, 1980-2015** |
| Managerial | Financial services | 40% |
| Managerial | Other professional and social services (eg engineering, accounting) | 17% |
| Professional specialists | Healthcare services | 15% |
| Managerial | Business and repair services (eg advertising, computer services) | 14% |
| Professional specialists | Legal services | 7% |
| Managerial | Healthcare services | 6% |
| Professional specialists | Business and repair services (eg advertising, computer services) | 6% |
| Managerial | Transportation, Communication, and Utilities | 5% |
| Professional specialists | Financial services | 4% |
| Professional specialists | Other professional and social services (eg engineering, accounting, computer) | 4% |
| Finance and sales | Business and repair services (eg advertising, computer services) | 4% |
| Professional specialists | Agriculture, mining, and manufacturing | 4% |
| Professional specialists | Education services | 3% |
| Professional specialists | Retail and wholesale trade | 3% |
| Professional specialists | Transportation, Communication, and Utilities | 2% |
| Finance and sales | Transportation, Communication, and Utilities | 2% |
| Managerial | Education services | 1% |
| Administrative | Financial services | 1% |
| Managerial | Construction services | 1% |
| Finance and sales | Other professional and social services (eg engineering, accounting) | 1% |
| Source: Author analysis of IPUMS USA. See replication code and related files for how categories were created using "ind1990" and "occ1990." The column shows the change for each occupation-sector group in the number of workers in the top1% from 2015 to 1980 divided by the total US change in the number of workers in the top1%. | | |

*International analysis*

Another approach to testing different theories on what predicts the level and rise in income inequality is to look across countries. This has the advantage of allowing for comparisons across different institutional regimes and countries with different characteristics and laws.

I compiled 61 variables that I classified into nine different theoretical viewpoints. Later, I will discuss some of the individual variables in each.

This evidence suggests that inequality is closely linked to racial diversity, measured as the share of population from various continents. The appendix discusses the sources in more detail. Given that races do not differ by their inherent capacity for work, as I argued in detail in the preceding, the fact that racial diversity predicts inequality is likely the result of discrimination, segregation, and other ways in which racial minorities are cut off from pull participation in markets and denied full access to high quality public services.

Demographic structure is also predictive of more inequality, particularly if the working age population is large relative to the retirement age population, but we will see this result is not robust.

What I refer to as political economy variables perform moderately well on average, though some of the individual measures are among the top performers. These measure the structure of earnings through the lens of occupations and industries. A summary measure of regulations on professional occupations that limit competition predicts greater inequality.

The capital vs labor variables perform rather poorly. Minimum wage regulations, union membership, the capital-labor share of income, regulations on firing workers are not well correlated with inequality;

The same is true for globalization measures, which include the share of the population that is foreign born, how it has changed, and measures of openness to trade.

Institutional quality, skill, technological innovation—measured by patenting—and the overall level of development all predict lower inequality and lower growth inequality. This makes it unlikely that skill-biased technological change is a serious driving force of inequality. Countries with more educated and inventive citizens, with higher cognitive ability tend to have low inequality.

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| Correlations with level and change in inequality by theoretical concept | | |
|  | Correlation with level of income inequality | Correlation with change in income inequality, 1980-2016 approx |
| Racial diversity | 0.78 | 0.18 |
| Demographic structure | 0.48 | 0.07 |
| Political economy | 0.22 | 0.09 |
| Capital vs labor | -0.15 | -0.13 |
| Globalization | -0.17 | -0.10 |
| Institutional quality | -0.30 | -0.04 |
| Skill | -0.35 | 0.06 |
| Technology | -0.36 | -0.11 |
| Level of development | -0.42 | -0.20 |

The individual variable with the highest absolute value correlation with inequality within the OECD is my preferred measure of professional elite economic power: the 90th percentile of earnings for professional workers relative to the national median. This has an incredibly high correlation of 0.91 with the level of inequality and 0.32 with the change in inequality.

Racial diversity is also highly predictive, as noted, followed by another measure of elite professional dominance (median salary of professionals divided by median salary of all workers). Managerial dominance is also highly correlated but the relationship is weaker than the professional worker relationship. Countries with larger tax revenue as a share of GDP—which may indicate their commitment to high quality public services—have lower inequality today and have seen lower growth in inequality.

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| Variables with the highest absolute value correlation with income inequality in the OECD | | | | |
|  | 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 top1%/total number of workers in top1% | 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 |
| See appendix files for details on sourcing and concepts | | | | |

These correlations should not be interpreted as causal, as omitted variables bias is prevalent in all of them, but they provide a baseline sense of what plausible causal relationships might look like.

To further investigate with I regressed inequality on the list of 61 variables, while controlling for racial diversity, the percentage of children raised by single parents, the patenting rate, the tertiary degree attainment rate, a trade freedom index, and the mean income, adjusted for purchasing power. The sources are documented in the external appendix files.

I used three measures of inequality: the UN Gini coefficient for the latest available year; the top 1% share of income from the World Inequality Database, and a composite measure of the UN Gini, the WID top1 share, and the Luxembourg Income Study Gini coefficient. This index should capture multiple related dimensions of inequality, given the different sources and offers a robust summary measure.

In the OECD, only Chile, Mexico, and Turkey are more unequal than the United States, which is 1.7 standard deviations above the mean on the average of its three inequality measures. Israel is close behind at 1.2. Denmark has the lowest inequality at -1.1 standard deviations below the mean. Notably, racial diversity and elite professional power are much more prevalent among the most unequal countries. For example, in Denmark, professionals at the 90th percentile are paid only 2 times as much (100% more) as the median worker, but in the United States they are paid 3.5 times as much (250% more). Only Mexico and Israel exhibit greater economic advantage for professionals than the United States.

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| Summary data on inequality, racial diversity, and elite professional power | | | | | |
|  | Inequality Index | UN Gini | Top 1% share of income | Racial diversity | Elite Professional Power |
| Chile | 3.2 | 53.3 |  | 0.51 |  |
| Mexico | 3.0 | 50.8 |  | 0.52 | 6.0 |
| Turkey | 2.0 | 42.4 | 21% | 0.20 |  |
| United States | 1.7 | 39.9 | 20% | 0.43 | 3.5 |
| Israel | 1.2 | 39.4 |  | 0.46 | 4.5 |
| Estonia | 0.5 | 36.5 |  | 0.02 | 3.1 |
| United Kingdom | 0.5 | 34.5 | 13% | 0.10 | 3.1 |
| Greece | 0.5 | 36.3 |  | 0.00 | 2.9 |
| Canada | 0.4 | 34.2 | 14% | 0.32 |  |
| Poland | 0.3 | 34.8 | 12% | 0.01 | 3.1 |
| Portugal | 0.2 | 38.2 | 10% | 0.03 |  |
| Latvia | 0.2 | 35.1 |  | 0.05 |  |
| Australia | 0.2 | 37.4 | 9% | 0.20 |  |
| Japan | 0.1 | 36.3 | 10% | 0.00 |  |
| Korea | 0.1 | 33.0 | 12% | 0.00 |  |
| Spain | 0.1 | 34.1 | 9% | 0.02 | 3.2 |
| Italy | 0.0 | 34.2 | 9% | 0.00 |  |
| Ireland | 0.0 | 35.1 | 11% | 0.00 | 3.0 |
| Germany | -0.1 | 30.2 | 13% | 0.06 | 3.3 |
| France | -0.2 | 31.4 | 11% | 0.13 | 3.3 |
| New Zealand | -0.2 | 35.6 | 8% | 0.31 |  |
| Switzerland | -0.3 | 30.3 | 11% | 0.03 | 2.4 |
| Hungary | -0.5 | 27.6 | 10% | 0.07 | 2.7 |
| Austria | -0.6 | 30.0 |  | 0.03 | 2.7 |
| Luxembourg | -0.6 | 30.0 |  | 0.02 | 3.0 |
| Belgium | -0.6 | 30.1 |  | 0.04 |  |
| Czech Republic | -0.7 | 29.9 | 9% | 0.00 |  |
| Slovakia | -0.8 | 29.2 |  | 0.01 |  |
| Finland | -0.9 | 29.2 | 7% | 0.00 | 2.2 |
| Norway | -0.9 | 29.3 | 8% | 0.00 |  |
| Netherlands | -0.9 | 29.8 | 6% | 0.08 | 2.3 |
| Sweden | -1.0 | 25.5 | 9% | 0.01 |  |
| Iceland | -1.0 | 28.8 |  | 0.00 | 2.1 |
| Slovenia | -1.0 | 26.7 |  | 0.00 | 2.3 |
| Denmark | -1.1 | 27.8 | 6% | 0.02 | 2.0 |

The regression results (which are available as external files) reveal only four variables to be consistently significant (5% p-values or lower) across the models: racial diversity (higher inequality), patenting (lower inequality), elite professional power (higher inequality), and tax burden as a share of GDP (lower inequality).

The following variables are all consistently insignificant: The labor share of income, the change in the labor share of income, the number of union members as a share of all workers, changes in unionization, the minimum wage, labor protections, the skill of the workforce, the gap in skills between top scoring students and the median student, the corporate tax rate, the individual tax rate, the progressivity of individual taxation, institutional quality as measured by the Heritage Foundation and World Bank, trade openness, and exposure to globalization.

These correlations and regression results do not provide direct evidence of a causal relationship. I rely on the logic of the book—and the history and form of the regulations responsible—rather than country level statistical analysis to make that case. I make all the data publicly available with the hope that others will find good use for it.

In short, the results are strongly consistent with the main theme of this book: providing high quality public services—funded by government—and curbing the power of elite professionals will lower income inequality. Racial diversity is a problem, only because black minorities and American-Indian minorities have been incorrectly deemed naturally inferior, leading to their exclusion from public services and markets. The patent finding suggests that innovation lowers inequality, but could also be the case that egalitarian societies are more innovative. I believe both are true. Combating racism and curbing professional privilege will sap the motivation and support for the unfair laws and behavior that generate and perpetuate inequality.

Markets that allow mutually beneficial exchange do not naturally lead to extreme inequality. They tend to reward more productive people, but nearly everyone can contribute to society productively. The distribution of talent is naturally egalitarian across individuals and completely so across groups. This is not to deny that some people are born more conscientious and brighter than others, but the extra rewards generated by these advantages are modest relative to the enormous gaps in income observed in many democracies today.

1. Piketty, Thomas, Emmanuel Saez, and Gabriel Zucman. *Distributional national accounts: Methods and estimates for the United States*. No. w22945. Cambridge, MA: National Bureau of Economic Research, 2016 [↑](#endnote-ref-1)
2. American Academy of Family Physicians, <https://www.udsmapper.org/zcta-crosswalk.cfm> [↑](#endnote-ref-2)
3. MABLE Geocorr2014, <http://mcdc.missouri.edu/websas/geocorr14.html> [↑](#endnote-ref-3)
4. Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at[www.ggdc.net/pwt](https://www.rug.nl/ggdc/productivity/pwt/related-research) [↑](#endnote-ref-4)
5. Life evaluation is measured by the following item on the Gallup World Poll: Please imagine a ladder, with steps numbered from 0 at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time? [↑](#endnote-ref-5)
6. https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD [↑](#endnote-ref-6)