What Do the States Tell us About Rising Top Income Shares?

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The share of income received by the top 1% and 10% of earners in the United States increased dramatically from 1980 to 2011. This growth in top income shares has been widespread across the 50 states; the income share of the top 1% grew by 8.2 percentage points on average. It has also been conspicuously uneven, with some states experiencing significantly more growth than others. The smallest growth in top income shares took place in Delaware, where the share of income received by the top 1% of earners grew by 3.8 percentage points from 1980 to 2011. At the other end of the spectrum, the income share of the top 1% grew by 17.6 percentage points in New York.[1] A compelling explanation for rising top income shares should account for the divergent paths taken by the states over the last 30 years. If rising top income shares are primarily the result of market forces rewarding certain groups of workers over others, then there should be differences in such market forces between states. If rising top income shares are primarily the result of policy decisions, there should be differences between states in terms of the policies they implement. In this paper, I test a number of common market and policy explanations for rising top income shares against these standards, with the hope of identifying whether there is stronger empirical support for certain explanations for rising top income shares than others.

My analysis implies that tax policy has played an important role in growing top income shares. I present robust evidence that reductions in top marginal tax rates on capital gains income significantly increase the income share of both the top 1% and top 10% of earners. I additionally present evidence that decreases in top marginal tax rates on wage income has contributed to rising top income shares, though this evidence is less robust than for capital gains. Finally, I find some evidence that raising state government expenditures reduce top income shares, though the size of this effect is small.

In addition to tax policy, I investigate several other explanations for rising top income shares. After constructing a new state panel data set on the college wage premium, I present evidence that the growing returns to college education have contributed somewhat to rising top income shares, particularly for the top 10% of earners. I additionally find some evidence that union membership and Democratic control of a state's governorship may reduce top income shares, but the size of the effect of both factors is

[1] Top 1% income share numbers in this paragraph are from Frank (2009).

small compared to other variables and the results are not robust across my models. Finally, my analysis implies that the growing role of finance in the economy and the declining value of the minimum wage have contributed very little to rising top income shares.

After testing a number of different hypotheses for rising top income shares, my analysis implies that we actually know very little about why state trends have diverged so significantly. The fixed effects models I present allow me to distinguish between the variance explained between states in a given year and within states over time. These models imply that we know a lot more about the changes within states over time than we do about differences between states. The most successful model I present explains only about 36% of the between-state variation in the income share of the top 1% of earners. This implies that there is a lot of room for further investigation into why states have followed such different courses since 1980. Going forward, policymakers and economists who aim to reverse the trend of growing top income shares should seek to identify better explanations for why state trends have diverged so significantly. The income distribution in the United States would look significantly more equal in 2011 if it had followed Delaware's trend since 1980.

Trends in Top Income Shares

Economists largely agree about the trend in the United States' top income shares during the twentieth century. The share of income received by top earners was very high in the late 1920s, but fell dramatically throughout the 1930s and 40s. After stabilizing during the 1950s and 60s, inequality began to rise during the 1970s, a trend that continues to this day. Piketty and Saez (2003) helped to establish the consensus on this version of events in the economic literature in 2003, when they published a data set describing the share of total income accrued by top earners during the 20th and 21st century. According to the most recent update of the data set, the share of total income going to top earners followed a "U-shaped" pattern (Saez 2013). Figure 1 clearly shows the long term pattern Piketty and Saez describe. The top 10% of earners accrued about 46.1% of national income in 1928, which dipped to a postwar low of 31.4% in 1953, and rose to a record high of 48.2% in 2012. The income earned by the top 1% of earners peaked in 1932 at 19.6%, dipped to a low of 7.7% in 1977, and reached 17.9% in 2012.

[Figure 1 Here]

A number of other scholars have corroborated Pikkety and Saez's description of the trend in top income shares. Mark Frank (2009) constructed a state level set of income inequality measures using data from the IRS *Statistics of Income* (SOI) publication, and his data showed the same "U-shaped" trend Piketty and Saez described. Mark Price and Estelle Sommeiller (2014) constructed a similar data set based on SOI data, but performed additional adjustments to make their estimates more closely match those of Piketty and Saez.. Wojciech Kopczuk, Emmanuel Saez, and Jae Song (2010) used payroll microdata from the Social Security Administration (SSA) to estimate the share of income accrued by the top 1% of earners, and found that it rose from about 6.4% in 1980 to a peak of about 13.0% in 2000. This broadly matches the trend that Piketty and Saez uncovered, though top income shares were slightly lower because payroll data excludes capital gains income. Lawrence Mishel and Nicholas Finio (2014) extended Kopczuk et al.'s data set, and found that in recent years the share of earnings received by the top 1% of earners returned to its early 2000's peak. In addition to the administrative data sets from the SSA and IRS, the Congressional Budget Office (2013) calculated their own estimate of top income shares using a combination of IRS data and Census Current Population Survey (CPS) data. Its numbers show more fluctuation than the administrative data sets, but a broadly similar trend. According the CBO, the share of income received by the top 1% of earners rose from 8.9% in 1979 to 14.9% in 2010.

[Figure 2 Here]

To better compare the trends described in these five data sets, I compiled data from each of the estimates of the income share of the top 1% mentioned above. The data sets from Frank and Sommeiller/Price data are aggregated from the state level using slightly different methodologies. Sommeiller and Price published an aggregated estimate of the nationwide trend, but Frank did not. Therefore, for the Frank data I calculated a yearly average weighted by state population to capture a nationwide average top income share. I display a comparison of these five data sets in Figure 2. In spite of the differences between the sets, all four estimates clearly show the income share of the top 1% of earners rising considerably since 1980. Four of the five data sets show that income share of the top 1% of earners effectively doubled, with the sole outlier (the CBO data) being a data set that excludes capital gains income.

Why is Inequality Growing?

Economists have offered a number of competing explanations about why income shares have grown in recent years. The two widest bodies of literature on this topic has focused on two potential culprits for rising inequality—falling income tax rates, and rising returns to education resulting from skill based technological change. Other common explanations include weakening labor market institutions, in particular declining union membership and the falling real value of the minimum wage. There is a body of sociological research focusing on the rising importance of finance in the economy as a whole, as well as in markets outside of the financial sector. Several political scientists and economists have argued that the ideology or partisan affiliation of a government in power could have an effect on income inequality. I briefly describe each of these literature bases in turn.

A. Taxes

Economists proposed several theoretical explanations for how tax policy can affect top income shares. Taxes are a particularly confusing topic in the context of income inequality because taxes directly affect the income distribution by collecting money from workers for government operations. In addition to this direct effect, economists have analyzed whether top marginal tax rates can affect the pre-tax share of income received by top earners. Oliver Bargain (2013) and his co-authors used decomposition analysis to measure how tax policy had contributed to pre and post-tax income inequality. The authors found that 12.5% of the change in the post-tax income share of the top 1% of earners is due to the direct effects of changes in tax policy between 1979 and 2007. Depending on the elasticity of top earners taxable income they assumed, the combined direct and indirect effects of tax policy accounted for between 12.5% and 22.4% of the total change in the share of post-tax income earned by the top 1% of earners.

Thomas Piketty, Emmanuel Saez, and Stefanie Stantcheva (2011) argue that there are three potential channels through which top marginal tax rates on wages can indirectly reduce top earners' incomes. First, there is the labor supply elasticity. In this model, higher taxes make labor less profitable relative to leisure for high income earners, and as a result they correspondingly supply fewer hours or less effort. Second, there is tax avoidance. As income taxes rise, higher income workers might seek to avoid taxation by changing their compensation to forms that are taxed at a lower rate. Third, there are “compensation bargaining responses,” where CEOs are able to influence compensation committees to pay them a wage that exceeds the marginal product of their labor. If top income taxes are high, CEOs have less marginal incentive to bargain. In addition to offering a theoretical model that explains how taxes could affect pre-tax income shares, Piketty et al. compare the tax rates and pre-tax income shares across a variety of developed countries to estimate what effect top marginal tax rates have on pre-tax income inequality. Using data from 18 OECD countries, the authors find that changes in log top marginal tax rates between 1960-64 and 2005-09 are highly correlated with changes in the log income share earned by the top 1%. They estimate that the elasticity of top income shares for top earners with regards to their top marginal tax rate is .47.

Thomas Volscho and Nathan Kelly (2012) add a fourth theoretical explanation as to how tax progressivity can affect top income shares. “…Taxes collect revenue that fund government appropriations...To the extent that higher tax rates spur spending on human capital formation…tax rates may reduce top shares” (Volscho and Kelly 2012, 683). Using data from Piketty and Saez, they proceed to model the effects of capital gains and wage tax rates on top income shares. Using single equation error correction models, they find that top marginal tax rates on capital gains and wage income reduce the income share of the top 1% of earners by -.032 and -.064, respectively, in their preferred model. Karel Mertens (2013) similarly conducted a vector auto-regression analysis of Piketty and Saez’s long term income data, and found further evidence that cuts in top marginal tax rates increase the pre-tax share of income received by top earners. His resulting analysis implies that an exogenous 1 percentage point cut to top marginal tax rates increase the income of top earners by .52% in the first year, and “by .97% and 1.02% in the following two years, after which there is a gradual decline.”[2]

[2] (Mertens 2013) Page 29.

Denvil Duncan and Klara Sabirianova Peter (2012) use cross-national data to estimate the effects of progressive taxation on income inequality as measured by GINI coefficient. Based on the assumption that countries compete for tax base by establishing relatively similar rates, the authors use the tax rates of neighboring states as an exogenous instrument for the progressivity of a country's tax code. They authors find that a one percentage point increase in a country's top marginal tax rate results in a statistically significant .95 percentage point decrease in a state's GINI coefficient. Christoph Gorgas and Christoph Schaltegger (2012) used a panel data set of Swiss cantons to estimate the effect of changing marginal tax rates on income shares in Switzerland between 1917 and 2007. Using a similar instrumental variable to Duncan and Sabirianova Peter, they found that 1% increase in the top marginal tax rate resulted in a decrease of .3% in the share of income accrued by top earners in their IV models.

B. Education and skill based technological change

The wage premium received by college educated workers grew significantly during the later part of the 20th century. Claudia Goldin and Lawrence Katz (2008) argue that the relationship between the college wage premium and technological change played a big role in fluctuating inequality. Throughout the twentieth century, technological change created a growing need for highly skilled workers. After 1980, the supply of college-educated workers grew at a slower pace than in the post-war period. As a result, employers needed to pay more to attract such workers, and the gap between high and low wage earners grew. Goldin and Katz called this dynamic the "race between education and technology." They argue that "from 1940 to 2005, changes in the wage structure were closely correlated with changes in the premium to college" (Goldin and Katz 2008, 291). Goldin and Katz also point to a decomposition analysis by Thomas Lemieux, which according to Goldin and Katz shows that "in recent decades, the lion's share of rising wage inequality can be traced to an increase in educational wage diferentials" (Goldin and Katz 2008, 291). Lemieux (2006) uses the change in wage variance as his measure of income inequality. His analysis shows that about 54% of the total change in wage variance is attributable to growing returns to post-secondary education (Lemieux 2006, 19).

Notably, both Lemieux and Goldin and Katz do not use top income shares as their dependent variable of interest. Goldin and Katz use the 90-10 log wage differential, and Lemieux uses variation in wages. Some authors have suggested that skill-based technological change may be playing a role in such measures of inequality, but cannot explain rising top income shares. Jacob Hacker and Paul Pierson, for example, make this claim, arguing "the return to schooling—and especially to a college degree—has risen. But, as we've seen, rising American inequality is not about the gap between the college-educated and the rest…It is about the pulling away at the very top" (Hacker and Pierson 2011, 34).

C. Other factors

In addition to taxes and education, economists have proposed a number of other explanations for rising top income shares. Declining unionization rates during the second half of the twentieth century are one popular explanation. Volscho and Kelly (2012, 692) fond that unionization had a large and statistically significant negative effect on top income shares. P. Chintrakarn (2011) used Frank's state-level panel data set to estimate the effects of unionization on a state's GINI coefficient. He found that unionization had a small but statistically significant negative effect on a state's inequality as measured by GINI coefficient. Bruce Western and Jake Rosenfeld (2011) used decomposition analysis, and found that declining unionization has significant effects on both union and non-union wages. They argue that this effect is similar in size to the effects of rising returns to education (Western and Rosenfeld 2011, 30).

Other authors have focused on the growing role of finance in the economy. Following Gretta Krippner (2012) this literature examines both the growth of the financial sector as well as the role played by finance in non-financial industries. Ken-Hou Lin and Donald Tomaskovic-Devey (2013) use industry level data to estimate the effects of "financialization" on income inequality. They define financialization as "the ratio of financial receipts—which include interest, dividends, and capital gains—to business receipts, the revenue generated form the selling of goods and services" (Lin and Tomaskovic-Devey 2013, 1297). The authors find that between 1971 and 1997, financialization significantly increased within-industry inequality as measured by earnings dispersion in a given industry. Between 1999 and 2008, however, this relationship is no longer statistically significant.

D. Analyses comparing multiple factors using cross-national analysis

While some authors have focused on one specific explanation for rising inequality, other analyses have used cross-national panel analysis to model several different explanations simultaneously. Scheve and Stasavage (2007) use a sample of 14 industrialized democracies between 1919 and 2000 to estimate the effects of a number of different labor market institutions on the share of income received by the top 1% and 10% of earners. Their model shows that decentralized wage bargaining and union density reduce top income shares. They found no evidence that having a left-leaning Prime Minister or President reduced inequality. Timothy Neal (2013) performed a similar analysis, instead using panel co-integration methods. Neal collected top income share data from 10 industrialized countries between 1950 and 2009. Neal found that union density, government expenditures, top marginal tax rates, and national GDP per hour worked had statistically significant negative effects on the share of income received by top earners. He found that ideologically conservative governments were correlated with rising top income shares, while openness to trade and the amount of private credit extended had mixed results.

Methodology

Defining Inequality

As my discussion of the literature implied, scholars have devised several different quantitative measures of the equality of a distribution of income or wealth. Some concentrate on gaps between certain percentiles of the income distribution, for example the 90-10 or 50-10 income gap. Other measures, such as the GINI coefficient, compare the shape the overall income distribution relative to a perfectly equal distribution. While each of these measures is valuable in its own right, I have chosen to focus on the income shares of the top 1% and 10% of all individuals. As I discuss in more detail below, this choice was partially the result of the availability of data. There are only two state-level data sets of inequality measures over time, and they only contain reliable estimates of top income shares. This decision also mirrors a growing body of literature which has chosen to focus on top income shares following the publication of Piketty and Saez’s time series data in 2003.

In addition to defining how I measure inequality, I want to explicitly clarify that my analysis focuses on the income share of the top 1% of earners prior to taxes. Although I use tax policy as an explanatory variable, the data sets I use for my dependent variables measures the share of income received by top earners prior to taxation.[3] Taxation may additionally reduce the post-tax income share of top earners by collecting a portion of their earnings. While such effects are interesting and worthy of further analysis, I am limited by my data set to a focus on income shares prior to taxation. While the indirect effects of taxation on the income distribution are perhaps less obvious than the direct effects, I discussed several potential avenues through which taxes may affect pre-tax top income shares above.

[Figure 3 Here]

Most of the existing literature explaining rising top income shares has focused on the nationwide trends or cross-national comparisons. Analyses that rely on data aggregated from across the United States throws out the wide variation in trends occurring at the state level. Figure 6 makes clear that income shares have not followed a single trend since 1980; the share of income accrued by the top 1% of earners has varied greatly between states. Even more interesting, the trends in different states have begun to diverge significantly. In 1980, the gap between the state with the largest share of income earned by the top 1% of earners and the smallest share was 4.6%. By 2011, that gap had grown to 16.0%. The standard deviation in state top income shares grew from 1.1% to 3.6% over the same period.

[Table 1 Here]

Analyzing the fifty state-level trends can provide insight into why top income shares have grown in the United States as a whole. Just as there is substantial variation in income inequality trends in the United States, there is substantial demographic and policy variation between states. While the income threshold required to be counted in the top 1% of earners may vary somewhat between states, analyzing the distribution within a state can provide insight in to the distribution of incomes subject to a particular policy regime. As my comparison in Figure 2 made clear, the aggregated trend of the 50 states is a good

[3] This is also true of the data set constructed by Piketty and Saez (2003).

approximation of the trend nationwide; a population-weighted average of Frank's data closely mirrors other estimates of the nationwide trends.

In this paper, I use panel analysis to exploit the variation between states and within states over time to estimate the relative contributions of various policy and demographic factors to rising top income shares. As my dependent variable, I use the share of income received by the top 1% and top 10% of earners in a given state and year. I use top marginal income and capital gains tax rates as my main explanatory variables. I estimate four models to test the robustness of the effect of tax policy on top income shares. As an additional check, I run each of the models described above on two separate panel data sets of top income shares. Model 1 is a simple pooled OLS model, which does not attempt to adjust for unobserved heterogeneity between states or time periods. Model 2 is a first differences model, which estimates how changes in top income shares move together with changes in tax rates and my other variables of interest. Model 3 is a one-way state fixed effects model, which controls for unobserved heterogeneity between states by demeaning the dependent and independent variables.[4] Model 4 is a two-way fixed effects model.

Model 1: Pooled OLS

$$IncomeShare_{it} = \beta_0 + \beta_1 Top\ Ratewages_{ij} + \beta_2 TopRateCapGains_{ij} + \sum \beta X_{it} + \varepsilon$$

In this model, $IncomeShare_{ij}$ is the share of income received by either the top 1% or top 10% of earners in a given state and year. $Total\ Top\ Ratewages_{ij}$ is the combined federal and state top marginal tax rate on wage income in a given state and year. $TotalTopRateCapGains_{ij}$ is the combined federal and state top marginal tax rate on capital gains income in a given state and year. $\sum \beta X_{ij}$ is a vector of control variables.

Model 2: First Differences

Model 2 uses the same variables of interest as the OLS model, but instead models their changes:

$$\Delta IncomeShare_{it} = \beta_0 + \Delta\beta_1 Top\ Ratewages_{ij} + \Delta\beta_2 TopRateCapGains_{ij} + \sum \Delta\beta X_{it} + \varepsilon$$

[4] This is the default method for estimating fixed effects models in STATA.

In this first differences model, changes in income share are modeled as a function of changes in wage and capital gains tax rates, as well as of changes in a vector of control variables.

Model 3: One-Way Fixed Effects

Model 3 is a one-way state fixed effects model. The functional form looks similar to the OLS model, but it instead separates the error term in to α_i, the time invariant error term for each state and ν_{it}, the time variant component of the error term.

$$IncomeShare_{it} = \beta_0 + \beta_1\ Top\ Ratewages_{ij} + \beta_2 TopRateCapGains_{ij} + \sum \beta X_{it} + \alpha_i + \nu_{it}$$

By demeaning the independent and dependent variables, I am able to subtract out the time invariant component of the error term. This allows me to estimate the following model:

$$\widetilde{IncomeShare}_{it} = \beta_0 + \beta_1 Top\ \widetilde{Ratewages}_{ij} + \beta_2 TopRate\widetilde{CapGains}_{ij} + \sum \beta \widetilde{X_{it}} + \nu_{it}$$

In this model $\widetilde{IncomeShare}_{it}$, $Total\ Top\ \widetilde{Ratewages}_{ij}$, $TotalTop\widetilde{RateCapGains}_{ij}$ and $\widetilde{X_{it}}$ represent demeaned versions of the variables from previous models.

Model 4:Two-Way Fixed Effects Model

$$IncomeShare_{it} = \beta_0 + \beta_1 TopRatewages_{ij} + \beta_2 TopRateCapGains_{ij} + \sum \beta X_{it} + \alpha_i + \eta_t, + \nu_{it}$$

The two-way fixed effects model is very similar to model 3, but it additionally contains the term η_t, which represents the common unobserved trend for a given year. This aspect of the error term is captured by year dummy variables, which allows me to estimate the following model.

$$\widetilde{IncomeShare}_{it} = \beta_0 + \beta_1\ Top\ \widetilde{Ratewages}_{ij} + \beta_2 TopRate\widetilde{CapGains}_{ij} + \sum \beta \widetilde{X_{it}} + year_t + \nu_{it}$$

In this equation, ν_{it} represents the time varying unobserved aspects of the error term (not captured by state effects and year trends).

Strengths and Weaknesses of Each Model

In panel analysis, there is tension between controlling for omitted variable bias and including enough variation in a model to test the effects of various policies. The wide variation in top income shares between states provides an opportunity to test the effects of various state-level policies, but also introduces the potential for omitted variable bias. New York, for example, has very high top income shares across all years—perhaps certain aspects of New York's economy or policy regime are the reason for such high inequality. Alternately, perhaps New York City's strong cultural attractions draw higher income people to the state. I control for such time-invariant omitted variables through state fixed effects and first differences, but these model specifications wash away any time invariant components of my treatment variables. Imagine a hypothetical scenario where New York's large financial sector did not grow as a share of the economy over the 31 years of my analysis. Controlling for α_i would wash out any effects of the financial sector on the state, even if those precise effects are part of the reason that New York's baseline level of inequality is higher across all periods. Controlling for unobserved time trends poses a similar tradeoff as for unobserved heterogeneity between states. If the collapse of the tech bubble in the early 2000s, for example, disproportionately impacted high earners, the addition of year fixed effects would capture omitted variable bias by subtracting out the common observed trend for that year. At the same time, year fixed effects washes out a substantial amount of the variation in my model's independent variables within states. Any changes in federal top marginal tax rates, for example, would be effectively washed out by the inclusion of year fixed effects.

[Table 2 Here]

In other words, state fixed effects or first differencing reduce the total *between group* variance; year fixed effects reduce the total *within group* variance. Table 2 describes the tradeoff between bias and variance, and the relative strengths of each model. This theoretical background is useful for understanding the results presented below. As I increase the degree to which my analysis controls for omitted variable bias, p values predictably grow, and several coefficients change signs. Given that state and year fixed effects wash out much of the variation in our variables of interest, an insignificant result in Model 4 does not necessarily indicate that a variable does not affect inequality—there may simply be insufficient variation within states over time to properly estimate the effects of a policy change. However, we can say with a higher degree of certainty that variables which are statistically significant in Model 4 are associated with top income shares, because they are less likely to suffer from omitted variable bias.

[Table 3 Here]

Variables Included and Data Sources

Top Income Shares

To my knowledge, only two state level data sets of top income shares exist; one from Mark Frank (2009) and one compiled by Estelle Sommeiller and Mark Price of the Economic Policy Institute (2014). Both Frank and Sommeiller/Price use the IRS Statistics of Income (SOI) publication to produce estimates of the share of adjusted gross income (AGI) income accrued by top earners for each state and year. AGI includes wage and salary income, capital gains and entrepreneurial income. The SOI publication reports the number of tax units in a given income range, meaning that both data sets must use interpolation to estimate the precise top income share. Frank uses a "split histogram interpolation method" (Frank 2009, 65), while Sommeiller and Price use Pareto Interpolation. Sommeiller and Price additionally performed a number of adjustments based on the Piketty and Saez data set, Census CPS Demographic data, and Bureau of Economic Analysis personal income data. Their resulting estimates are missing for the years 1983-1985.[5] While the data sets show broadly similar trends (r=.8134 between the data sets for the years 1980-2011, excluding 1983-1985), there is enough disagreement between the two data sets about specific data points that I have chosen to run my analysis using both estimates of the dependent variable. Table 4 compares the mean differences between these two data sets by state. Sommeiller and Price tend to show larger top income shares in high-inequality states in the northeast, such as New York, Connecticut, Massachusetts and New Jersey.

[Table 4 and Figure 4 Here]

Data sets based on administrative tax return data are likely to be more reliable than those based on survey data for at least two reasons. First data collected from the CPS is generally top-coded, which prevents detailed analysis of trends at the top of the income distribution. Second, Frank points to an analysis by Hafiz Akhand and Haoming Liu (2002) which indicates that individuals at the high end of the income distribution tend to understate their income on the CPS, while individuals at the lower end of the

[5] This data is not publicly available, but Frank was able to obtain it from the IRS by special request.

income distribution tend to overstate it. Although higher income individuals in particular may have some incentive to understate their income when filing their taxes, the penalty for doing so is larger than it is for the CPS. As Frank puts it, "The IRS, unlike the March CPS or Bureau of the Census, will penalize respondents for income reporting errors."[6]

Top Marginal Tax Rates

For my treatment variable I used a data set of top marginal federal and state tax rates for each state between 1977 and 2011 that was built using Daniel Feenberg's (1993) TAXSIM simulator. This data set estimates the marginal tax rate paid on an additional $1,000 of income paid by a married couple filing jointly with a combined income of $1,500,000. It further assumes that this couple claims a mortgage interest deduction of $150,000, and that dollars paid in state income taxes are deducted from federal tax rates. The deductibility of state taxes is extremely important, because it means that increases in state marginal tax rates are partially offset by decreases in the effective federal tax rate. This deduction makes quite a large difference in the effective tax rate paid by a given taxpayer. In 2011, the hypothetical couple described above would have paid a marginal state tax rate on wage income of 11% in Hawaii, but 0% in Alaska. After accounting for the deductibility of state taxes, however, the effective federal tax rate would be 31.15% in Hawaii and 35% in Alaska. As a result, the gap between these states in total marginal tax rate would only be 7.15%, even though their state top marginal rates were 11% apart. Given the interrelationship of these two variables, it does not make sense to model their effects separately, and as a result I've used the total combined state and federal tax rate as my treatment variable.

[Table 4 here]

There is significantly greater variation in top marginal tax rates between states than within them. Table 5 displays the variation in top marginal tax rates on wages and capital gains. The "Between" values indicate how much states vary from the nationwide average tax rate in a given year. The "Within" values indicate the degree to which tax rates in a given state deviate from the average tax rate in that state across all periods observed. For both capital gains and wages, the standard deviation of the tax rate within the

[6] (Frank 2009) Page 58.

state is about three times greater than the standard deviation between the states. Figure 9 provides visual confirmation of the pattern in table 5. Most of the variation in combined tax rates on wages is the result of changes in the federal top marginal tax rate, which affects all states simultaneously.

[Figure 5 Here]

State Expenditures and Tax Collections

Top marginal tax rates affect the share of pre-tax income received by top earners through both behavioral channels and their effects on government revenue generation. As I explained above, Piketty et al (2011) describe three behavioral channels through which high top marginal tax rates reduce the pre-tax income shares of top earners: labor supply, tax evasion, and bargaining effects. Volscho and Kelly (2012) provide a fourth potential explanation; higher top tax rates raise additional revenue that can finance government expenditures on behalf of lower and moderate income individuals. Still, by controlling for the degree to which a state collects tax revenue or spends money, I test Volscho and Kelly's hypothesis that government expenditures may reduce top income tax shares. To measure state expenditures and revenue collections, I used historical data from the United States Census Bureau (2013; 2014). I used two variables—the total tax revenue collected by a state government in a given year, and the total state expenditures in a given year. To normalize such data across states of different populations, I calculated expenditures and revenues per capita using Census population estimates aggregated by the University of Kentucky Center for Poverty Research (2014). To allow for comparisons across years, I converted state taxes and expenditures in to 2013 dollars using the Bureau of Labor Statistics CPI-U measure of inflation. I obtained inflation conversion factors from Robert Sehr's (2014) website hosted by Oregon State University's Political Science Department. After adjusting for inflation, I converted tax revenue and expenditures per capita to log dollars to limit the influence of outlier states.

College Wage Premium and % of State with Bachelor's Degree or Higher

To measure the effects of growing returns to education on top income shares, I needed state level estimates of the college wage premium as well as the share of the population with college degrees or higher. To my knowledge, no state level panel data set of the college wage premium currently exists. In order to estimate the importance of returns to education, I built such a data set using the Outgoing Rotation Group (ORG) files from the Census CPS. To maintain consistency between the education variables, I used the ORG files to estimate both the college wage premium and the share of the population in a given state and year with a bachelor's degree or higher.

The ORG survey is the only portion of the CPS that directly asks workers about wages, and economists consequently tend to use the ORG survey for calculating the wage premium[7]. Rather than using the raw Census data, I used the ORG data files hosted by the Center for Economic and Policy Research (CEPR) (Center for Economic and Policy Research 2014). I opted to use CEPR's files because they contain an "adjusted wage" variable that fixes several errors, inconsistencies, and omissions in the raw ORG data. These problems include top-coding of wages, likely data errors at very high and low wage levels, inconsistent treatment of tip wages, and workers who report that their "hours vary." As a result of these fixes, CEPR's wage estimate is more consistent than the raw estimates from the NBER (Schmitt 2003).

To estimate the returns to college education in a given state and year, I used a model with a similar structure as Goldin and Katz and Autor et al. (2008 and 1998, respectively):

$$Ln(Wage) = \beta_0 + \beta_1 HS\ Degree + \beta_2 SomeCollege + \beta_3 Bachelor's + \beta_4 Advanced + \beta_5 Age + \beta_6 Age^2 + \beta_7 Age^3 + \beta_8 Age^4 + \beta_9 Female + \beta_{10} NonWhite + \beta_{11} PartTime + \sum Age * Female + \sum Age * Nonwhite$$

This model estimates a worker's log wage as a function of his or her education level, a quartic estimator of experience, and dummy variables indicating if a worker was female, non-white, or a part-time worker. It additionally includes interaction terms for the quartic of experience and the female and non-white indicators. Although Goldin and Katz recommend using dummy variables for each year of education, the CEPR data set includes only dummy variables indicating that a worker has less than a high school degree, a high school diploma, a bachelor's degree, or an advanced degree. While finer-grained education data was available for the years 1992 and later, including dummy variables for specific advanced degrees resulted in inconsistent and outlier values for smaller states. In order to obtain more consistent estimates, I

[7] This is the data set used, for example, by Goldin and Katz (2008) and Autor et al. (1998).

used a somewhat simplified version of Goldin and Katz's equation, with dummy variables indicating whether an individual had a high school diploma, bachelor's degree, or an advanced degree. Finally, following Goldin and Katz, I restricted my analysis to only individuals who were employed at the time of the survey.

Using this model, I am able to estimate how much a worker's log wage is likely to increase as the result of receiving a college or high school education. Following Goldin and Katz, I weighted the estimate of the college wage premium by the share of workers receiving in a given state and year with either college or advanced degrees. Algebraically, the estimation is as follows:

$$CWP_{it} = \frac{BP_{it} * BachShare_{it} + AP_{it} * AdvShare_{it}}{Bachshare_{it} + AdvShare_{it}} - HSP_{it}$$

In this estimation, CWP_{it} is the college wage premium in a given state and year. $BachShare_{it}$ and $AdvShare_{it}$ are the share of workers in a state with either a bachelor's or advanced degree. HSP_{it}, BP_{it}, and AP_{it}, are the wage premiums received by high school, bachelors, and advanced degree holders, respectively. Figure 5 displays the 50 state trends of the college wage premium in grey, with the US average college wage premium overlaid in black. My data set broadly matches the trend in Goldin and Katz. In my data set the average log college wage premium across all states rose about .23 from 1980 to 2011 (from .25 to .48). Goldin and Katz's data implies that the log wage premium grew by .009 per year between 1980 and 2005, which is equal to about .225 over that 25 year period (Goldin and Katz 2008, 297).

Union Membership:

To test the effects of union activity on inequality, I added a panel data set of union coverage and membership by state from Barry Hirsch and David Macpherson (2003). As Table 6 indicates, there is significant variation in union membership rates both across and between states. The "Between" numbers the degree to which states deviate from the average level of union membership in a given year. The "Within" numbers measure how much states vary from their mean union membership across all years.

While the variation in union membership is greater between states than it is within states, the variation is more than sufficient to test the effects of union membership using two-way fixed effects.

Effects of the Financial Sector

To estimate the effects of the financial sector, I collected data from the Bureau of Economic Analysis (BEA) on the share of a state's GDP represented by the financial services sector. (US Department of Commerce 2014) In 1997, the BEA switched from using the Standard Industrial Classification (SIC) to the North American Industry Classification System (NAICS). As a result of this change, it is difficult to compare industry shares from years before and after 1997. For the financial sector, the biggest differences between these two classification systems are how they classify holding companies and real estate. Under the SIC coding system, the real estate sector and holding companies were classified as part of "Finance, Insurance and Real Estate," while NAICs system codes real estate as its own category and holding companies as management services.

In order to allow comparisons between these two classification groups, I subtracted the real estate and holding company portions of GDP for all years prior to 1997. The only year in which data is available using both classification systems is 1997. After subtracting real estate and holding companies from the SIC estimates of the financial sectors, the differences between the SIC and NAICS estimates of the size of the financial sector in a given state were very close, with a mean difference of -.2 percentage points. The only states where the classification systems showed a difference greater than 1% were Nevada, New York, and Delaware, where NAICS implied that finance was 1.1 percentage points, 1.2 percentage points, and 5.3 percentage points smaller than SIC, respectively. Given that Delaware was already an extreme outlier in terms of the size of its financial sector (32% of GDP in 1997 according to SIC, almost double the next largest financial sector), these differentials in measurement should not significantly hamper comparisons across these two classification systems. Given the lack of other available data, this was the best available estimate of the size of the financial sector across both state and the time periods under consideration.

Other Variables

I include in my model several variables in addition to those mentioned above. Because some economists (e.g. Goldin and Katz 2008, 351) have suggested that the eroding value of the minimum wage may have worsened market driven inequality, I include a control for the inflation-adjusted minimum wage in a given state and year.[8] To test for the effects of partisan control of state government, I include a control that indicates whether the governor is a Democrat in a given state or year. Both the minimum wage and partisanship variables were collected from the University of Kentucky Center for Poverty Research's (UKCPR) database of state policy variables (UKCPR 2014). To control for the overall economic climate, I included the unemployment rate in a given state and year, as well as inflation-adjusted personal income per capita (both were collected from the UKCPR data set). As with the tax and expenditure variables, I adjusted the personal income data for inflation and estimated the variable in log form.

While gross state product is a more conventional measure of a state's economic output in a given year, I chose to use personal income because it more specifically measures the income received by individuals in a given state. Personal income excludes corporate profits, social insurance payments, and indirect taxes. By excluding such variables, I may miss some of the economic activity in a given state and year, but I gain a variable that more closely tracks adjusted gross income, which is a component of my dependent variable. By using this variable I hope to both control for the economic environment in a given state and year well as the "size of the income pie."

Results:

I present the results of my analysis in Tables 8 and 9. Before presenting the results, I want to highlight two methodological issues that arose while analyzing my data. First, I conducted tests for both heteroskedasticity and serial correlation, and all of my models showed the presence of both problems in both data sets. As a result, I used Stata's heteroskedasticity robust (Huber/White) standard errors and clustered standard errors by state. Josh Angrist and Jörn-Steffen Pischke (2008, Kindle Location 5039) argue that the naïve application of clustered standard errors in Stata is sufficient to correct for serial

[8] The minimum wage variable is calculated as the higher of the state and federal minimum wage.

correlation when working with 50-state panel data sets. Second, I chose not to present the results from my first differences model using Sommeiller and Price's data because data was missing for the years 1983-1985. While the absence of these years was problematic for all of my models, the first differences model was particularly problematic because differencing reduced the number of years available from both before and after the data gap. In addition, differencing meant that four years were missing rather than three. For the sake of transparency the results from this model are included in the appendix in Table 9.

[Tables 8 and 9 Here]

Capital Gains Tax Rates

Of all the explanatory variables considered in my analysis, decreases in top marginal rates on capital gains income are the most consistently associated with rising top income shares. Depending upon the model considered, a 1 percentage point increase in the top marginal tax rate on capital gains income is associated with between a .10 and .59 percentage point decrease in the share of income received by the top 1% of earners. This finding is strongly statistically significant ($p<.01$) in both data sets in all four models tested. Top marginal tax rates on capital gains appear to have similar effects on the income shares of the top 10% of earners, though the findings are slightly less robust. A 1 percentage point increase in the top marginal tax rate is associated with a decrease of between .08 percentage points and .65 percentage points in the income share of the top 10% of earners. The coefficient is highly statistically significant ($p<.01$) in five of the seven models tested, and at least borderline significant in the other two.[9]

Tax Rates on Wages

I find some evidence that top marginal tax rates on wages significantly reduce top income shares, but the size of this effect is smaller and notably less robust than for capital gains tax rates. For the top 1% of earners, three of the seven models tested show that higher top marginal tax rates on wages are associated with declines in top income shares. These models imply that a 1 percentage point increase in top tax rates on wages is associated with a decrease of between .09 and .13 percentage points in the

[9] It is significant in Model 1 ($p<.05$) using Frank's data and borderline so in Model 3 ($p<.1$) with Frank's data.

income share of the top 1% of earners. These effects are highly statistically significant ($p<.001$). The Sommeiller and Price data set in particular seems to tell a different story. In Model 3, a 1 percentage point increase in the top marginal tax rate on wages is actually associated with a .03 percentage point *increase* in top income shares for this data set. The two-way fixed effects model (4) shows no significant effect in either data set.

The results of my model of the income share of the top 10% are similar to but more consistent than the results for the top 1% of earners. Models 1-3 imply that a 1 percentage point increase in the top marginal tax rate on wage income is associated with decreases of between .03 and .60 percentage points in the income share of the top 10% of earners. These results are highly statistically significant ($p<.01$) in four of the model/data set combinations tested, and close to significant one other.[10] Model 4 shows no significant effect in the Sommeiller and Price data set, and actually shows a statistically significant and large positive effect ($\beta = .475$) in the Frank data set.

State Expenditures Per Capita

I find some evidence that expenditures by state governments can reduce top income shares, but this evidence is not particularly robust. In four of the fourteen models tested, increases in state expenditures per capita are associated with statistically significant ($p<.01$) decreases in top income shares. For the top 1% of earners, the first differences model implies that a 1% increase in state expenditures reduces top income shares by .28 percentage points, while the two way fixed effects model using Sommeiller and Price's data implies that this effect is .50 percentage points. For the top 10% of earners, these effects are .12 and .48 percentage points, respectively. These results are confusing, because the income share of the top 10% includes the income share of the top 1%, meaning we would expect larger effects for this group unless expenditures had a small (or potentially negative) effect on the income share of the 90th through 99th percentiles of earners.

College Wage Premium

[10] Using Sommeiller and Price's data, the results are borderline significant in Model 3 ($p<.1$).

The college wage premium appears to be contributing somewhat to rising top income shares. The size of this effect varied dramatically between models. The college wage premium variable was statistically significant or almost so in four of the seven models tested. A 1% increase in the college wage premium was associated with between a .07 and .10 percentage point increase in the income share of the top 10% of earners. These effects were highly statistically significant in the fixed effects model ($p<.01$) and borderline significant in the OLS model ($p<.1$). Neither data set showed a significant effect in Model 4. Five of the seven models of the income share of the top 10% showed a statistically significant positive effect of the college wage premium. The effects measured were larger than for the top 1% of earners. Depending on the model tested, a 1% increase in the college wage premium was associated with between a .06 and .25 percentage point increase in the income share of the top 1% of earners.

Union Membership

Contrary to previous research, I find very little evidence that union membership is driving rising top income shares. For both the top 1% and top 10% of earners, the union membership variable is only statistically significant in the first differences model and in the OLS model using Frank's data. When statistically significant effects are present, they are small. My models imply that a 1 percentage point increase in a state's union membership would reduce the income share of the top 1% by between .06 and .08 percentage points. These effects are, however, highly statistically significant ($p<.01$) in Models 1 and 2. These models imply that a 1 percentage point increase in union membership would reduce the income share of the top 10% by between .03 and .15 percentage points. The OLS results are highly statistically significant ($p<.01$) in Frank's data, while the first difference results are borderline so ($p<.1$). None of the results for Model 4 imply that union membership has a statistically significant effect on top income shares. Given that only one model containing controls for time invariant characteristics of states was statistically significant; the evidence that unions have played a large role in rising top income shares is weak.

Size of the Financial Sector

I find scant evidence that the size of the financial sector effects top income shares. In all fourteen models tested across both data sets and both dependent variables, the finance as a share of GDP variable is statistically significant in none of them. The strongest evidence in favor of this explanation is that all of the coefficients have a positive sign, but the highest t-value of any coefficient on this variable is 1.52.

Presence of a Democratic Governor

I find little evidence that the presence of a Democratic governor reduces the income share of the top 1% of earners. This variable is only borderline significant ($p<.1$) in the one-way fixed effects model using Sommeiller and Price's data set. This model implies that the presence of a Democratic governor in a given year and state reduces the income share of the top 1% by .31 percentage points. The evidence that the presence of a Democratic governor reduces the income share of the top 10% is slightly stronger. The presence of a Democratic governor is associated with a decrease of between .38 and .63 percentage points in the income share of the top 10% of earners. These effects are significant in both data sets using the one-way fixed effects model, with $p<.1$ and $p<.01$ in Frank and Sommeiller/Price, respectively. It is also highly significant in the OLS model using the Frank data set.

Minimum Wage

My results for the minimum wage are too inconsistent to be meaningful. The first differences models seem to imply that raising the minimum wage reduces the income share of both the top 1% and the top 10%, but the results are internally contradictory. These models imply that an inflation adjusted $1 increase in the minimum wage reduces the income share of the top 1% by .35 percentage points and the top 10% by .11 percentage points. Yet more confusing are the results for the fixed effects models. In Model 4, ostensibly the most rigorous of the models, a $1 increase in the inflation adjusted minimum wage is associated with increases of between .41 and .82 percentage points in top income shares. These results are highly statistically significant ($p<.01$).

Analysis

The Mystery of Diverging State Trends

The models I present above do a good job of explaining why top income shares within states grew as much as they did. Model 3, the one-way fixed effects model explains between 72% and 86% of the within state changes in top income shares over the last three decades. Model 4, which has the additional explanatory power of year dummy variables, explains between 80% and 93% of the within state variance. On the other hand, the models I present are fairly ignorant about why state trends have diverged. Models 3 and 4 explain between 24% and 36% of the between-state variance in top income shares over the last 30 years. To put it in more specific terms, my models do a good job of explaining why California's income share rose in the last 30 years, but a comparatively bad job of explaining why top income shares rose more in New York than Delaware. A deeper analysis of the variation between states is an important direction for future research in state trends in top income shares. Even so, explaining within-state variation is still theoretically and empirically important. As Table 11 shows, there is more variation within states than there is between them. Understanding why income shares have grown so significantly within states is therefore a useful way to understand the wider trend of rising top income shares in the US.

Tax Policy Matters, Particularly Capital Gains Taxes

My results contain strong evidence that tax policy, in particular top marginal tax rates, affect the pre-tax income distribution in the United States. Even if reducing top income shares is assumed to be a desirable outcome of policy decisions, the policy recommendations that flow from my analysis are far from clear. The desirability of raising top marginal tax rates on wages and capital gains depends on the mechanism by which such policy changes reduce top income shares. My analysis cannot clearly identify how big of a role the three mechanisms (labor supply, tax evasion, and bargaining effects) described by Piketty et al. (2011) play in reducing top income shares. Even so, my results provide several insights into how tax policies affect pre-tax top income shares.

Because year fixed effects wash out any changes in federal tax rates, one way to interpret my results is to see the first differences and one-way fixed effects models as estimating the effect of the combined federal and state top tax rates, while the two-way fixed effect models the effects of year-over-year changes in the state tax rate. Model 4 implies that state-level changes in top tax rates on wages have very little effect on top income shares, or that there is insufficient variation in tax rates between states to identify a significant effect. None of my four model specifications show statistically significant effects in the hypothesized direction, and the Frank data set actually shows a large statistically significant effect in the wrong direction. This result appears in only one model and runs counter to theory, so it isn't wise to conclude that state changes in top marginal tax rates on wages increase inequality. Instead, I take this as strong evidence that year-over-year changes in top state tax rates do not have a large effect on top income shares. It's possible that such effects are at least partially washed out by the deductibility of state income taxes; every increase in top marginal state tax rates corresponds with a partially offsetting cut to federal income taxes as a result of this deduction.

While state top marginal tax rates on wages do not appear to significantly reduce top income shares, my analysis implies that federal rates do. Models 1-3 do not wash out changes in top marginal federal tax rates with year fixed effects. These models largely imply that increases in combined state and federal top marginal tax rates are associated with decreases in pre-tax top income shares. These effects are most consistent in the Frank data set, which shows statistically significant negative effects in both the first differences and state fixed effects models for the income share of both the top 1% and the top 10%. The magnitude of these effects varies, but is larger for the top 1% of earners. This makes sense, because every individual in the top 1% of earners is likely to pay the top marginal rate, whereas only some of the top 10% of earners are likely to be subject to the top marginal rate. The data from Sommeiller and Price tells a less consistent story. In Model 3, the state fixed effects model, the Sommeiller and Price data actually implies that an increase in the top marginal tax rate on wages is associated with an increase in the income share of the top 1%. For the top 10%, the coefficient is in the correct direction, but the effect is less significant in Sommeiller and Price than in Frank. Even given this result, the balance of the evidence indicates that changes in the federal top marginal tax rate on wages have a negative effect on top income shares. This effect is statistically significant and in the right direction in all six of the model/data set combinations for the top 10% of earners (Models 1-3). It is also statistically significant and in the right direction in 3 of the five data sets tested of the top 1% of earners.

The results were much more consistent for top rates on capital gains. Models 1-3 in both data sets imply that falling top marginal tax rates on capital gains were associated with rising top income shares. The size of this effect was within the same order of magnitude in each data set. Model 4 was once again an outlier, in that the coefficients in this model were more than double the largest coefficients observed in Models 1-3. If Model 4 measures year over year changes in state taxes on capital gains, it seems strange that such changes would be almost twice as large as changes in the combined federal/state tax rate on capital gains. Some back of the envelope math reveals that this coefficient is implausibly high. On average, states saw top marginal tax rates on capital gains fall by 9.9 percentage points from 1980-2011. If the true value of the coefficient was -.5, it would imply that cuts to the capital gains tax caused top income shares to rise by 4.96 percentage points, which is about 60% of the average total change in the income share of the top 1% over that period (8.20 percentage points). I hypothesize that this result likely reflects tax avoidance effects. Capital is very mobile, particularly between states. It is easy to imagine that a high income earner would shift capital out of the state in anticipation of an increase in the capital gains tax rate the following year, particularly if she intended to report a capital gain on her taxes. As a result, the adjusted gross income reported in the state implementing the tax change would drop the following year, reflecting that top earners shifted their capital earnings to other states.

I additionally find evidence that higher tax rates on high earners could reduce top income shares by facilitating additional government expenditures. Volscho and Kelley hypothesize that health and education spending in particular help promote human capital formation. Given that state governments' largest budgetary line items are education and Medicaid, it seems plausible that state spending could reduce top income shares through this hypothesized mechanism. At the same time, my analysis implies that it may be more likely that state government expenditures reduce top income shares through other mechanisms. The log state expenditures per capita variable is statistically significant in the first differences model and in the two-way fixed effects model using Sommeiller and Price's data set. Model 2 implies that in years when states increase their expenditures, top income shares fall. Model 4 implies that in years where states spend more relative to their 30 year average and the nationwide trend for a given year, they see decreases in top income shares.

Given that human capital formation is a long term process, it seems unlikely that it would be significantly affected by year over year changes in state expenditures. As a result, Volscho and Kelly's focus on human capital formation as a mechanism for reducing top income shares seems unlikely. There are a number of ways that government expenditures could reduce top income shares through shorter term mechanisms. State capital expenditures could result in jobs or higher wages for middle class construction workers. State expenditures on current operations could similarly increase wage incomes in the middle and bottom of the income distribution by directly hiring public sector workers. While my data cannot identify the precise mechanism through which state can reduce top income shares, future analysis could seek to test identify such a mechanism by testing which categories of state expenditures are most closely associated with reductions in top income shares.

The College Wage Premium Matters

My results from the college wage premium are mostly quite robust. The only model which implies that the college wage premium does not play a role in rising income shares is the first differences model. Because the college wage premium variable was built using the coefficients from a previous regression equation, it is possible that there was more year-over-year random fluctuation due to measurement error, which could explain why the results from Model 2 were insignificant. The OLS and one-way fixed effects model consistently showed that the college wage premium increased top income shares, and the two-way fixed effects model found a statistically significant result using the Someiller and Price data set for the top 10% of earners. Because Model 4 contains the strictest controls for omitted variable bias, we can say with a high degree of confidence that there appears to be a relationship between the wage premium and the income share of the top 10%.

At the same time, my models imply that the college wage premium appears to have a smaller effect on the income share of the top 1%. This result has a lot of intuitive validity, for at least two reasons.

First, it seems likely at least some of the wages of workers in the top 1% are reflective of abilities or skills beyond just their education, and as a result, such workers may see relatively less benefit from rising returns to education. The top 1% of earners made about $350,000 in 2011 (Sommeiller and Price 2014). In 2005, the largest occupational categories of individuals in the top 1% were executives (30.0%), doctors (14.2%), financial workers (13.2%) and lawyers (7.7%) (Bakija, Cole, and Heim 2012, 35). While such individuals certainly accrue some benefits from an economy that increasingly rewards college-educated workers, their compensation is high enough that it also reflects that they have special abilities, skills or occupational specializations. Most managers, doctors and lawyers don't make $350,000; the salaries of the highest paid individuals in such professions are likely not primarily as a function of skill-based technological change.

In addition to occupational characteristics, the top 10% of earners is likely to benefit more from the college wage premium than the top 1% because it represents a larger portion of all college education workers. In 2011, for example, the about 26.6% of the residents of the average state had college degrees or higher, according to the MORG data used for my analysis.[11] A large portion of the top 1% and 10% of earners are likely to have college degrees. To illustrate this point, imagine that the entirety of each population is college educated. In that case, the top 1% of earners would represent a much smaller share of the college educated population (about 3.8%) than the top 10% of earners (36.6%). The dependent variable in my analysis is a proportion—the income share of top earners divided by the income share of all earners. The returns to higher education received by the returns college educated workers outside of the top 1% or 10% would be represented in the denominator. Because the top 10% of earners represents a larger portion of all college educated workers, a larger relative share of the total returns to education are included in the numerator. As a result, we would expect the income share of the top 10% to be more sensitive to increases in the college wage premium. In this context, my results make a lot of sense.

Evidence for Unionization is Unconvincing

[11] This is not population-weighted, so it does not represent the share of all Americans with college degrees.

Unionization was only statistically significant in the least empirically rigorous OLS model and the first differences model. While the first differences model at least controls for time invariant heterogeneity between states, it is still susceptible to omitted variable bias from common trends in time. Unlike tax rates, unionization did not bounce up and down over the past 30 years; it declined steadily. While top income shares did bounce around during the 2000s, their path has been a mostly consistent trend upward over the same period. Union membership rarely grew, and top income shares rarely fell. The statistical significance in the first differences model may merely reflect a spurious correlation resulting from the steadiness of the trend in both variables. As such, the lack of statistical significance in Model 4 is particularly concerning for advocates of the unionization explanation of rising top income shares. This is especially true given the large between and within state variance observed in the union membership variable; the lack of significance in Model 4 can't be explained away due to low variance and the resulting lack of explanatory power (as was the case for the top marginal tax rate variables). Finally, even if we accept the results of the first differences model, the effect of unionization is quite small. Union membership fell by an average of 10.28 percentage points from 1980-2011. Using the estimates from the first differences model, this implies that union membership was responsible for an increase of .59 percentage points in the income share of the top 1% and .34 percentage points in the income share of the top 10%.

Democratic Governors Have a Small Effect, if Any

My analysis find slight evidence that the presence of a Democratic governor in a given state and year reduces top income shares. This variable is only significant in four of the fourteen models I tested, and it is only significant at the $\alpha = .05$ level in two. Even so, the signs on the coefficients are consistently negative, and the effects on the income share of both the top 1% and 10% appear to be consistently between -.75 and 0. These results are mostly interesting from a theoretical perspective. If there is any evidence that Democratic governors reduce top income shares, that's a sign that there are policy variables that reduce top income shares that are not captured by my model. My model contains controls for a number of different state policy choices, including total taxes collected, total state spending, state tax rates on top earners and the minimum wage. The potential significance of the governor's partisanship implies that future research into the effects of state government policies on top income shares may be fruitful.

The Minimum Wage

Very low income workers receive an extremely small share of total income in a state, and I am therefore not surprised that my models imply that the minimum wage does not appear to reduce top income shares. The minimum wage's main goal is to lift up incomes at the bottom of the distribution, rather than reduce incomes of those at the top. Even if wage increases in low-income workers were a direct transfer from top earners, it is unlikely that such increases would be statistically detectable. One analysis showed that increasing the federal minimum wage to $10.10 in 2011 would provide an additional $35 billion in income to low wage workers nationwide (Cooper 2013). Even if that change would be meaningful for Americans earning the minimum wage, that total represents about .2% of the approximately $13 billion in personal income earned in the United Sates in the year 2011 (Bureau Of Economic Analysis 2014). Minimum wage workers are a relatively small share of the population, and by definition they earn very little income. Changes in their economic situation have very little bearing on the income shares of top earners.

The relatively small effect of lower wage workers on the total income distribution makes the results I received for the minimum wage confusing. The two-way fixed effects model implies that increases in the minimum wage are associated with rising top income shares in three of the four versions of Model 4 tested. Given that this model contains the most rigorous controls for omitted variable bias, these results are difficult to explain. Even if the minimum wage caused significant disemployment effects, my model controls for the unemployment rate in a given state and year, meaning that some other mechanism is driving this effect. Such a result is more than likely a spurious correlation between the minimum wage and top income shares, or with some other factor. One potential explanation is cost of living. States with high costs of living such as New York and California may be particularly attractive to higher income earners, and the presence of such earners may drive up the cost of living by increasing the demand for higher end goods and services. States may feel compelled to increase the minimum wage to respond to the higher cost of living, which could cause a spurious correlation between the minimum wage and top income shares.

Conclusion

As income inequality has grown in political salience, explanations for rising top income shares have proliferated. If policymakers aim to reverse this trend, it will be important that academic literature clearly identify whether policy decisions have the capacity to reduce or reverse the trend of rising top income shares. Analyzing the historical evidence of the effects of policy changes has the potential to identify which policies matter the most, and which would be most effective in altering the trend of rising inequality in the future. The 50 states differ greatly in their policy regimes and market decisions. As a result, they can be extremely helpful in explanting whether past policy decisions have affected trends in income inequality. They can also help identify how much particular market forces are contributing to this trend.

Given the lack of existing scholarship that aims to analyze the effects of policy and market conditions on income inequality on the state level, this paper is a methodological proof of concept that focusing on the states can yield important insights with policy implications. By analyzing the trends in the states, I identified strong evidence that raising top marginal tax rates can reduce pre-tax income shares of top earners. I confirmed that growing returns to college education have also contributed to rising top income shares. I presented evidence that declining unionization is not the most important cause of rising top income shares, and that the size of the financial sector has almost no effect. I showed that the effect of the minimum wage on top income shares is ambiguous, but it is unlikely that raising the wage will have a noticeable effect at the top of the income distribution.

Policymakers who wish to implement policies that reduce the income shares of top earners should take several lessons from my analysis. First, tax policy seems like a much more promising mechanism for reducing inequality than other solutions commonly proposed. Raising the minimum wage, reigning in the growth of the financial sector or encouraging union membership may be desirable policies for any number of reasons. They may even reduce inequality as measured by GINI coefficient or the 90-10 wage gap, but my analysis implies that there is little evidence that such policies reduce top income shares. Inequality is not a single phenomenon, and as such does not have a single policy solution. There is very strong evidence that top income shares have grown dramatically over the last 30 years, and policymakers wishing to reverse this trend will need to identify which policy tools are likely to be effective. Of the variables I considered, tax policy is likely to be the most efficacious route to reducing top income shares, even if their direct effects on after-tax income are ignored.

Second, federal capital gains taxes in particular appear to be particularly effective in reducing top income shares. Of all the variables I tested, higher top marginal tax rates on capital gains were most consistently associated with reductions in top income shares. These effects were of a similar size in Models 1-3, indicating that my results for this variable were consistent as well as robust. The fact that Model 4 showed effects that were around three times larger than in Models 1-3 implied that there is significant evidence that attempting to implement reduce top income shares through changes in state capital gains tax rates may be ineffectual. State taxes on capital gains are easier to evade than federal, because state borders are more porous to capital than are federal borders. My analysis implies that policymakers and advocacy groups who wish to reduce top income shares without causing significant tax evasion ought to focus their attention on federal capital gains tax rates.

Third, the effects of top marginal tax rates on wages were more mixed in my models, but they still imply that increases in both federal and state tax rates on wages could help reduce top income shares. Unlike with capital gains tax rates, there was little evidence that top marginal state tax rates on wages were provoking tax evasion. The coefficients on the wage tax rate variable actually appeared to move in the opposite direction from the coefficients on the capital gains variable in Model 4. Unlike with capital gains, states that changed their top tax rates on wages did not see large drops in the income share of the top 1%, implying that there was little attempt to evade such taxes by leaving the state. At the same time, increases in state top marginal tax rates on wages did not appear to significantly reduce top income shares in my model. This result has important, but nuanced policy consequences. State tax rates on wages are unlikely to be an effective mechanism for reducing pre-tax top income shares through their behavioral effects on top earners. As with capital gains taxes, my analysis implies that the federal government is a more appropriate target for advocacy groups who aim to reduce pre-tax top income shares through such channels. At the same time, my analysis implies state policymakers may be able to raise top marginal income tax rates without provoking significant changes in the behavior of top earners, either through reduced labor supply or tax evasion. Such tax increases would certainly reduce the post-tax income shares of top earners, and to the extent that they finance additional state government expenditures, they may actually reduce pre-tax top income shares as well.

Fourth, the results of my analysis for the college wage premium to some extent confirms existing literature that suggests that the college wage premium has played a role in rising inequality. Still, this result is noteworthy in that it offers empirical support for the idea that growing returns to education may be affecting inequality as measured by top income shares. Hacker and Pierson (2011), for example, argue that returns to education may explain growth in other measures of inequality, but it cannot explain growing income shares for top earners.[12] My analysis provides evidence to the contrary, at least on this point. Hacker and Pierson additionally argue that inequality within groups of workers with the same levels of education has also grown, which indicates that skill based technological change alone cannot explain growing top income shares. While this explanation is also plausible, it does not preclude the possibility that the growing college wage premium has disproportionately benefited workers in the top 1% and top 10% of earners; it may even corroborate such a hypothesis.

My analysis indicates that the income share of the top 1% and 10% of workers increases as the college wage premium grows, even though such workers represent fewer than half of all college educated workers. This suggests that the growing average gap in average wages between college educated and non-college educated workers has particularly benefited those at the top of the income distribution. This implies that policies which merely encourage more workers to get college educations may not be successful in reducing top income shares, because not all workers benefit from a college education to the

[12] Importantly, Hacker and Pierson point to the role of policy in shaping the pre-tax income distribution. My results on tax policy largely corroborate this part of their argument.

same degree as top earners. Indeed, the variable in my models for the share of workers with college degrees was not consistently significant. Going forward, further research will be helpful in identifying what role education has played in growing top income shares. My analysis is not fine-grained enough to identify precisely who benefits from growing returns to college education, and how such returns shape the overall distribution of income.

Finally, my analysis implies that most common explanations for rising inequality can explain changes in top income shares within states over time, but we know very little about what makes state income distributions different from one another. While between-state variation in income inequality is a mystery as of my analysis, it has the potential to be extremely policy relevant. Future research has the potential to uncover what policy, market, or demographic factors have made a state's income distribution equal relative to other states. The old cliché calls the states the laboratories of democracy; future research may reveal that the states can also be laboratories of equality.

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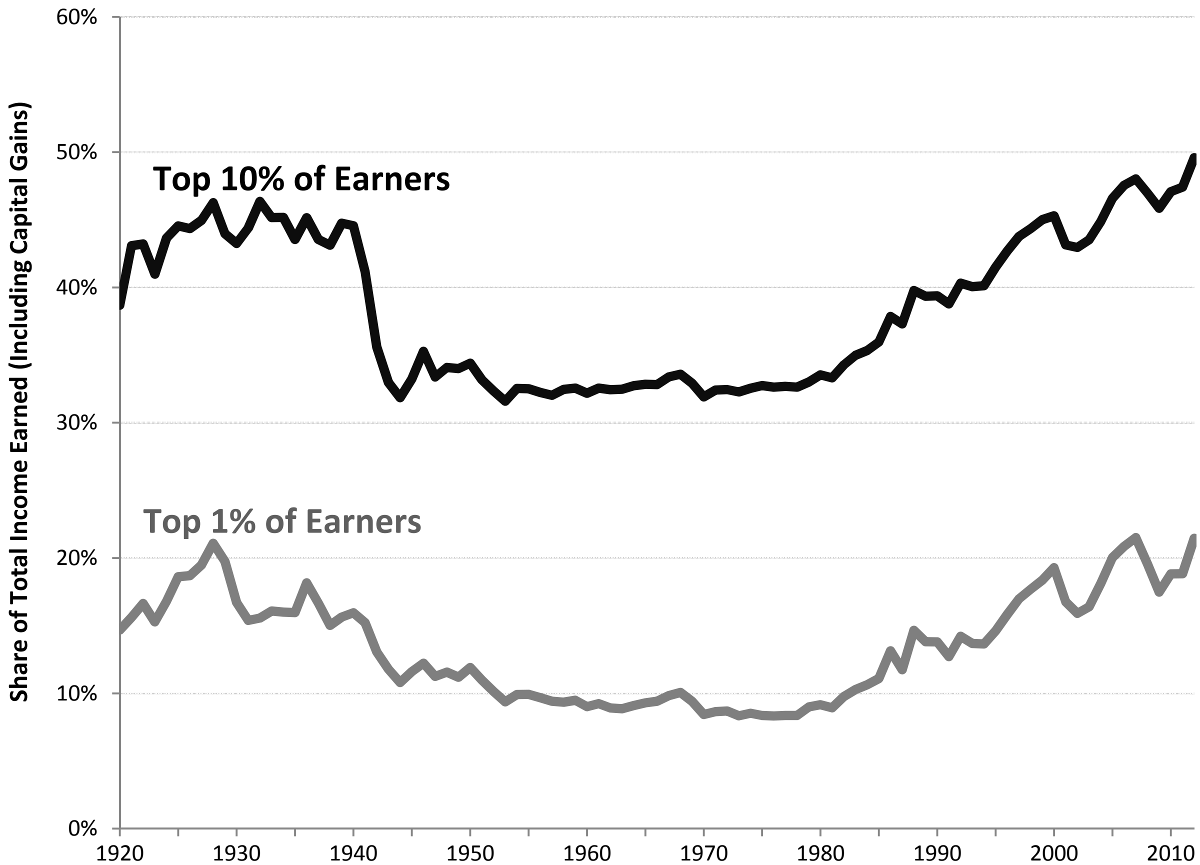
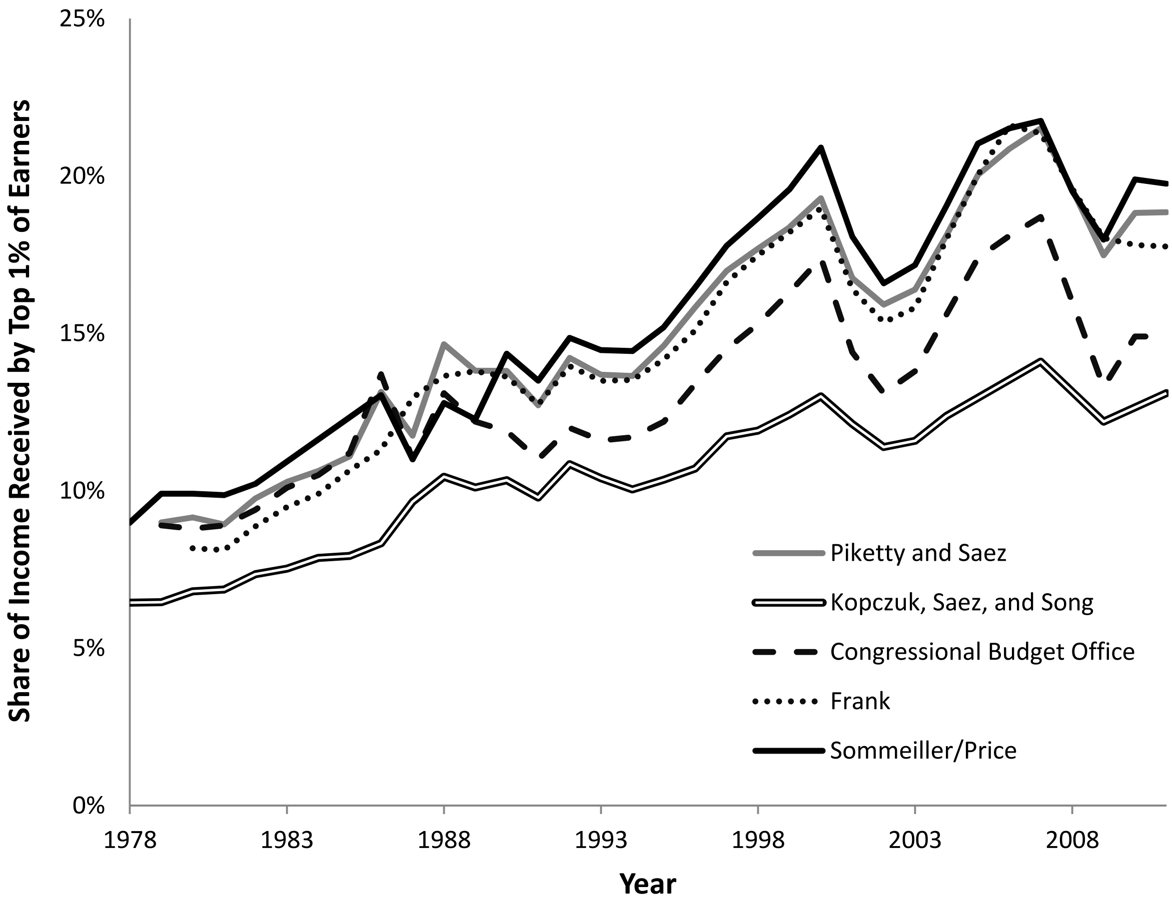
Appendix 1: Tables and Figures

Figure 1: Income Shares of Top Earners in the United States, 1920-2012



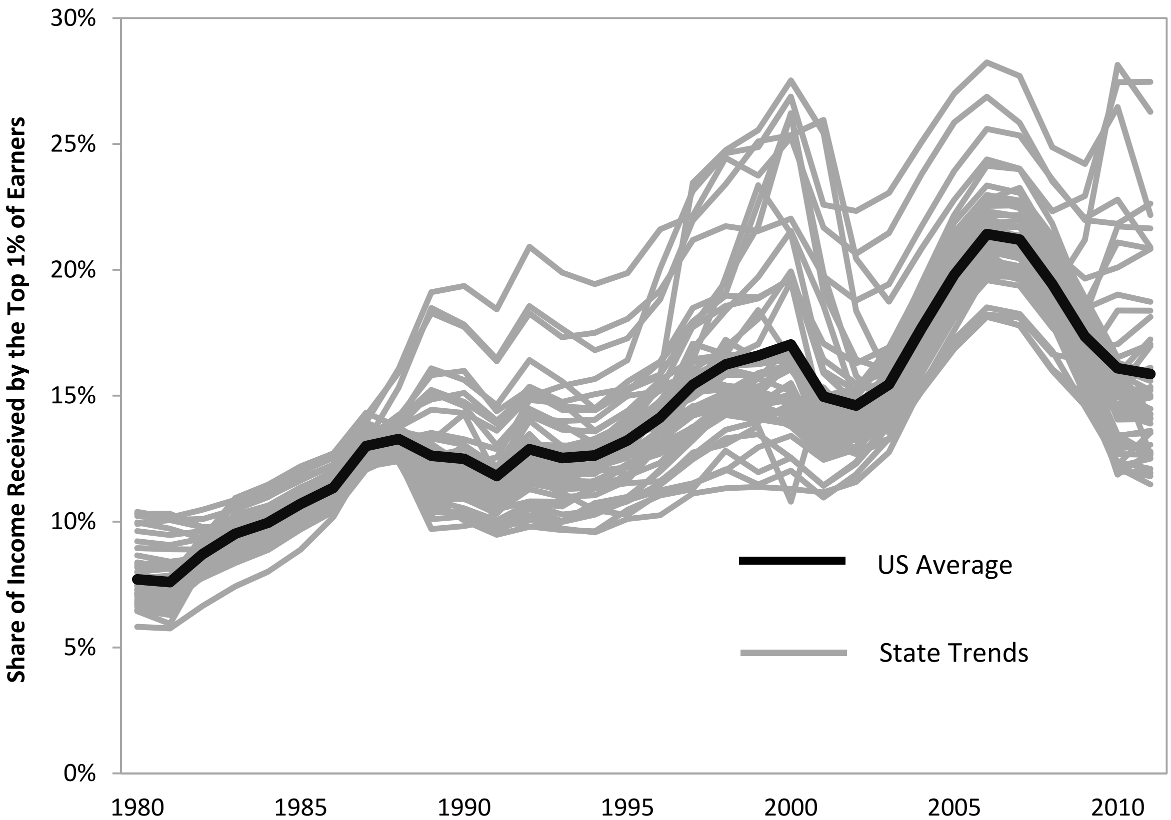
Trends in income shares in Piketty and Saez. Updated data from Saez (2013)

Figure 2: Comparing Estimates of the Income Share of the Top 1% of Earners



Data from Emmanuel Saez (2013) Kopczuk, Saez and Song (2010) (augmented by Mishel and Finio(2014)), the Congressional Budget Office (2013), Frank (2009), and Sommeiller and Price (2014). I calculated a nationwide average from Frank's state level data by weighting states by population. While their data set is also state level, Sommeiller and Price provide their own estimate of the nationwide trend.

Figure 3: State Trends in Top 1% Income Shares, 1980-2010



Data from Frank (2009).

Table 1: Variation in Top Income Shares has Grown Significantly Since 1980

	1980	2011
	Top 1% Income Share	
Smallest Share	Alaska: 5.8%	Hawaii: 11.5%
Largest Share	Texas: 10.4%	New York: 27.5%
Range	**4.6%**	**16.0%**
Standard Deviation	1.1%	3.6%

Data from Frank (2009).

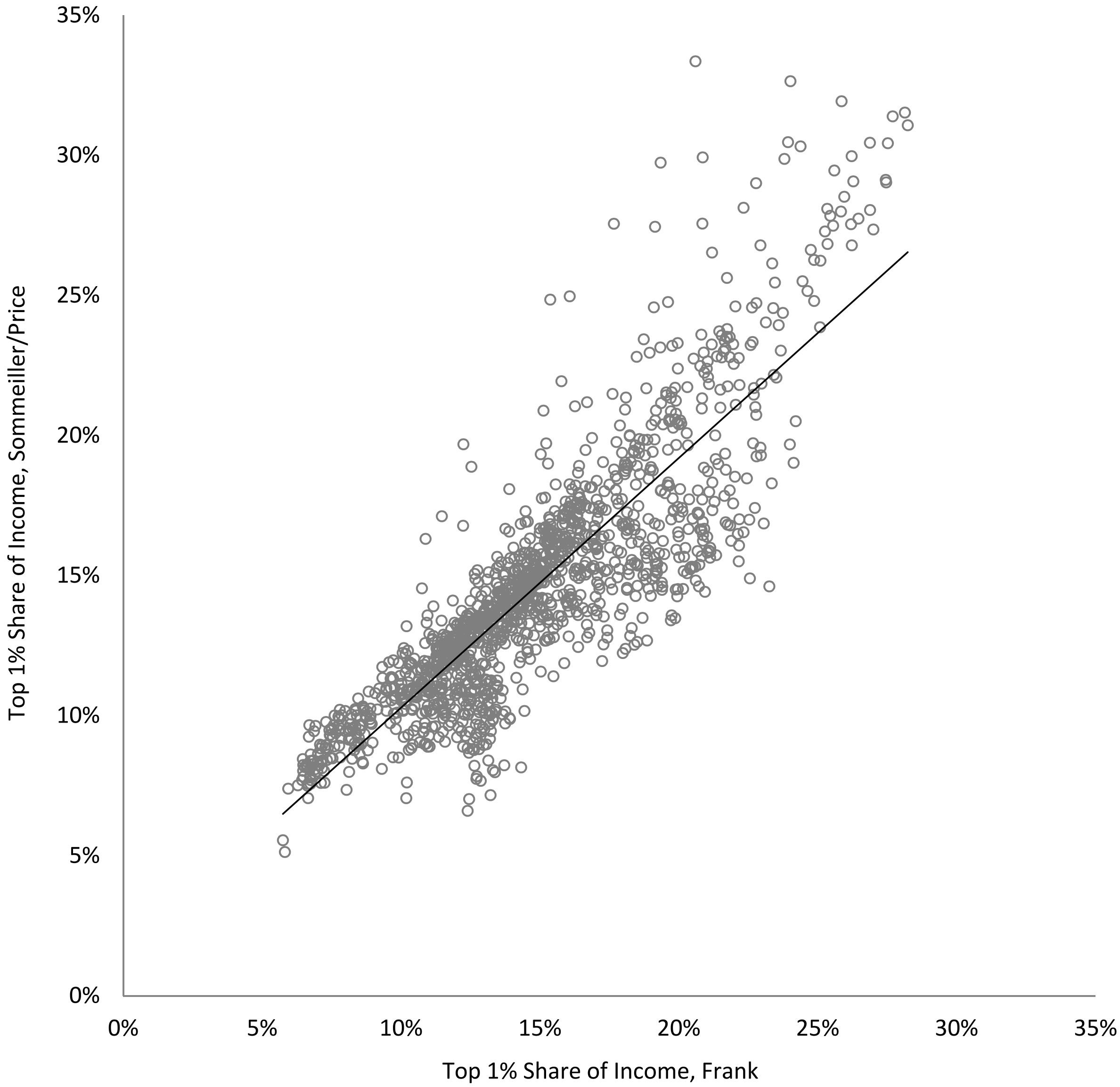
Table 2: Tension between Variation and Omitted Variable Bias

	Model 1: Pooled OLS	**Models 2 & 3: First Differences and Fixed Effects**	**Model 4: Two-way fixed effects**
Variance	High between and within group variance	Low between group variance, high within group variance.	Low within and between group variance.
Omitted Variable Bias	High risk of omitted variable bias due to time invariant characteristics of states and unobserved time trends.	Low risk of omitted variable bias due to time invariant characteristics of states. High risk of bias due to unobserved time trends.	Low risk of omitted variable bias due to time invariant state characteristics or unobserved time trends. Still at risk of omitted variable bias due to time variant characteristics.

Table 3: Variables Included and Summary Statistics

Variable	Source	Range: Min.	Range: Max.	Summary Statistics: Mean	Summary Statistics: St. Dev.
Dependent Variables					
Top 1% Income Share (Frank)	(Frank 2009)	5.75	28.24	14.21	4.21
Top 1% Income Share (S&P)	(Sommeiller and Price 2014)	4.34	33.35	14.44	4.34
Top 10% Income Share (Frank)	(Frank 2009)	28.48	54.63	38.90	5.07
Top 10% Income Share (S&P)	(Sommeiller and Price 2014)	25.08	61.04	40.59	5.20
Tax Variables					
Top Marginal Tax Rate (Wages)	(Feenberg 1993)	28	56.9	42.69	6.68
Top Marginal Tax Rate (Capital Gains)	(Feenberg 1993)	11.24	29.19	20.58	5.26
Education Variables					
College Wage Premium	(Center for Economic and Policy Research 2014)	0.098	0.654	0.399	0.091
% w/Bachelor's Degrees	(Center for Economic and Policy Research 2014)	7.39	50.34	20.56	5.69
Controls					
Log Taxes Per Capita	(United States Census Bureau 2013)	6.57	9.53	7.67	0.31
Log State Expend. Per Capita	(United States Census Bureau 2014)	7.61	9.88	8.44	0.35
Union Membership	(Hirsch and Macpherson 2003)	2.3	38.3	14.23	6.66
Minimum Wage	(UKCPR 2014)	3.1	8.67	4.81	1.37
Log Personal Income Per Capita	(UKCPR 2014)	9.86	11.21	10.43	0.21
Unemployment Rate	(UKCPR 2014)	2.3	17.4	6.04	2.15
Finance Share of GDP	(US Department of Commerce 2014)	1.44	37.33	6.44	4.09
Governor is a Democrat	(UKCPR 2014)	0	1	0.51	0.50

Figure 4: Comparing Panel Data Sets from Frank (2009) and Sommeiller/Price (2014)



Data from Frank (2009) and Sommeiller/Price(2014)

Table 4: Mean Differences between Sommeiller and Price and Frank Data Sets By State

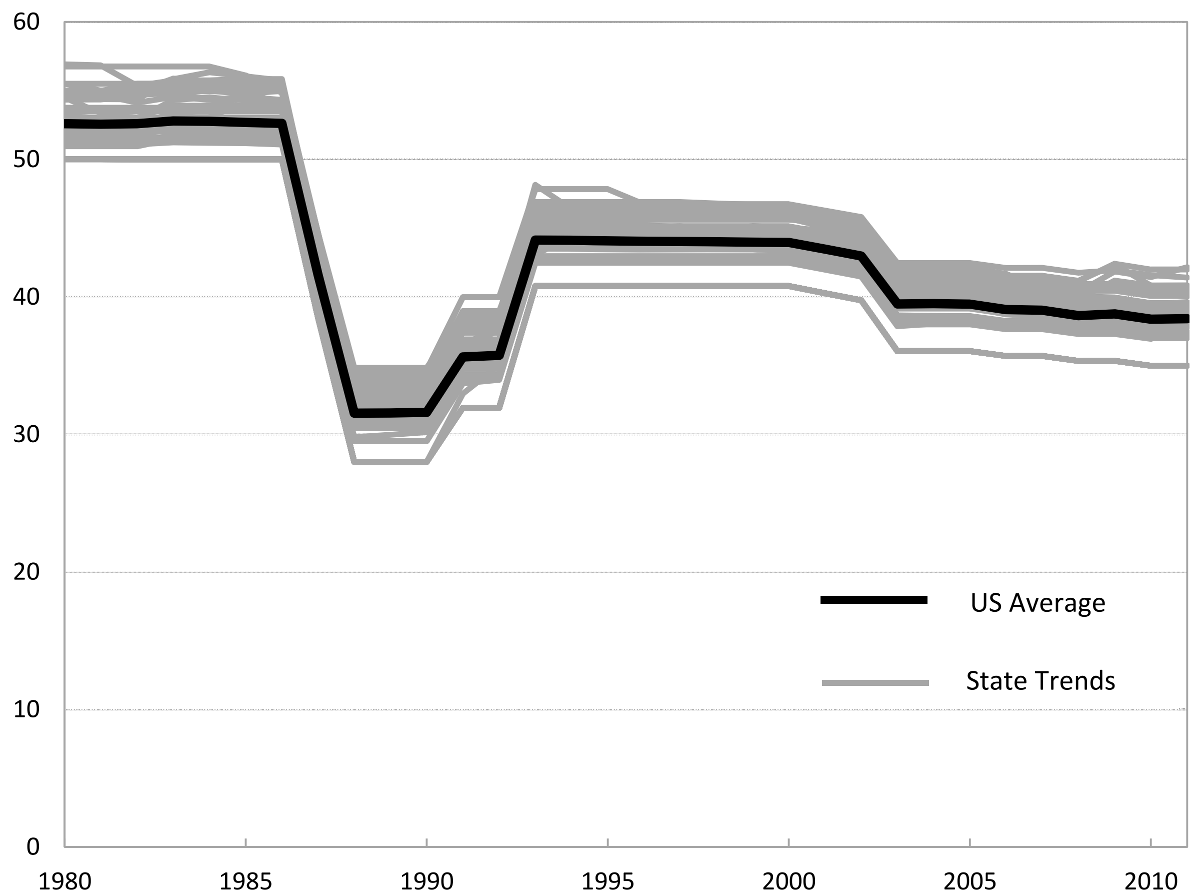
State	Mean Difference (Frank - SP) Top 1	Top 10	State	Mean Difference (Frank - SP) Top 1	Top 10
Connecticut	-4.14	-3.87	Oregon	0.36	-1.79
New York	-2.57	-2.93	Vermont	0.46	-1.63
Massachusetts	-1.85	-3.26	Kentucky	0.51	-2.59
New Jersey	-1.78	-3.05	South Carolina	0.53	-1.92
Florida	-1.75	-2.78	Wisconsin	0.53	-1.42
Nevada	-1.39	-1.83	North Carolina	0.53	-0.76
District of Columbia	-1.04	1.42	Missouri	0.64	-1.14
Illinois	-0.73	-1.73	Louisiana	0.65	-0.92
California	-0.66	-0.78	Ohio	0.69	-1.29
Delaware	-0.49	-2.19	Indiana	0.70	-1.82
Arizona	-0.41	-2.58	Maine	0.74	-1.63
Washington	-0.36	-2.22	Arkansas	0.80	-1.73
Rhode Island	-0.27	-2.86	Mississippi	0.96	-2.01
New Hampshire	-0.23	-1.92	Kansas	0.98	0.28
West Virginia	-0.18	-6.48	Utah	1.02	0.55
Pennsylvania	-0.07	-2.14	New Mexico	1.04	-0.82
Maryland	-0.07	-1.01	Oklahoma	1.22	0.62
Michigan	-0.04	-3.55	Montana	1.25	-0.04
Georgia	0.06	-1.14	Iowa	1.55	0.70
Colorado	0.16	-0.09	Idaho	1.57	1.21
Minnesota	0.17	-0.90	North Dakota	1.61	1.15
Virginia	0.21	-0.52	Hawaii	1.85	2.68
Alabama	0.27	-2.80	Nebraska	1.97	2.65
Texas	0.28	0.31	Alaska	2.18	5.28
Wyoming	0.32	0.72	South Dakota	2.24	3.37
Tennessee	0.33	-1.51			
		US Average		**-0.62**	**-1.91**

Table 5: Variation in Top Marginal Tax Rates Between and Within States (Combined State and Federal)

	Top Marginal Tax Rate (Wages)			Top Marginal Tax Rate (Capital Gains)		
	Overall	Between	Within	Overall	Between	Within
St. Dev.	6.7	1.9	6.4	5.6	1.6	5.4
Minimum	28.0	39.5	29.2	15.0	22.2	15
Maximum	56.9	45.8	55.1	37.0	28.1	35.1

Between and within values calculated using Stata's xtsum command. Within variation measures the extent to which top tax rtes deviate from their average value across the 31 years included in my analysis. Between variation measures the extent to which states vary from the average value across all states in a given year.

Figure 5: Variation in Top Marginal Tax Rates on Wages



Source: Feenberg 1993

Figure 6: Log College Wage Premium by US State, 1980-2010

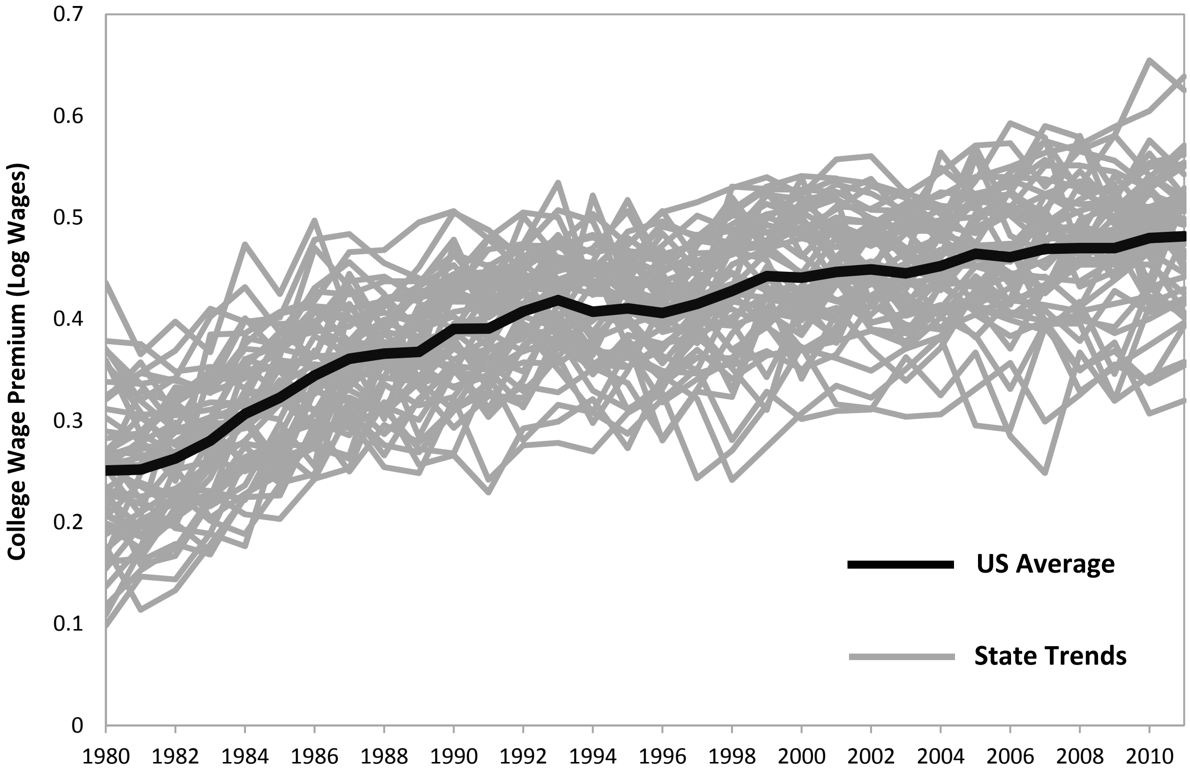


Table 6: Variation in Union Membership Between and Within States

	Overall	Between	Within
St. Dev.	6.7	5.9	3.2
Minimum	2.3	4.6	6.6
Maximum	38.3	27.6	34

Table 7: Variation in Finance Share of GDP Between and Within States

	Overall	Between	Within
St. Dev.	4.1	3.6	2.0
Minimum	1.4	2.7	-13.1
Maximum	37.3	25.5	18.3

Between and within values calculated using Stata's xtsum command. Within variation measures the extent to which union membership and finance shares deviate from their average value across the 31 years included in my analysis. Between variation measures the extent to which states vary from the average value across all states in a given year.

Table 8: Results for the Income Share of the Top 1%

	Model 1: OLS		Model 2: FD	Model 3: One-Way FE		Model 4: Two-Way FE	
Data Set	Frank	S&P	Frank	Frank	S&P	Frank	S&P
Tax Variables							
Top Marginal Tax Rate	-0.126***	-0.00851	-0.0906***	-0.0981***	0.0312***	0.287	0.476
(Wages)	(0.0219)	(0.0254)	(0.00498)	(0.00911)	(0.0112)	(0.180)	(0.347)
Top Marginal Tax Rate	-0.243***	-0.133***	-0.0973***	-0.209***	-0.0872***	-0.504***	-0.585***
(Capital Gains)	(0.0280)	(0.0330)	(0.00758)	(0.0202)	(0.0162)	(0.107)	(0.149)
Log Taxes Per Capita	0.885	0.902	1.882	0.224	-0.00446	0.00431	0.65
	(1.128)	(1.343)	(1.151)	(1.150)	(0.983)	(0.534)	(0.617)
Log State Expend. Per Capita	-0.138	-2.439	-2.797***	-1.463	-2.637	-1.92	-4.974**
	(1.179)	(1.660)	(0.584)	(1.197)	(1.687)	(1.504)	(2.209)
Education Variables							
College Wage Premium	7.214*	10.05*	0.921	6.642***	10.06***	1.666	3.443
	(3.921)	(5.484)	(0.761)	(1.984)	(2.413)	(1.747)	(2.322)
% w/Bachelor's Degrees	-0.157	-0.239*	-0.043	-0.0215	0.065	-0.138	-0.033
	(0.0981)	(0.138)	(0.0341)	(0.0886)	(0.124)	(0.0843)	(0.136)
Other Variables							
Union Membership	-0.0810*	-0.0831	-0.0576***	-0.036	-0.0512	-0.0295	0.00865
	(0.0457)	(0.0705)	(0.0188)	(0.0487)	(0.0692)	(0.0382)	(0.0548)
Finance Share of GDP	0.024	0.057	0.163	0.0793	0.151	0.0364	0.0995
	(0.0769)	(0.0944)	(0.113)	(0.0627)	(0.0989)	(0.0509)	(0.0931)
Minimum Wage	-0.726***	0.125	-0.349***	-0.671***	0.233*	-0.225	0.568**
	(0.230)	(0.290)	(0.0888)	(0.138)	(0.121)	(0.147)	(0.229)
Governor is a Democrat	-0.308	-0.386	-0.014	-0.19	-0.314*	-0.0738	-0.128
	(0.192)	(0.265)	(0.0809)	(0.159)	(0.177)	(0.114)	(0.156)
Log Personal Income Per Capita	10.46***	18.03***	8.650***	13.09***	13.52**	9.147***	10.55**
	(3.345)	(4.854)	(2.192)	(3.523)	(5.166)	(2.705)	(4.391)
Unemployment Rate	-0.152*	0.068	-0.225***	-0.240***	-0.228**	0.151*	0.00293
	(0.0808)	(0.0999)	(0.0381)	(0.0680)	(0.0877)	(0.0793)	(0.0950)
State Fixed Effects				X	X	X	X
Year Fixed Effects						X	X
N	1600	1450	1550	1600	1450	1600	1450
R-Squared	0.69	0.602	0.213	0.645	0.537	0.793	0.627
R-Squared Within				0.786	0.723	0.879	0.810
R-Squared Between				0.242	0.317	0.347	0.358

Legend: * p<.1, ** p<.05, *** p<.01. Standard errors adjusted for heteroskedasticity and serial correlation using heteroskedasticity robust standard errors and by clustering standard errors by state. Year fixed effects were added to Model 4 using year dummy variables. State fixed effects implemented using Stata's xtreg command, which applies fixed effects through demeaning.

Table 9: Results for the Income Share of the Top 10%

	Model 1: OLS		Model 2: FD	Model 3: One-Way FE		Model 4: Two-Way FE	
Data Set	Frank	S&P	Frank	Frank	S&P	Frank	S&P
Tax Variables							
Top Marginal Tax Rate	-0.128***	-0.0423	-0.100***	-0.0805***	-0.0281*	0.475**	0.459
(Wages)	(0.0274)	(0.0299)	(0.00542)	(0.0118)	(0.0143)	(0.225)	(0.373)
Top Marginal Tax Rate	-0.0803**	-0.118***	-0.0575***	-0.0285*	-0.0962***	-0.518***	-0.646***
(Capital Gains)	(0.0310)	(0.0418)	(0.00575)	(0.0157)	(0.0216)	(0.113)	(0.193)
Log Taxes Per Capita	-0.00121	0.986	1.075	-1.361	-0.328	-0.513	0.810
	(1.575)	(1.580)	(0.872)	(0.984)	(1.140)	(0.532)	(0.761)
Log State Expend. Per Capita	0.407	-2.895	-1.241**	-0.0311	-1.503	-1.562	-4.807**
	(1.306)	(1.969)	(0.572)	(1.381)	(1.918)	(1.697)	(2.309)
Education Variables							
College Wage Premium	13.33***	25.21***	1	9.779***	15.01***	2.892	6.273**
	(4.046)	(5.797)	(0.667)	(2.330)	(2.741)	(1.754)	(2.660)
% w/Bachelor's Degrees	-0.105	-0.132	-0.013	0.165	0.136	0.0361	0.00644
	(0.101)	(0.141)	(0.0287)	(0.114)	(0.122)	(0.112)	(0.134)
Other Variables							
Union Membership	-0.151**	-0.062	-0.0330*	-0.096	-0.109	-0.038	0.019
	(0.0593)	(0.0762)	(0.0187)	(0.0592)	(0.0775)	(0.0536)	(0.0655)
Finance Share of GDP	0.0058	0.0592	0.11	0.100	0.158	0.0525	0.107
	(0.0923)	(0.101)	(0.0744)	(0.0853)	(0.114)	(0.0649)	(0.107)
Minimum Wage	0.028	0.144	-0.113**	0.0596	0.205	0.410**	0.826***
	(0.268)	(0.376)	(0.0493)	(0.110)	(0.162)	(0.178)	(0.270)
Governor is a Democrat	-0.630***	-0.261	-0.036	-0.490***	-0.377*	-0.207	-0.186
	(0.225)	(0.320)	(0.0468)	(0.165)	(0.204)	(0.128)	(0.185)
Log Personal Income Per Capita	14.91***	14.56***	6.944***	14.70***	10.34*	8.489***	3.962
	(3.564)	(4.847)	(1.658)	(3.902)	(5.316)	(3.117)	(4.811)
Unemployment Rate	-0.006	0.368***	-0.194***	-0.235***	-0.0756	0.0629	0.011
	(0.0829)	(0.125)	(0.0306)	(0.0736)	(0.102)	(0.0744)	(0.109)
State Fixed Effects				X	X	X	X
Year Fixed Effects						X	X
N	1600	1450	1550	1600	1450	1600	1450
R-Squared	0.764	0.614	0.263	0.703	0.534	0.785	0.567
R-Squared Within				0.886	0.741	0.936	0.799
R-Squared Between				0.309	0.276	0.296	0.298

Legend: * p<.1, ** p<.05, *** p<.01. Standard errors adjusted for heteroskedasticity and serial correlation using heteroskedasticity robust standard errors and by clustering standard errors by state. Year fixed effects were added to Model 4 using year dummy variables. State fixed effects implemented using Stata's xtreg command, which applies fixed effects through demeaning.

Table 10: Results from Model 2 using S&P Data set

	Model 2: Sommeiller and Price	
	Top 1%	Top 10%
Top Marginal Tax Rate (Wages)	-0.0378***	-0.0653***
	(0.00617)	(0.00932)
Top Marginal Tax Rate (Capital Gains)	-0.199***	-0.165***
	(0.0120)	(0.0175)
Log Taxes Per Capita	0.417	1.186
	(0.871)	(1.155)
Log State Expend. Per Capita	-0.0666	0.431
	(1.130)	(1.267)
College Wage Premium	2.264*	1.834
	(1.286)	(1.419)
% w/Bachelor's Degrees	-0.0444	-0.0767
	(0.0496)	(0.0504)
Union Membership	-0.0619*	-0.0611
	(0.0323)	(0.0374)
Finance Share of GDP	0.0942	0.0986
	(0.175)	(0.200)
Governor is a Democrat	0.129	0.164
	(0.106)	(0.108)
Minimum Wage	0.0613	-0.136
	(0.0877)	(0.104)
Log Personal Income Per Capita	8.002*	-4.845
	(4.528)	(5.988)
Unemployment Rate	-0.317***	-0.243***
	(0.0553)	(0.0826)
_cons	0.0434	0.285***
	(0.0535)	(0.0654)
R^2	0.195	0.0895
N	1350	1350

Table 11: Between and Within Variation of Top Income Shares

	Top 1% Income Share (Frank)			Top 1% Income Share (S&P)		
	Overall	Between	Within	Overall	Between	Within
St. Dev.	4.21	1.73	3.85	4.34	2.80	3.33
Minimum	5.75	11.63	19.23	5.13	9.81	22.22
Maximum	28.24	19.23	25.05	33.35	22.22	26.81

	Top 10% Income Share (Frank)			Top 10% Income Share (S&P)		
	Overall	Between	Within	Overall	Between	Within
St. Dev.	5.07	2.60	4.37	5.20	3.48	3.90
Minimum	28.48	34.62	26.39	25.08	32.98	24.48
Maximum	54.63	45.82	49.72	61.04	49.76	53.95

Between and within values calculated using Stata's xtsum command. Within variation measures the extent to which top income shares deviate from their average value across the 31 years included in my analysis. Between variation measures the extent to which states vary from the average value across all states in a given year.