Regulation and Income Inequality in the United States

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Dustin Chambers and Colin O'Reilly. "Regulation and Income Inequality in the United States." Mercatus Working Paper, Mercatus Center at George Mason University, Arlington, VA, May 2020.

Abstract

Income inequality in the United States has risen over the past several decades. Over the same period, federal regulatory restrictions have increased. An emerging literature shows that regulations can have regressive effects on the distribution of income, exacerbating inequality. The Federal Regulation and State Enterprise (FRASE) index quantifies the regulatory restrictions that apply to each US state by industrial composition. We construct a panel of 50 US states from 1997 to 2015 to test whether states exposed to more federal regulatory restrictions have higher levels of income inequality. The results indicate that a 10 percent increase in federal regulation is associated with an approximate 0.5 percent increase in income inequality as measured by the Gini coefficient. When states are rank-ordered by average Gini coefficient, a 0.5 percent increase in income inequality will typically result in a two-position decline in state ranking.

JEL codes: D31, D63, L51

Keywords: regulation, income inequality, FRASE, regressive effects

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This paper can be accessed at https://www.mercatus.org/publications/regulation/regulation-income-inequality-united-states

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1. Introduction

Since the 1970s, income inequality has steadily risen in the United States (Frank 2009; Piketty and Saez 2014). While this alarming trend has received considerable press coverage and great interest among economists, little consensus has emerged regarding the underlying causes of the increase in inequality, much less a suitable policy response. Over the same period, the number of federal regulatory restrictions has also sharply increased (McLaughlin and Sherouse 2019). Though a rapidly growing strand of the literature now documents the unintended and regressive effects of regulation, the link between regulations and inequality has been generally neglected by economists. This paper contributes to the literature on the regressive effects of regulation by studying the relationship between federal regulations and income inequality in US states.

Our thesis is that regulations exacerbate income inequality by generating compliance costs that disproportionately impact small businesses and low-income households while giving rise to costly regulatory barriers to entry, which shelter incumbents and inhibit competition. If true, the concomitant rise of both federal regulations and US income inequality over the past 40 years was no coincidence.

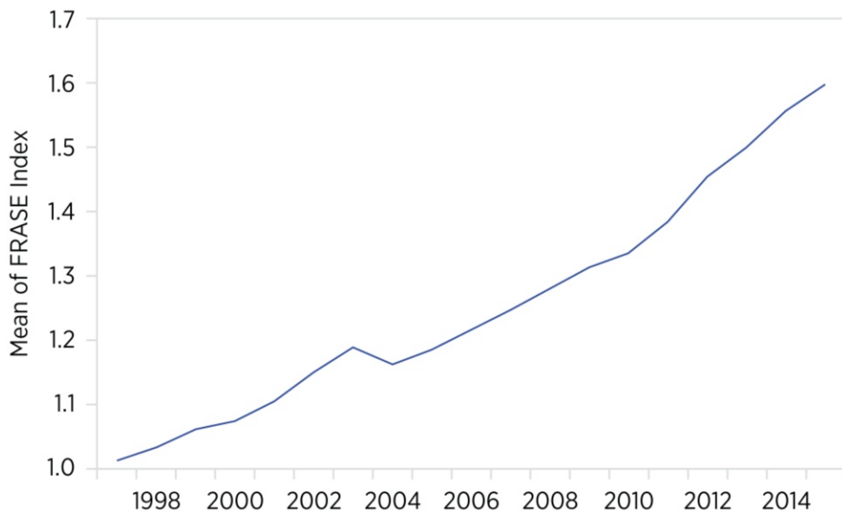
Evidence indicates that regulations disproportionately impact small businesses and stifle entrepreneurship. Looking at all forms of business regulation across a wide array of industries, Crain and Crain (2014) estimate that small businesses faced 29 percent higher average per-employee compliance costs than large firms ($11,724 versus $9,083). At the US state level, Bailey and Thomas (2017) find that entry regulation is associated with fewer firm births and slower growth in employment. Chambers, McLaughlin, and Richards (2018) find that an increase in industry-specific regulations is associated with fewer small firms and reduced small-firm employment. Similarly, Gutierrez and Philippon (2019) demonstrate that regulations have reduced small firms' market entry and growth relative to their larger competitors. Chambers and Guo (2019) empirically test the dynamic general equilibrium model of Dhawan and Guo (2001) and demonstrate that more industry-specific federal regulations reduce both the output share and employment share of small firms in the US economy. Apart from acting as a costly barrier to entrepreneurs starting new businesses (Klapper, Laeven, and Rajan 2006), regulation impacts income inequality in other ways.

Regulations may also increase inequality in the labor market. Occupational licensure increases the cost of entering a profession and tends to increase the wages of license holders (Kleiner and Krueger 2013; Kleiner and Park 2010). Others (Bailey, Thomas, and Anderson 2019; Mulholland 2019) provide evidence that federal regulation in the United States may lead to greater wage inequality between occupations and within occupations.

To the extent that regulation reduces entrepreneurship, slows employment growth, exacerbates wage inequality, and increases poverty in the United States, regulation should be associated with aggregate measures of the distribution of income. Indeed, Chambers, McLaughlin, and Stanley (2019b) find that states exposed to greater federal regulation because of the composition of industry in that state tend to have higher poverty rates. Using the Federal Regulation and State Enterprise (FRASE) index of state-level regulatory burden, they find that a 10 percent increase in regulatory burden increases the poverty rate by 2.5 percent. Therefore, it is not surprising that our empirical results indicate that the regulatory burden, as measured by the

FRASE index (see figure 1), is associated with higher income inequality in a panel of US states between 1997 and 2015.

Figure 1. FRASE Index (1997 to 2015)



Source: McLaughlin and Sherouse (2019); data are accessible via https://www.quantgov.org/download-data.

The remainder of the paper is organized as follows. First, we briefly review the literature regarding the determinants of income inequality, with an emphasis on the relationship between regulations and inequality. Second, we provide a description of the data and describe our empirical model. Next, we discuss the estimation results, including several robustness exercises, followed by the conclusion.

2. The Impact of Regulation on Income Inequality

Until the mid-20th century, most economists accepted the public interest theory of Arthur Pigou (1932). This theory holds that government regulation is required to protect the public from market failures; therefore, the government should regulate both firms and service providers to ensure that they comply with minimum standards for providing goods and services. Public interest theory was challenged by the public choice theory of regulation, first postulated by George Stigler (1971).[1] This more skeptical view of the regulatory process held that special interest groups could effectively lobby both regulators and politicians for new laws and regulatory restrictions designed to shelter incumbent firms and practitioners from competition. These regulations may protect relatively more established producers at the expense of younger, less experienced would-be market entrants, thereby reducing competition and increasing rents. A similar logic applies to special interests in labor markets. Consistent with public choice theory and highly relevant to the present research question, Shughart, Tollison, and Yan (2003) find that states with more influential special interest groups (and hence more lobbying) also have statistically significantly higher Gini coefficients. Apart from this indirect evidence that regulations increase income inequality, a relatively new but growing body of research, briefly summarized below, strongly supports the connection between regulations and inequality.

The emerging literature explores the relationship between regulation and aggregate measures of the income inequality. For instance, evidence from large panels of countries indicates that financial regulation is associated with income inequality as measured by the Gini coefficient (de Haan and Sturm 2017; Delis, Hasan, and Kazakis 2014; Manish and O'Reilly 2019). Calderón, Chong, and Valdés (2004) use cross-country data on two forms of labor market regulation: unofficial (de facto) and statutory (de jure) regulation that is enforced administratively. Interestingly, they find that only de facto labor market regulations reduce

[1] Earlier critics of regulation, including Milton Friedman (1962), argued that the distribution of income (i.e., "winners and losers") reflected the operation of market forces subject to individual choices and initial endowments. Government regulation, to the extent that it alters these market outcomes, must also impact the distribution of income.

income inequality while de jure regulations have no effect. Regulations on starting a business may also have distributional effects. Using a cross-country panel containing measures of startup regulations from the World Bank and income inequality, Chambers, McLaughlin, and Stanley (2019a) find that a one standard deviation increase in startup regulations (measured in required steps) elevates a nation's Gini coefficient by 12.9 percent. Chambers and O'Reilly (2019) revisit this relationship at the regional or subnational geographic level using similar data and find that a 1 percent increase in startup regulations (measured by startup costs) is associated with a 3 percent jump in income inequality.

Empirical evidence indicates that federal regulations in the United States as measured by the RegData index have distributive effects. Federal regulations are associated with higher consumer prices between 2000 and 2012 (Chambers, Collins, and Krause 2019). Federal regulation may also influence wages. Bailey, Thomas, and Anderson (2019) find that regulation may increase wages in high-wage occupations (which may be associated with compliance), whereas the costs of regulation are disproportionately shouldered by low-wage workers. Alternatively, wage inequality within occupations tends to be greater in more regulated industries. Mulholland (2019) finds that between 2002 and 2014, regulations explain more than 40 percent of the increase in within-occupation wage inequality (as measured by the ratio of average wages at the 90th and 10th percentiles of the wage distribution). These studies, along with the finding of Chambers, McLaughlin, and Stanley (2019b) that federal regulations are associated with higher state-level poverty rates, suggest that federal regulations influence the income distribution in US states.

3. Identification Strategy and Data

In the sections that follow, we describe our identification strategy for modeling the impact of regulations on state income inequality. Additionally, we describe the data in greater detail and provide some basic exploratory analysis.

3.1. Identification Strategy

The development economics literature contains many studies that estimate the determinants of income inequality. Beginning with the seminal work of Kuznets (1955), income inequality (typically the Gini coefficient) is regressed on the log of income per capita (y) and the square (y^2). This modeling assumption reflects the empirical observation (Kuznets 1955) that higher per capita income initially increases income inequality during the early stages of economic development, but after a critical level of development is achieved, higher income is associated with declining inequality. Subsequent research by Ahluwalia (1976), Robinson (1976), and others provided strong support for the hypothesis, although the bulk of this evidence rested on the use of cross-section regression techniques. With the publication of the Deininger and Squire (1996) panel dataset, new income inequality models were developed, most notably that of Barro (2000). Using country-level panel data, Barro (2000) regresses the Gini coefficient on country fixed effects, log gross domestic product (GDP), and its square to capture the Kuznets curve, various measures of human capital, trade openness, and a series of dummy variables that correct for heterogeneity in the measurement and construction of the underlying Gini coefficients.[2] It is worth noting that Barro (2000) uses static measures of governance quality (i.e., rule of law and a democracy index) in his seemingly unrelated regression (SUR) models, but he could not include said measures in his fixed-effect panel model as they did not vary over time. This parsimonious regression model has become a popular baseline specification for most subsequent empirical research into the determinants of income inequality. Consequently, we follow Chambers, McLaughlin, and Stanley (2019a) and Chambers and O'Reilly (2019) by using Barro (2000) as a baseline specification for estimating the impact of regulations on income inequality within a panel model.

We model the inverted U-shaped relationship between inequality and per capita income using quadratic measures of development (i.e., the natural log of real per capita state GDP and its square). Human capital, which is likely to vary across states and over time, is captured by higher education completion rates. In the context of US states, trade policy is set by the federal government and states are forbidden to erect trade barriers in restraint of interstate commerce. Likewise, rule of law and other institutional differences, which vary between nations, are unlikely to vary between US states. Therefore, our model's period effects capture any changes in federal policy (which are common to all states) while fixed state effects capture any static, idiosyncratic differences between the states (e.g., differences in the state legal code, social welfare programs, and so on). However, we are able to capture changes in state economic policy by including policy indices pertaining to taxation, government spending, and labor market policy (see section 3.4 for more details). Finally, our primary variable of interest, regulation, is

[2] Deininger and Squire (1996) collected Gini coefficient measures from different sources using different methodologies and units of measure. Therefore, Barro (2000) includes dummies for whether the Gini is derived from data on net income or spending and individual or household units of measure. These issues do not pertain to our Gini data from Frank (2009) as all data are derived from Internal Revenue Service tax filings, so methodology is consistent.

measured by way of the FRASE index, which measures the burden of federal regulations that pertain to a given state in a given year (see section 3.3 for more details).

3.2. Measures of Income Inequality

Frank (2009) constructs measures of inequality for US states derived from Internal Revenue Service (IRS) filings. These data offer high-quality annual estimates of the Gini coefficient for 50 US states and are updated yearly (Frank 2014). The Gini coefficient, our measure of income inequality, provides estimates of income inequality across the full income distribution. The Gini coefficient is bounded from 0 to 1, where 0 is perfect equality and 1 is perfect inequality.[3] Gini coefficients are bounded by construction, making the presence of a unit root unlikely. However, it is possible that the Gini coefficient may trend for limited periods of time (as seen in figure 2 between 2003 and 2007). To ensure that our inequality panel does not exhibit nonstationary behavior, we conduct a Levin, Lin, and Chu (2002) panel unit root test that rejects the null hypothesis of a common unit root process.[4]

[3] Frank (2009) notes that negative income values from IRS data are truncated at zero.
[4] The Levin, Lin, and Chu (2002) test statistic equals –2.145 and is asymptotically *t*-distributed with a corresponding *p*-value of 0.016.

Figure 2. Gini Coefficient (1997 to 2015)

Source: Mark W. Frank, "U.S. State-Level Income Inequality Data," accessed April 16, 2020, https://www.shsu.edu/eco-mwf/inequality.html.

3.3. Measuring Federal Regulation—The FRASE Index

To measure the extent of federal regulation that corresponds to each state, we use the FRASE index, which combines federal regulatory data from RegData and state-specific economic data from the Bureau of Economic Analysis (BEA). To calculate the FRASE index score for each state, McLaughlin and Sherouse (2019) begin with the number of regulatory restrictions pertaining to each industry, as estimated in the RegData 2.2 dataset.[5] These industry-specific regulatory restriction measures are then weighted by each industry's relative importance to a particular state's private-sector economy. These weighted measures of industry regulation are separately summed for each state-year and then normalized by the weighted sum of industry regulation for the overall US economy in 1997. The FRASE index is scaled such that a value less than 1 indicates that a state faces fewer federal regulatory restrictions than the national

[5] The RegData dataset is constructed by counting the number of regulatory restrictions in the *Code of Federal Regulations*. Regulatory restrictions are quantified by the number of times certain phrases associated with regulatory compliance or prohibition occur in the *Code of Federal Regulations*. Regulations are assigned to industries using a machine-learning algorithm. See McLaughlin and Sherouse (2019) for more detail on the construction of the RegData dataset.

average in 1997, whereas a value greater than 1 indicates that a state faces more restrictions than the national average in 1997.

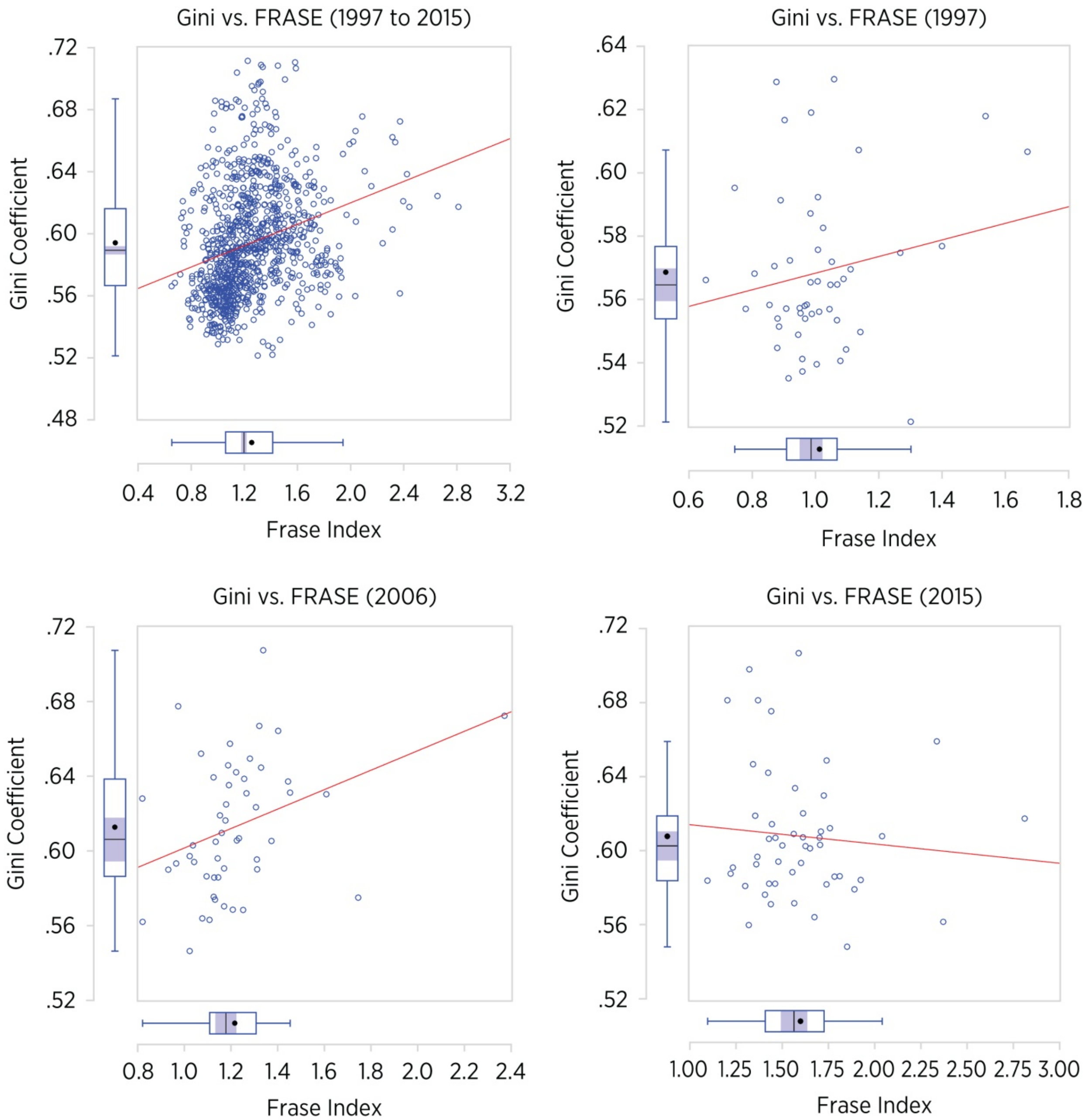
By construction, variation in the FRASE index arises from two sources: (1) differences over time in the number of federal regulations applicable to each industry in a state's economy and (2) year-to-year changes in the relative distribution of industries in each state (as measured by each industry's contribution to gross state product). Neither state nor period fixed effects capture the evolution of state economies and the ever-changing levels of industry-specific federal regulation.

Finally, we treat the FRASE index as exogenous since it is unlikely that an omitted variable is related to both income inequality and industry composition and would vary with said variables in a predictable, systematic way. A state may lose output share in an industry with high or low levels of regulation but by construction will gain output share in other industries that may be heavily or lightly regulated. Likewise, changes in output shares can be driven by the decline of specific industries or the rapid growth of others, and the corresponding wages in declining industries may be relatively high or low, whereas the wages in rapidly growing industries may be relatively high or low compared to the state average. Therefore, the net effect of changes in industrial composition is unpredictable. Moreover, for these changes to be in any way endogenous, said evolutionary changes in industry concentration must also have a predictable impact on income inequality, which lacks obvious theoretical justification.

Figure 1 plots the average FRASE index from 1997 to 2015, and figure 2 plots the average Gini coefficient over the same period. Regulatory restrictions follow an increasing trend with almost no interruption, whereas inequality follows an increasing trend interrupted by decreased inequality in the early 2000–2010 period and the late 2000–2010 period. The scatterplots in figure 3 show a positive association between regulations and inequality in the pooled sample and in cross-sectional samples from 1997 and 2006, though the correlation weakens and turns negative in 2015. Figure 4 plots the annual cross-sectional correlation between the Gini coefficient and the FRASE index; over most of the period, the two series exhibit a positive correlation.

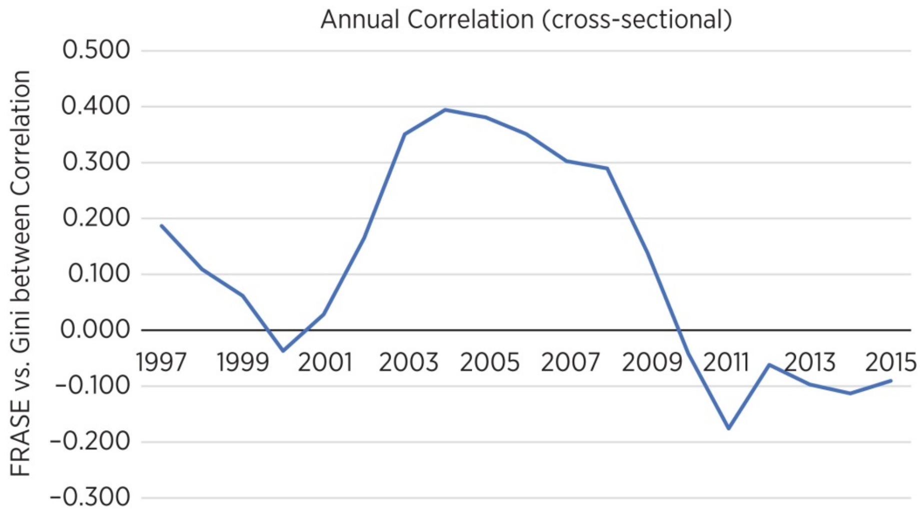
The presence of a trend in both series raises the possibility of spurious correlations and how best to model the temporal component of these series. In a cross-country context, de Haan and Sturm (2017) estimate the relationship between financial regulation and income inequality but choose not to include period-specific effects, though Manish and O'Reilly (2019) argue that the inclusion of period effects changes the interpretation of their results. Therefore, in most specifications we included year-specific effects to account for trends in the series and to assuage concerns of shocks common to all states such as business cycles. As an additional robustness check, regressions are run on series in first differences.

Figure 3. Scatterplots of FRASE Index vs. Gini Coefficient



Source: Authors' calculations.

Figure 4. Correlation between FRASE Index and Gini Coefficient in Each Annual Cross-Section



Source: Authors' calculations.

3.4. Remaining Control Variables

We follow the literature on income inequality in selecting control variables. To account for the well-documented Kuznets curve, the inverted U relationship between income per capita and inequality, we control for the log of income per capita and the square of the log of income per capita from the Bureau of Labor Statistics. Skill-biased technological change may also contribute to inequality (Mulholland 2019). Following Apergis, Dincer, and Payne (2011), among others, we account for human capital by controlling for educational attainment—specifically the percentage of the state population that are high school graduates (Frank 2009).[6]

Finally, to account for the possibility that time-varying changes in state economic policy influence income inequality, we control for a set of variables included in the Economic Freedom of North America (EFNA) dataset (Stansel, Torra, and McMahon 2018). The EFNA dataset

[6] The series is updated yearly; for the updated series, see M. W. Frank, "U.S. State-Level Income Inequality Data," accessed April 16, 2020, https://www.shsu.edu/eco_mwf/inequality.html.

includes three component variables, each measuring an aspect of state economic policy: tax policy, spending policy, and labor market policy. Each component is constructed from equally weighted subcomponents and is coded on a scale of 0 to 10,[7] with 10 indicating the least state involvement in the economy. The government spending component consists of government consumption, transfers and subsidies, and insurance and retirement payments, each measured as a percentage of state income. The tax policy component consists of four subcomponents, including a measure of top marginal tax rates as well as three measures expressed as a proportion of state income: income and payroll tax revenue, property and other tax revenue, and sales tax revenue. Finally, the labor market policy component includes a measure of the minimum wage as a percentage of per capita income, government employment as a percentage of total state employment, and union membership as a percentage of state employment. We estimate specifications that control for each aspect of state economic policy individually, as well as specifications that include only the composite index of state economic policy from EFNA.[8]

The FRASE regulation measure is available from 1997 to 2015 and is the constraint on our sample. Therefore, all analysis is conducted on a balanced panel of states from 1997 to 2015. Table 1 presents descriptive statistics for each variable for the full sample period, while table 2 provides mean values for each variable by state.

[7] Each subcomponent is standardized on a scale of 0 to 10. Stansel, Torra, and McMahon (2018) offer a detailed description of how each component is constructed.
[8] The full composite EFNA index is an equally weighted index of the three component indices.

Table 1. Variable Descriptions

Variable	Description	Mean	Standard Deviation	Minimum	Maximum
Gini Coefficient	Gini coefficient (bounded between 0 and 1)	0.59	0.036	0.52	0.71
FRASE Index	Index of federal regulations corresponding to each state	1.26	0.288	0.65	2.81
Education	High school completion rate	0.64	0.039	0.53	0.75
Log Income	Log of real gross state product per capita	10.95	0.174	10.48	11.46
EFNA Overall	Index of state economic freedom	5.96	0.947	3.53	8.07
EFNA1 Spending	Index of state government spending	6.52	1.728	0.00	9.69
EFNA2 Taxation	Index of state taxation	5.72	0.898	2.86	8.14
EFNA3 Labor Markets	Index of labor market regulation	5.65	1.004	2.88	8.72

Note: The overall EFNA index is an equally weighted average of the three components: spending, taxation, and labor market regulation. See Stansel, Torra, and McMahon (2018) for a detailed description of how the index is constructed.

Table 2. Mean Data Values by State

	Mean Value by State							
State	Gini Coefficient	FRASE Index	Education	Log Income	EFNA Overall	EFNA1 Spending	ENFA2 Taxation	EFNA3 Labor Markets
Alabama	0.59	1.35	0.61	10.75	6.04	5.92	7.02	5.19
Alaska	0.57	1.84	0.63	11.18	4.06	0.87	7.12	4.18
Arizona	0.59	1.06	0.60	10.84	6.62	7.76	6.12	5.99
Arkansas	0.60	1.36	0.60	10.71	6.04	6.88	5.66	5.59
California	0.64	1.18	0.60	11.09	4.66	4.47	4.50	5.01
Colorado	0.59	1.16	0.65	11.12	6.93	7.95	6.05	6.80
Connecticut	0.65	1.18	0.66	11.34	6.42	7.77	5.30	6.21
Delaware	0.56	1.12	0.64	11.02	6.07	6.64	5.55	6.01
Florida	0.66	1.06	0.65	10.90	7.28	8.43	6.69	6.72
Georgia	0.61	1.34	0.60	10.92	6.72	7.64	5.91	6.61
Hawaii	0.56	1.17	0.66	11.02	5.13	6.31	4.46	4.63
Idaho	0.61	1.29	0.61	10.88	6.06	7.22	5.32	5.63
Illinois	0.61	1.21	0.64	11.06	5.90	6.78	5.50	5.40
Indiana	0.57	1.42	0.63	10.88	6.48	7.86	6.04	5.53
Iowa	0.55	1.25	0.66	10.95	5.90	6.77	5.61	5.33
Kansas	0.58	1.32	0.64	11.01	6.56	8.26	5.48	5.95
Kentucky	0.58	1.44	0.61	10.73	5.46	5.36	5.81	5.20

(continued on next page)

	Mean Value by State							
State	Gini Coefficient	FRASE Index	Education	Log Income	EFNA Overall	EFNA1 Spending	ENFA2 Taxation	EFNA3 Labor Markets
Louisiana	0.62	2.10	0.59	10.82	5.85	5.57	6.38	5.60
Maine	0.56	1.16	0.69	10.79	4.96	5.68	3.97	5.23
Maryland	0.56	1.07	0.65	11.20	6.81	7.20	5.98	7.24
Massachusetts	0.61	1.06	0.67	11.18	6.47	7.40	5.67	6.33
Michigan	0.59	1.17	0.65	10.86	5.41	6.06	5.68	4.49
Minnesota	0.57	1.19	0.67	11.09	5.34	5.63	4.69	5.68
Mississippi	0.61	1.32	0.58	10.64	5.44	5.97	5.73	4.63
Missouri	0.59	1.19	0.64	10.88	6.58	7.53	6.50	5.72
Montana	0.62	1.50	0.68	10.78	5.58	6.19	5.74	4.82
Nebraska	0.59	1.43	0.65	11.03	6.72	8.72	5.26	6.19
Nevada	0.64	0.90	0.62	11.00	6.73	8.30	6.25	5.65
New Hampshire	0.57	0.86	0.68	11.11	7.69	9.11	7.04	6.91
New Jersey	0.61	1.20	0.65	11.23	5.75	6.84	4.61	5.80
New Mexico	0.60	1.16	0.60	10.73	4.93	4.39	5.85	4.55
New York	0.66	1.25	0.64	11.09	4.03	4.19	3.39	4.51
North Carolina	0.58	1.24	0.60	10.88	6.43	7.00	5.81	6.49
North Dakota	0.58	1.24	0.66	10.99	6.48	6.99	6.13	6.33
Ohio	0.56	1.19	0.65	10.87	4.84	4.19	5.22	5.11
Oklahoma	0.60	1.20	0.62	10.89	6.61	7.66	6.38	5.81
Oregon	0.58	0.98	0.66	10.87	4.77	4.76	5.56	3.99
Pennsylvania	0.59	1.30	0.66	10.95	6.03	6.20	5.89	6.01
Rhode Island	0.58	0.95	0.63	10.93	4.87	4.79	4.42	5.39
South Carolina	0.59	1.31	0.61	10.75	5.57	5.18	5.75	5.80
South Dakota	0.61	1.29	0.64	10.98	7.58	8.86	7.25	6.64
Tennessee	0.60	1.24	0.61	10.84	7.10	7.50	7.40	6.41
Texas	0.63	1.38	0.56	11.02	7.19	8.25	6.68	6.65
Utah	0.58	1.24	0.60	10.99	5.93	5.97	5.80	6.01
Vermont	0.58	1.06	0.69	10.89	5.13	5.74	4.31	5.34
Virginia	0.57	1.15	0.64	11.15	7.36	8.03	6.29	7.74
Washington	0.58	1.28	0.66	11.07	5.36	5.74	6.18	4.17
West Virginia	0.56	1.52	0.63	10.56	4.82	5.30	5.11	4.05
Wisconsin	0.56	1.14	0.66	10.95	5.40	6.04	4.79	5.37
Wyoming	0.64	1.77	0.66	11.14	6.03	5.96	6.18	5.96

4. Empirical Model and Results

In the sections below, we describe several variants of the baseline panel model central to our analysis, which is followed by a discussion of the estimation results.

4.1. Panel Model

To test whether federal regulations influence state-level income inequality, we estimate the following panel fixed-effects model:

$$ineq_{it} = \beta_1 frase_{it} + \beta_2 edu_{it} + \beta_3 y_{it} + \beta_4 y_{it}^2 + \beta_5 efna_{it} + \tau_t + \mu_i + \varepsilon_{it}, \qquad (1)$$

where $ineq_{it}$ is a measure of income inequality in state i at time t, $frase_{it}$ is the natural log of the FRASE index (our measure of federal regulations at the state level), and edu_{it} is our control for human capital in each state. The log of real income per capita (y_{it}) and its square (y_{it}^2) are included to account for the U-shaped Kuznets curve. Some specifications also include controls for various measures of state economic policy from the EFNA index, $efna_{it}$. Time-invariant state characteristics are accounted for by state fixed effects, μ_i, and most specifications also include annual period effects, τ_t, to account for time-specific common shocks such as business cycles or exogenous trends in inequality.

Although we have controlled for the common influence of national business cycle on US states using period fixed effects, it is likely that exogenous shocks may influence multiple states simultaneously, especially neighboring states and states within the same region. Because of this, state panels exhibit cross-sectional dependence (i.e., contemporaneous shocks to different states are likely correlated). While common exogenous shocks do not generate bias in coefficient estimates, they do impact standard errors and inferential test statistics. Following common practice, we compensate by using White robust cross-sectional standard errors (i.e., standard errors clustered by time period) in assessing the statistical significance of coefficient estimates.

4.2. Estimation Results with Full Sample

Table 3 shows the estimation results for nine variants of equation (1). While each variant includes $frase_{it}$ as well as state and period fixed effects, each column adds an additional control variable to assess the sensitivity of our coefficient of interest (β_1). For each model, we employ the natural log of the Gini coefficient as our preferred measure of inequality for two reasons. First, the Gini coefficient is the most common measure of income inequality in the literature, making our results more comparable with previous studies. Second, by using a natural log transformation, the coefficient on the log of the FRASE index (β_1) has an elasticity interpretation—that is, the percentage change in Gini coefficient for each 1 percent increase in federal regulations applicable to a state.

In column 1 of table 3, we regress the log of the Gini coefficient on the log of the FRASE index as well as state and period fixed effects. The coefficient on log FRASE (0.0549) is statistically significant at the 1 percent level, implying that a 1 percent increase in federal regulations binding at the state level increases income inequality by 0.0549 percent. While the magnitude of this effect is small, it still implies that a 10 percent increase in binding regulations increases income inequality by nearly 0.55 percent. Considering that over the sample period (1997 to 2015), the average FRASE index value increased by 58 percent, our elasticity estimate implies a corresponding increase in the Gini coefficient equaling 3.18 percent. Adding the human capital covariate in column 2 of table 3 has virtually no effect on the elasticity coefficient (0.0547), and the statistical significance remains at the 1 percent level. Columns 3 and 4 add log income and its square to account for the Kuznets curve. In both columns, the estimated regulation-inequality elasticity coefficients decline slightly (0.0387 and 0.0368, respectively), but both remain statistically significant. In table 3, columns 5 to 9 incorporate various combinations of indices from the EFNA dataset. These indices capture state-level economic policies that impact economic freedom and conceivably income inequality. In columns 6 and 7, in which measures of economic freedom related to taxation and labor markets are included, the estimated regulation-inequality elasticity coefficients are both statistically significant and similar in magnitude to the previously reported results (equaling 0.0352 and 0.0429, respectively). In each model that includes the EFNA measure of state spending, whether explicitly (columns 5 and 8) or implicitly (column 9), the resulting regulation-inequality elasticity coefficients range in value from 0.0287 to 0.0367 but are, in every case, statistically insignificant.

Although the baseline estimation results over the full sample yield very consistent estimates of the regulation-inequality elasticity coefficient (ranging from 0.0287 to 0.0549) that are statistically significant in two-thirds of the model specifications, there is strong reason to believe that outlier states may be biasing the estimation results.

Table 3. Baseline Model (Log Gini Coefficient)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log FRASE	0.0549***	0.0547***	0.0387*	0.0368*	0.0287	0.0352*	0.0429**	0.0307	0.0367
	(0.0181)	(0.0181)	(0.0207)	(0.0212)	(0.0222)	(0.0202)	(0.0189)	(0.0191)	(0.0223)
Education		0.0339	–0.0349	–0.0097	0.0096	–0.0107	–0.0054	0.0153	–0.0095
		(0.0889)	(0.0903)	(0.0779)	(0.0747)	(0.0788)	(0.0696)	(0.0645)	(0.0807)
Log Income			–0.0843***	7.1085	7.4359	7.1114	6.3052	6.7143	7.1131
			(0.0203)	(4.7639)	(4.6873)	(4.7389)	(4.4531)	(4.306)	(4.7769)
(Log Income) Squared				–0.3276	–0.3413	–0.3279	–0.2945	–0.3118	–0.3278
				(0.2175)	(0.214)	(0.2163)	(0.2034)	(0.1967)	(0.2181)
EFNA1 Spending					–0.0072***	—	—	–0.0084***	—
					(0.0015)			(0.0013)	
EFNA2 Taxation						0.0040	—	0.0069	—
						(0.0056)		(0.0050)	
EFNA3 Labor Markets							0.0225***	0.0219***	—
							(0.0062)	(0.0057)	
EFNA Overall									–0.0002
									(0.0054)
Observations	950	950	950	950	950	950	950	950	950
Goodness of Fit	0.781	0.781	0.785	0.797	0.801	0.798	0.808	0.813	0.797

Notes: Dependent variable is the natural log of the Gini coefficient. State and period fixed effects are included but not reported. Standard errors are clustered by period. ***, **, and * denote 1 percent, 5 percent, and 10 percent statistical significance, respectively.

4.3. Estimation Results with Outlier States Removed

In development studies, it is common practice to remove countries with atypical economies from data panels (e.g., tax havens, nations earning most of their national income from the sale of oil or other commodities). For example, in a study of the impact of regulations on entrepreneurship in a panel of low-, middle-, and high-income countries, Chambers and Munemo (2019) exclude eight countries known to be offshore financial centers (i.e., Belize, Cyprus, the Isle of Man, Liechtenstein, Malaysia, Panama, Samoa, and Vanuatu). In the United States, a number of states and regions earn a bulk of their income from natural resources (e.g., Alaska, the Gulf Coast) or from financial services or special tax or corporate treatment (e.g., Delaware, northeastern United States).

To determine which states (if any) are acting as outliers and unduly influencing or biasing our results, we reestimate the simplest version of equation (1),[9] each time removing the observations from a single state and using the remaining 49 states' data to reestimate the regulation-inequality elasticity coefficient. Repeating this process 50 times (once for each excluded state) yields table 4, in which the results are sorted in descending order by the resulting regulation-inequality elasticity coefficient *p*-value. Two states immediately stand out: Connecticut (CT) and Alaska (AK)—the top and bottom excluded states in our rank ordering. If one excludes any state other than Connecticut or Alaska (i.e., the middle 48 results reported in table 4), the regulation-inequality elasticity coefficient lies in a very narrow range, 0.0404 to 0.0654, and is always statistically significant, with the coefficient *p*-value ranging from 0.0026 to 0.0464. However, if Connecticut is excluded, the regulation-inequality elasticity coefficient nearly doubles in magnitude (to 0.0905), and the *p*-value is reduced by an order of magnitude (to 0.0002). Likewise, when Alaska is excluded, the regulation-inequality elasticity

[9] See table 3, column 1.

coefficient is nearly halved (to 0.0262) and the *p*-value increases by a factor of 4 (to 0.2011). Clearly, both Connecticut and Alaska behave like classic outliers, strongly influencing both the magnitude of the estimated model coefficients and their corresponding statistical significance.

Table 4. Reestimation of Baseline Model while Individually Excluding a Single State

	Regulation-Inequality Elasticity Coefficient (β1)			
Excluded State	**Coefficient Estimate**	**Robust SE**	***T*-Statistic**	***P*-Value**
CT	0.0905	0.0192	4.7243	0.0002
MS	0.0537	0.0153	3.4966	0.0026
AL	0.0587	0.0169	3.4674	0.0027
NE	0.0654	0.0194	3.3708	0.0034
WA	0.0598	0.0179	3.3419	0.0036
CA	0.0588	0.0177	3.3234	0.0038
NJ	0.0559	0.0169	3.2995	0.0040
SD	0.0602	0.0184	3.2753	0.0042
MT	0.0577	0.0180	3.2084	0.0049
MA	0.0565	0.0181	3.1209	0.0059
NM	0.0584	0.0187	3.1194	0.0059
ID	0.0588	0.0189	3.1061	0.0061
FL	0.0605	0.0195	3.0996	0.0062
OK	0.0559	0.0182	3.0673	0.0066
IA	0.0569	0.0186	3.0558	0.0068
ND	0.0574	0.0188	3.0531	0.0068
OH	0.0560	0.0184	3.0509	0.0069
NH	0.0557	0.0185	3.0176	0.0074
WI	0.0558	0.0185	3.0122	0.0075
TX	0.0559	0.0187	2.9931	0.0078
VA	0.0522	0.0175	2.9739	0.0081
MO	0.0548	0.0185	2.9615	0.0084
TN	0.0544	0.0184	2.9572	0.0084
MN	0.0549	0.0186	2.9553	0.0085
SC	0.0555	0.0188	2.9531	0.0085
PA	0.0548	0.0186	2.9522	0.0085

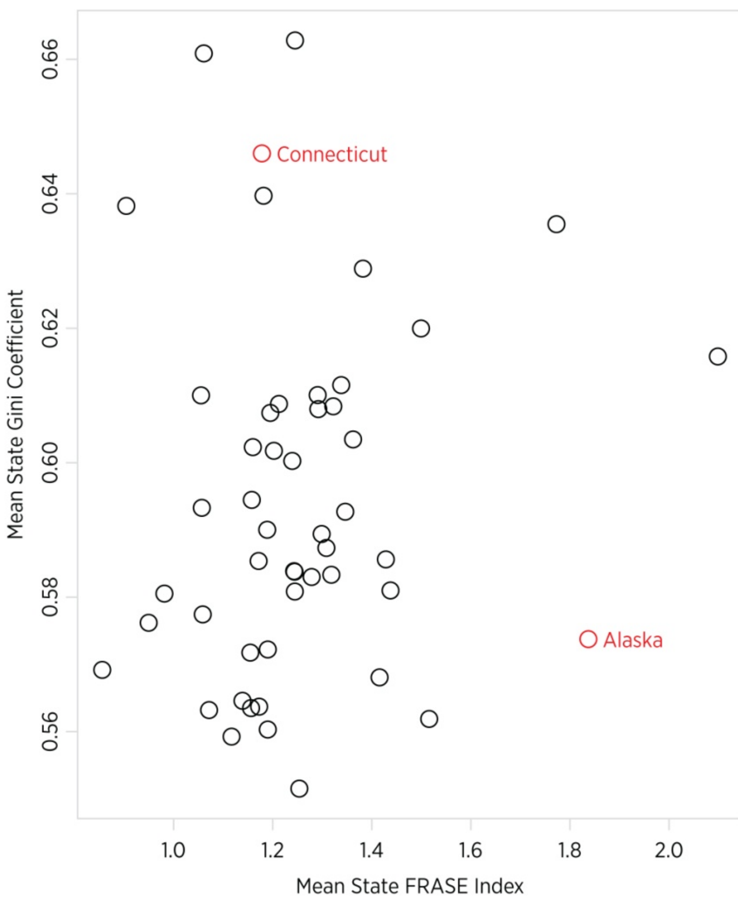
(continued on next page)

	Regulation-Inequality Elasticity Coefficient (β1)			
Excluded State	**Coefficient Estimate**	**Robust SE**	***T*-Statistic**	***P*-Value**
NC	0.0538	0.0183	2.9343	0.0089
CO	0.0532	0.0182	2.9232	0.0091
MI	0.0537	0.0184	2.9231	0.0091
GA	0.0538	0.0184	2.9191	0.0092
RI	0.0541	0.0186	2.9059	0.0094
KS	0.0542	0.0187	2.8920	0.0097
NY	0.0545	0.0189	2.8780	0.0100
IN	0.0567	0.0197	2.8765	0.0100
UT	0.0544	0.0189	2.8760	0.0101
DE	0.0514	0.0180	2.8613	0.0104
AZ	0.0534	0.0187	2.8459	0.0107
VT	0.0537	0.0189	2.8402	0.0109
OR	0.0541	0.0190	2.8396	0.0109
KY	0.0529	0.0187	2.8214	0.0113
AR	0.0525	0.0188	2.7954	0.0120
IL	0.0536	0.0192	2.7898	0.0121
MD	0.0511	0.0183	2.7854	0.0122
HI	0.0521	0.0187	2.7838	0.0123
WV	0.0563	0.0212	2.6505	0.0163
ME	0.0498	0.0199	2.5023	0.0222
WY	0.0475	0.0192	2.4802	0.0232
LA	0.0404	0.0184	2.1913	0.0418
NV	0.0436	0.0204	2.1384	0.0464
AK	0.0262	0.0197	1.3269	0.2011
Median	0.0547	0.0186	2.9526	0.0085

Notes: The dependent variable (natural log of the Gini coefficient) is regressed onto the log of the FRASE index and state and period fixed effects. Standard errors (SE) are clustered by period.

Figure 5 plots the average FRASE index against the corresponding average Gini coefficient for each state and labels both Alaska and Connecticut. The figure reveals that Alaska is one of the most heavily regulated states (FRASE equals 1.84) but has a relatively low level of income inequality (Gini equals 0.57). The large FRASE index reflects the extensive regulation associated with commodity extraction (especially oil and natural gas), while the low level of income inequality may reflect both high wages and state transfer payments (dividends) vis-à-vis the Alaska Permanent Fund.[10] Connecticut, on the other hand, is a very lightly regulated state (FRASE equals 1.18), reflecting light industrialization and very little commodity extraction, while the relatively high level of income inequality (Gini equals 0.65) may reflect that the southern region of the state is a bedroom community for high-income residents who commute to New York City.

Figure 5. Mean State FRASE Index vs. Gini Coefficient (1997 to 2015)



Sources: Authors' calculations.

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[10] Between 1997 and 2015, dividend payments per resident averaged $1,429. For more details, see Alaska Department of Revenue (2020).

To verify that both Alaska and Connecticut are outliers and that their absence yields a dataset that does not contain any additional outliers, we remove both Alaska and Connecticut (yielding a panel containing 48 states) and repeat the above exercise—that is, we reestimate the simplest version of equation (1), each time removing the observations from a single state and using the remaining 47 states' data to reestimate the regulation-inequality elasticity coefficient. Repeating this process 47 times (once for each excluded state) yields table 5, in which the results are sorted in descending order by the resulting regulation-inequality elasticity coefficient *p*-value. Unlike in table 4, none of the remaining 47 states have much individual influence on the estimation results. Specifically, the regulation-inequality elasticity coefficient ranges in value between 0.0473 and 0.0769 (median equals 0.0635) with *p*-values ranging from 0.0011 to 0.0384 (median equals 0.0079). Clearly, the magnitude and statistical significance of the regulation-inequality elasticity coefficient is robust to the inclusion or exclusion of any of the remaining 48 states.

Table 5. Reestimation of Baseline Model while Excluding Identified Outliers and Each State

	Regulation-Inequality Elasticity Coefficient (β1)			
Excluded States	**Coefficient Estimate**	**Robust SE**	***T*-Statistic**	***P*-Value**
AK & CT & MS	0.0619	0.0160	3.8750	0.0011
AK & CT & AL	0.0684	0.0194	3.5261	0.0024
AK & CT & NE	0.0769	0.0224	3.4386	0.0029
AK & CT & WA	0.0701	0.0204	3.4294	0.0030
AK & CT & NJ	0.0655	0.0193	3.3843	0.0033
AK & CT & CA	0.0692	0.0208	3.3230	0.0038
AK & CT & SD	0.0702	0.0213	3.2879	0.0041
AK & CT & MT	0.0664	0.0207	3.2049	0.0049
AK & CT & FL	0.0706	0.0222	3.1815	0.0052
AK & CT & MA	0.0662	0.0212	3.1190	0.0059
AK & CT & NH	0.0650	0.0209	3.1119	0.0060

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	Regulation-Inequality Elasticity Coefficient (β1)			
Excluded States	**Coefficient Estimate**	**Robust SE**	***T*-Statistic**	***P*-Value**
AK & CT & ID	0.0682	0.0220	3.1025	0.0061
AK & CT & IA	0.0662	0.0213	3.1015	0.0062
AK & CT & ND	0.0676	0.0219	3.0911	0.0063
AK & CT & OH	0.0651	0.0212	3.0720	0.0066
AK & CT & WI	0.0651	0.0213	3.0587	0.0068
AK & CT & VA	0.0606	0.0198	3.0529	0.0068
AK & CT & TX	0.0648	0.0213	3.0462	0.0070
AK & CT & OK	0.0646	0.0213	3.0297	0.0072
AK & CT & MN	0.0640	0.0212	3.0158	0.0074
AK & CT & TN	0.0630	0.0209	3.0077	0.0076
AK & CT & CO	0.0618	0.0206	3.0024	0.0076
AK & CT & MO	0.0635	0.0212	3.0008	0.0077
AK & CT & IN	0.0669	0.0224	2.9900	0.0079
AK & CT & SC	0.0640	0.0215	2.9804	0.0080
AK & CT & MI	0.0628	0.0211	2.9757	0.0081
AK & CT & PA	0.0635	0.0213	2.9748	0.0081
AK & CT & NM	0.0672	0.0226	2.9659	0.0083
AK & CT & NY	0.0637	0.0215	2.9656	0.0083
AK & CT & NC	0.0625	0.0212	2.9541	0.0085
AK & CT & GA	0.0626	0.0212	2.9532	0.0085
AK & CT & UT	0.0631	0.0214	2.9528	0.0085
AK & CT & RI	0.0628	0.0213	2.9504	0.0086
AK & CT & KS	0.0634	0.0218	2.9128	0.0093
AK & CT & AZ	0.0624	0.0216	2.8924	0.0097
AK & CT & MD	0.0594	0.0206	2.8845	0.0099
AK & CT & KY	0.0608	0.0212	2.8751	0.0101
AK & CT & VT	0.0621	0.0216	2.8706	0.0102
AK & CT & IL	0.0624	0.0218	2.8596	0.0104
AK & CT & AR	0.0605	0.0212	2.8578	0.0105
AK & CT & OR	0.0627	0.0221	2.8394	0.0109
AK & CT & DE	0.0594	0.0211	2.8198	0.0113
AK & CT & HI	0.0598	0.0214	2.7982	0.0119
AK & CT & WY	0.0546	0.0210	2.6027	0.0180

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	Regulation-Inequality Elasticity Coefficient (β1)			
Excluded States	**Coefficient Estimate**	**Robust SE**	***T*-Statistic**	***P*-Value**
AK & CT & WV	0.0644	0.0254	2.5320	0.0209
AK & CT & ME	0.0571	0.0227	2.5185	0.0215
AK & CT & LA	0.0473	0.0196	2.4160	0.0265
AK & CT & NV	0.0510	0.0228	2.2346	0.0384
Median	0.0635	0.0213	2.9852	0.0079

Notes: The dependent variable (natural log of the Gini coefficient) is regressed onto the log of the FRASE index and state and period fixed effects. Standard errors (SE) are clustered by period.

4.4. Estimation Results with Outliers Removed

Removing the two identified outliers from our panel (i.e., Alaska and Connecticut), we reestimate the baseline models from section 4.2. The results are provided in table 6.

In column 1 of table 6, we regress the log of the Gini coefficient on the log of the FRASE index as well as state and period fixed effects. The coefficient on log FRASE (0.0636) is statistically significant at the 1 percent level and implies that a 1 percent increase in federal regulations binding at the state level increases income inequality by nearly 0.064 percent. Considering that over the sample period (1997 to 2015) the average FRASE index value increased by 58 percent, our elasticity estimate implies a corresponding increase in the Gini coefficient equaling 3.69 percent. Adding the human capital covariate (column 2 in table 6) has no effect on the elasticity coefficient (0.0636), and the statistical significance remains at the 1 percent level. Columns 3 and 4 add log income and its square to account for the Kuznets curve. In both columns, the estimated regulation-inequality elasticity coefficients decline slightly (0.0469 and 0.0421, respectively), but both remain statistically significant. Following section 4.2, columns 5 to 9 in table 6 incorporate various combinations of indices from the EFNA dataset. In columns 6, 7, and 9, which include measures of economic freedom related to taxation, labor markets, and overall economic freedom, the estimated regulation-inequality elasticity coefficients are universally statistically significant and similar in magnitude to the previously reported results (ranging from 0.0402 to 0.0429). In each model that explicitly includes the EFNA measure of state spending (columns 5 and 8 in table 6), the resulting regulation-inequality elasticity coefficients are similar (ranging from 0.0361 to 0.0384) but statistically insignificant.

On balance, the results in table 6 are similar and consistent with those reported in table 3. Comparing the corresponding columns in tables 3 and 6, the statistical significance of the regulation-inequality elasticity coefficient improved in two model specifications (see columns 3 and 9) and was unchanged in the remaining seven model variants. The estimated regulation-inequality elasticity coefficients increased on average 16 percent (i.e., 0.0399 versus 0.0463) while the coefficient of variation in the elasticity estimates declined by about 6 percent (23.54 percent to 22.19 percent). Taken together, the results suggest that a 10 percent increase in federal regulations binding at the state level increases income inequality by nearly 0.5 percent. To put this magnitude in perspective, if states are ranked in ascending order by average Gini coefficient, the median difference in income inequality between states is 0.24 percent. Therefore, increasing a single state's Gini coefficient by 0.5 percent (all else equal) typically results in a two-position slide in state inequality ranking.

Table 6. Baseline Model (Log Gini Coefficient) with Outliers Removed

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log FRASE	0.0636***	0.0636***	0.0469**	0.0421*	0.0384	0.0402*	0.0428**	0.0361	0.0429*
	(0.0207)	(0.0206)	(0.0225)	(0.0246)	(0.0258)	(0.0235)	(0.0217)	(0.0222)	(0.0248)
Education		0.0046	–0.0621	–0.0390	–0.0225	–0.0415	–0.0306	–0.0131	–0.0445
		(0.0760)	(0.0725)	(0.0659)	(0.0672)	(0.0667)	(0.0583)	(0.0586)	(0.0686)
Log Income			–0.0788***	6.9480	7.2027	6.9545	6.3920	6.7387	6.8280
			(0.0201)	(4.9928)	(4.9816)	(4.9385)	(4.6585)	(4.5599)	(4.9936)
(Log Income) Squared				–0.3203	–0.3311	–0.3208	–0.2985	–0.3134	–0.3154
				(0.2281)	(0.2275)	(0.2256)	(0.2129)	(0.2083)	(0.2280)
EFNA1 Spending					–0.0047***	—	—	–0.0059***	—
					(0.0016)			(0.0013)	
EFNA2 Taxation						0.0060	—	0.0066	—
						(0.0059)		(0.0052)	
EFNA3 Labor Markets							0.0226***	0.0217***	—
							(0.0060)	(0.0055)	
EFNA Overall									0.0046
									(0.0055)
Observations	912	912	912	912	912	912	912	912	912
Goodness of Fit	0.790	0.790	0.794	0.805	0.806	0.805	0.815	0.818	0.805

Notes: The dependent variable is the natural log of the Gini coefficient. State and period fixed effects are included but not reported. Standard errors are clustered by period. ***, **, and * denote 1 percent, 5 percent, and 10 percent statistical significance, respectively. Outliers (Alaska and Connecticut) are removed from the sample.

4.5. First Difference Estimation Results with Outliers Removed

Finally, to ensure that our results are robust to any autocorrelation due to persistence in state-level income inequality, we take the first difference of equation (1):

$$\Delta ineq_{it} = \beta_1 \Delta frase_{it} + \beta_2 \Delta edu_{it} + \beta_3 \Delta y_{it} + \beta_4 \Delta y_{it}^2 + \beta_5 \Delta efna_{it} + \delta_t + u_{it}, \quad (2)$$

where $\Delta ineq_{it}$ is the year-over-year growth rate of income inequality in state *i* between periods *t* and *t−1*, $\Delta frase_{it}$ is the year-over-year growth rate of the FRASE rate, Δy_{it} is the growth rate of real per capita state output, $\Delta efna_{it}$ is the year-over-year change in the various indexes of economic freedom, and δ_t is a period fixed effects.[11] Equation (2) has various advantages: (1) Any invariant, state-specific heterogeneity is eliminated (hence the state fixed effects are no longer required); (2) any persistence in the dependent variable (and potential autocorrelation in the residuals) is reduced; (3) the slope coefficients (and particularly the regulation-inequality elasticity coefficient) retain their original interpretation; and (4) estimation in first differences should assuage any concerns about nonstationarity. The estimation results for equation (2) (with outliers removed) are provided in table 7.

[11] The act of first differencing equation (1) eliminates any invariant, state-specific heterogeneity, thus the state fixed effects (α_i) are not included.

Table 7. First Difference of Baseline Model (Log Gini Coefficient) with Outliers Removed

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Log FRASE	0.0331*	0.0329*	0.0328*	0.0326*	0.0318*	0.0312*	0.0348**	0.0322**	0.0337**
	(0.0170)	(0.0168)	(0.0170)	(0.0171)	(0.0174)	(0.0165)	(0.0163)	(0.0159)	(0.0169)
Δ Education		0.0612	0.0588	0.0601	0.0624	0.0574	0.0588	0.0597	0.0564
		(0.0550)	(0.0571)	(0.0538)	(0.0538)	(0.0530)	(0.0527)	(0.0518)	(0.0550)
Δ Log Income			–0.0099	0.4371	0.4430	0.5491	0.3474	0.4633	0.4417
			(0.0311)	(3.0502)	(3.0449)	(3.0984)	(2.9735)	(3.0097)	(3.0569)
Δ ([Log Income] Squared)				–0.0203	–0.0204	–0.0259	–0.0170	–0.0223	–0.0210
				(0.1396)	(0.1394)	(0.1418)	(0.1363)	(0.1379)	(0.1400)
Δ EFNA1 Spending					–0.0015	——	——	–0.0022	——
					(0.0021)			(0.0022)	
Δ EFNA2 Taxation						0.0064**	——	0.0058*	——
						(0.0031)		(0.0031)	
Δ EFNA3 Labor Markets							0.0081***	0.0077***	——
							(0.0028)	(0.0030)	
Δ EFNA Overall									0.0053
									(0.0034)
Observations	864	864	864	864	864	864	864	864	864
Goodness of Fit	0.452	0.454	0.454	0.454	0.455	0.457	0.461	0.464	0.456

Notes: The dependent variable is the first difference of the natural log of the Gini coefficient. Period fixed effects and common intercept are included but not reported. Standard errors are clustered by period. ***, **, and * denote 1 percent, 5 percent, and 10 percent statistical significance, respectively. Outliers (Alaska and Connecticut) are removed from the sample.

Two characteristics of the results stand out (see table 7). First, the estimated regulation-inequality elasticity coefficients are nearly identical in every column (ranging in value from 0.0312 to 0.0348), implying that a 10 percent increase in binding federal regulations at the state level increases income inequality by between 0.312 percent and 0.348 percent. Second, the estimated regulation-inequality elasticity coefficients are statistically significant in *every* variant of equation (2).

These results, when taken in context with the other findings of this paper, confirm that there is a very robust association between the binding federal regulations at the state level (as measured by the FRASE index) and state income inequality (as measured by the Gini coefficient). Controlling for human capital accumulation, economic development (vis-à-vis the Kuznets curve), economic policy, state invariant heterogeneity, exogenous period effects, persistence in income inequality, and cross-sectional dependence, the estimated regulation-inequality elasticity coefficient values are very similar in magnitude (the median values from table 3, table 6, and table 7 cluster tightly, ranging from 0.0328 to 0.0428) and generally statistically significant (81 percent of the reported regulation-inequality elasticity coefficient values are statistically significant at the 10 percent level or better).

5. Conclusion

Regulations may influence the distribution of income by increasing the cost of production, protecting incumbent firms, and contributing to wage inequality. Recent evidence from studies using the RegData measure of federal regulations suggests that federal regulations in the United States have regressive effects by increasing consumer prices and exacerbating wage inequality. We contribute to the literature on the regressive effects of regulation by testing if states exposed to more federal regulation by industrial composition tend to have higher income inequality.

The FRASE index quantifies the extent to which each state is exposed to federal regulations as measured by the RegData database of federal regulations. Building on Chambers, McLaughlin, and Stanley (2019b), who find that regulations measured by the FRASE index are associated with higher state-level poverty rates, we test whether the regulations measured by the same index are associated with income inequality. The results indicate that a 10 percent increase in regulation corresponds to a 0.5 percent increase in income inequality. The positive relationship is robust to controlling for several control variables, as well as period fixed effects and estimation in first differences to assuage concerns of a spurious correlation.

As expected, our study of the state-level income distribution finds a more modest and noisier estimate of the effect relative to industry- or occupational-level studies because the distribution of income at the state level is influenced by a wider set of unobservable factors. Though the magnitude of the effect of regulation on income inequality appears small, the effect is economically significant because of the large change in regulation in the past two decades. Between 1997 and 2015, the FRASE index increased by 58 percent, which according to our estimates corresponds to an increase in the Gini coefficient of about 3.7 percent.

A growing literature has identified channels by which federal regulation may increase inequality, but no study has tested whether the federal regulations that increase consumer prices and within-occupation wage disparities lead to greater aggregate inequality. The present study fills this gap in the literature by showing that the federal regulations are associated with greater income inequality at the state level. Part of the well-documented increase in income inequality in the United States is likely owing to the growth of federal regulations.

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