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# Regulation and poverty: an empirical examination of the relationship between the incidence of federal regulation and the occurrence of poverty across the US states

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**Abstract**
We estimate the impact of federal regulations on poverty rates in the 50 US states using the recently created Federal Regulation and State Enterprise (FRASE) index, which is an industry-weighted measure of the burden of federal regulations at the state level. Controlling for many other factors known to influence poverty rates, we find a robust, positive and statistically significant relationship between the FRASE index and poverty rates across states. Specifically, we find that a 10% increase in the effective federal regulatory burden on a state is associated with an approximate 2.5% increase in the poverty rate. This paper fills an important gap in both the poverty and the regulation literatures because it is the first one to estimate the relationship between the two variables. Moreover, our results have practical implications for federal policymakers and regulators because the greater poverty that results from additional regulations should be considered when weighing the costs and benefits of additional regulations.

**Keywords** Regulation · Poverty · States · FRASE · Regressive effects · RegData

**JEL Classification** D31 · I32 · J38 · K20 · R10

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## 1 Introduction

Poverty is one of the most pressing challenges that public policymakers face. Unfortunately, little consensus exists on how to remedy that stubbornly persistent problem. We argue in this paper that federal regulatory reform may offer a way forward.

The link between poverty and regulatory policy has generally been neglected by economists. As such, this paper is the first to examine the relationship between poverty and federal regulations across the US states. Although both regulation and poverty are interesting in their own right, we argue that an underappreciated connection exists between them that policymakers should consider when drafting new rules. Estimating the relationship empirically was impossible until recently because of the unavailability of state-level regulatory data. However, in this paper, we use the recently created Federal Regulation and State Enterprise (FRASE) index, which ranks the 50 states and the District of Columbia according to how federal regulations affect each of the 51 subfederal jurisdictions. Specifically, we characterize the association between poverty and regulation by exploiting variation across space and time in poverty rates and in the FRASE index among the states. Although variation in poverty rates is observational and remains to be explained, variation in the FRASE index arises by construction from two sources: (1) differences over time in the quantity of federal regulations targeting each industry in a state's economy and (2) year-to-year changes in the mix and relative importance of industries in each state (as measured by value added to the state's GDP).[1]

Before the release of the FRASE dataset, anyone seeking to study the impact of federal regulations at the state level faced a daunting task. The 2016 *Code of Federal Regulations* (CFR), which compiles annually all current federal regulations, spans 236 volumes and is more than 175,000 pages long (McLaughlin and Sherouse 2016). Manually reading the CFR, classifying each regulatory restriction by industry, and repeating that process for each prior year to construct a panel dataset would take decades.[2] Fortunately, RegData, a suite of data-mining and machine-learning algorithms developed by Al-Ubaydli and McLaughlin (2015) and McLaughlin and Sherouse (2016) has made it possible for computers to mine the CFR, identify regulatory restrictions, and probabilistically match the restrictions to the four-digit North American Industry Classification System (NAICS) codes to which they apply.[3]

Although federal regulations apply to all states, each state's economy comprises a different mix of industries. As a result, regulations that affect a specific industry will affect states in different ways. To address that problem, McLaughlin and Sherouse, the creators of the FRASE index, matched and weighted national-level regulations (from RegData) by the relative importance of each industry to each state using input–output data available from the Bureau of Economic Analysis (BEA).

We focus on regulations because economists have long recognized that they have both real and distributive effects on the economy. Friedman (1962) emphasizes that the relative distribution of income is a reflection of the operation of the market economy, given the

[1] For complete details on how the FRASE index is calculated, see the appendix to McLaughlin and Sherouse (2016, pp. 29–31).

[2] The Mercatus Center estimates that the average reader (reading at a rate of 300 words per minute) would take nearly 3 years to read the current CFR if reading it were a full-time job: https://quantgov.org/regdata/the-code-of-federal-regulations-the-ultimate-longread/.

[3] For more information on RegData, see https://quantgov.org/regdata/.

initial endowments and preferences of participants and the successes or failures of their individual economic decisions. Government policies, such as federal regulations, influence the identities of economic winners and, hence, the resulting income distribution. Higgs (1987) stresses that regulations reduce the sphere of private economic decision-making because through its regulations and restrictions, the government effectively makes choices for the private sector. Given that government's predetermined choices are likely to be dynamically inefficient, the result is both less freedom and poorer long-run economic performance.

Consistent with those theories, a growing number of recent papers estimate empirically the negative impact of federal regulations on the US economy. Using an older and less reliable measure of federal regulations (i.e., the number of pages in the CFR), Dawson and Seater (2013) find that since 1949, the growth of federal regulations has significantly reduced the rate of US economic growth. Specifically, they estimate that the cumulative loss of output between 1949 and 2011 totals \$38.8 trillion.[4] Crain and Crain (2014) estimate that the annual cost of federal regulations equals \$2 trillion. Coffey et al. (2016) find that if federal regulations had been frozen in 1980 and subsequently never increased, then by year 2012 the US economy would have been approximately 25% larger than it actually was. Collectively, those results demonstrate that federal regulations represent a significant economic headwind that slows economic growth and reduces real incomes. Even in a best-case scenario whereby regulation's impacts affect all income groups proportionately (i.e., no change in income inequality occurs), the absolute income levels of low-income individuals would be reduced and more people would be living below any absolute poverty threshold. Unfortunately, recent research finds ample evidence that regulations have regressive effects—that is, that regulations negatively impact poorer households disproportionately.

The body of literature on the regressive effects of regulations is growing. Such effects include risk mitigation, higher consumer prices, barriers to entry (such as those created by occupational licensure and business startup regulations), compliance costs and mandates. Those strands of the literature both individually and collectively demonstrate that regulations disproportionately hurt the most vulnerable in society, including would-be entrepreneurs; those with less education, fewer skills and less job experience, as well as those with lower incomes and less political clout. Therefore, it is not unreasonable to hypothesize that more active regulatory intervention, all else being equal, diminishes economic mobility and reduces the economic opportunities of low-income individuals, thereby making it harder to escape poverty. We next briefly summarize each of these facets of the literature on the regressive effects of regulation.

Thomas (2012) argues that regulations aimed at reducing health and safety risks tend to be regressive. High-income earners, relative to low-income earners, have a greater willingness to pay to mitigate low-probability risks. When federal regulations target low-probability risks—especially those that are costly to mitigate—all households pay for enforcing them in the form of lower wages and higher prices. Such costs are disproportionately borne by low-income earners. Chambers et al. (2017) report empirical evidence that the poorest households spend larger proportions of their incomes on goods and services that are heavily regulated, suggesting that the regulations have regressive effects.

[4] To put that number into perspective, note that nominal GDP in 2011 equaled \$15.8 trillion (see http://www.bea.gov). Therefore, the cumulative impact of regulations from 1949 to 2011 was roughly 2.5 times the size of the US economy in 2011.

Small business owners and would-be entrepreneurs likewise are disproportionately affected. Crain and Crain (2010) find that small businesses bear most of the costs of regulation. Chambers et al. (2018) find that countries with more barriers to business entry tend to experience more income inequality. Chambers and Munemo (2017) find that nations with more business startup regulations also have lower rates of entrepreneurship. Bailey et al. (2018) find that regulations lead to an increase in the relative demand for compliance-oriented professionals (e.g., lawyers and accountants), which means slower wage growth and fewer job prospects for less educated, noncompliance workers. McLaughlin et al. (2014) find that occupational licensing has a disparate impact on the economically vulnerable, including ethnic minorities. Kleiner and Krueger (2013) estimate that nearly one-third of workers were affected by occupational licensure regulations as of 2008. Taken together, these findings suggest that regulations diminish opportunities for upward social mobility and economic advancement, thus stranding many people in lives of poverty.

Although the previous literature on regulation has focused on its regressive impact on prices, entrepreneurship, or income inequality, all of which are determinants of poverty, no study has provided a comprehensive analysis of the impact of regulation on poverty itself. This paper fills that gap in the literature by examining the relationship between regulation and poverty rates across US states. We find a significant and positive relationship between the FRASE index and cross-state poverty levels. Specifically, we find that a 10% increase in the effective federal regulatory burden on a state is associated with an approximate 2.5% increase in that state's poverty rate.

In the remainder of the paper, we describe the benchmark empirical poverty rate model commonly used in the economic development literature, from which we build our model of interest. We discuss the data used in our analysis and present the regression results and associated robustness tests before concluding.

## 2 The benchmark empirical model

If a poverty line can be expressed as a threshold monetary value, Dhongde (2006) shows that the poverty rate ($P$) can be expressed as function of mean income ($Y$) and the Lorenz curve ($\mathscr{C}$) by way of the following identity:

$$P \equiv f(Y, \mathscr{C}(Y)). \tag{1}$$

In practice, data on the precise distribution of income are unavailable, so a summary measure of the relative income distribution, typically the Gini coefficient, is used as a proxy for the Lorenz curve. That substitution yields the model below, wherein $\varepsilon$ captures variation in the poverty rate explained by the Lorenz curve, but not the Gini coefficient:

$$P = g(Y, Gini) + \varepsilon. \tag{2}$$

Equation (2) represents the core functional relationship from which we derive the linear benchmark regression model. Following the economic development literature, that equation can easily be adapted to fit a panel data framework. For example, Meng et al. (2005) and Chambers et al. (2008) use a similar double-log benchmark model to study poverty rates in Chinese provinces:

$$p_{it} = \alpha_i + \beta_1 \eta_t + \beta_2 y_{it} + \beta_3 gini_{it} + \varepsilon_{it}, \tag{3}$$

where $p_{it}$ is the natural log of the poverty rate; $\alpha_i$ is a cross-sectional fixed effect that captures idiosyncratic differences in the mean poverty rate for a province, state, or nation not otherwise explained by the other independent variables; $\eta_t$ is an exogenous time trend (i.e., $\eta_t = t$); $y_{it}$ is the natural log of mean income; $gini_{it}$ is the natural log of the Gini coefficient; and $\varepsilon_{it}$ is a mean zero error term. Many papers in the development literature have sought to estimate the coefficient on log mean income (i.e., $\beta_2$), also known as the growth elasticity of poverty. In this strand of the literature (see, for example, Adams 2004; Ram 2007; Chambers and Dhongde 2011), common practice is to start with model (3) and transform it by way of taking first differences. This exercise has the advantage of removing both the cross-sectional fixed effects ($\alpha_i$) and the exogenous trend, yielding a simpler regression model:

$$\Delta p_{it} = \beta_1 + \beta_2 \Delta y_{it} + \beta_3 \Delta gini_{it} + u_{it}, \tag{4}$$

where deltas denote first differences—that is, $\Delta p_{it} = p_{it} - p_{it-1}$, $\Delta y_{it} = y_{it} - y_{it-1}$ and $\Delta gini_{it} = gini_{it} - gini_{it-1}$. In the analysis to follow, we extend both benchmark specifications to estimate the relationship between regulatory burdens and poverty across the US states.[5]

## 3 The regulation-poverty empirical model

To estimate the impact of federal regulations on poverty across the 50 US states and the District of Columbia, we add the FRASE index to the benchmark models in Sect. 2. Given the poverty decomposition formulated by Dhongde (2006), adding the FRASE index to the benchmark models implicitly assumes that when federal regulations are more burdensome in a given state, the result is a change in the underlying distribution of income. That assumption is consistent with the arguments of Friedman (1962) mentioned earlier. By influencing and affecting market outcomes, federal regulations likely affect the resulting income distribution (i.e., government policies help to influence the identities of economic winners and losers). The literature also reports empirical evidence that regulations affect an economy's overall level of output (see Dawson and Seater 2013; Crain and Crain 2014; Coffey et al. 2016, among others), which suggests that including both the FRASE index and mean income in a linear regression model likely introduces some multicollinearity. Although this effect does not bias the coefficient point estimates, it will inflate standard errors and reduce statistical significance. Adding the FRASE index to Eq. (3) yields the following:

$$p_{it} = \alpha_i + \beta_1 \eta_t + \beta_2 y_{it} + \beta_3 gini_{it} + \beta_4 frase_{it} + \varepsilon_{it}, \tag{5}$$

where $frase_{it}$ is the natural log of the FRASE index; the remaining variables retain their original specifications and interpretations. Adding the FRASE index to Eq. (4) yields the following:

$$\Delta p_{it} = \beta_0 + \beta_1 \eta_t + \beta_2 \Delta y_{it} + \beta_3 \Delta gini_{it} + \beta_4 \Delta frase_{it} + u_{it} \tag{6}$$

where $\Delta frase_{it}$ is the first difference of the natural log of the FRASE index, as before; the remaining variables retain their original specifications and interpretations.[6] Thus, Eqs. (5)

[5] The decomposition of changes in poverty into changes in income distributions (inequality) and changes in mean income (growth) has a long history in development economics. It was first pioneered by Datt and Ravallion (1992) and was later used by many subsequent scholars (see, for example, Bourguignon 2003).

[6] Following common practice, we retain the period fixed effect in Eq. (6) despite its first-differenced specification.

and (6) will serve as the benchmark regression models to test the empirical impact of the federal regulatory burden upon the poverty rates of states.

## 4 Data

The data we use on poverty come from the US Census Bureau and measure the proportion of households with incomes that fall below the poverty line, i.e., a threshold dollar amount, for a family of their size and composition.[7] For example, in 2016, the poverty line for a four-person family consisting of two adults and two children was $24,339.[8] The poverty line does not vary by state, and it is adjusted annually for inflation. The data on mean incomes are from the BEA and equal the real per capita GDP for each state in chained 2009 dollars.[9] The Gini coefficient panel is an update of the one constructed by Frank (2009), which is derived from individual income tax returns filed with the Internal Revenue Service.[10]

Finally, we use the FRASE index, which measures the burden of federal regulations in a given state using state-specific industry weights to determine the regulatory exposure.[11] The FRASE index relies on a combination of regulatory data from RegData and economic data from the BEA. To calculate the FRASE index score for each state, McLaughlin and Sherouse (2016) start with the number of regulatory restrictions targeting each industry, as estimated in the RegData 2.2 dataset.[12] Those levels of industry-specific regulatory restrictions are then weighted according to each industry's importance to a particular state's private-sector economy relative to that industry's importance to the nation as a whole. Thus, if an industry contributes twice as much to a state's private sector as it does to the nation's, the restrictions count twice as much for that state. In this paper, we sum the results across all industries and scale the score to that of the nation overall.

The calculation shows the impact of federal regulation on states relative both to the nation and to other states. A FRASE index score of 1 means that federal regulations affect a state to precisely the same extent that they affect the nation as a whole. A score greater than 1 means that federal regulations have a larger impact on the state than on the nation, whereas a score less than 1 means that they have a lower impact on the state.

[7] To calculate the povety rate, the Census Bureau estimates the proportion of Americans living in households with income below the poverty threshold. Based on the assumption that a poor household spends one-third of its income on food, the poverty income threshold is equal to triple the inflation-adjusted cost of a minimally nutritious diet in 1963, with adjustments for household size and the age of the respective members.

[8] Poverty rates and threshold values can be obtained from the Census Bureau website: http://www.census.gov/topics/income-poverty/poverty.html.

[9] Data on real per capita GDP can be accessed at the BEA's website: https://www.bea.gov/regional/.

[10] The Gini panel can be downloaded from Frank's website: http://www.shsu.edu/eco_mwf/inequality.html.

[11] The FRASE index can be downloaded from the Mercatus Center's RegData website: https://quantgov.org/50states/.

[12] RegData 2.2 includes a variable called "regulatory restrictions" that contains quantifications of words like "shall" or "must" in federal regulation that are likely to obligate or prohibit a specific action and another variable called "industry relevance" that contains estimates of the probability that a given regulatory restriction pertains to a particular industry. See McLaughlin and Sherouse (2018) for a detailed description of RegData 2.2.

**Table 1** Mean panel values, 1997–2013

| State | Poverty rate (%) | Real GDP per capita (2009) | Gini coefficient | FRASE index |
|---|---|---|---|---|
| Alabama | 15.47 | 35,585 | 0.59 | 1.27 |
| Alaska | 9.46 | 64,084 | 0.58 | 1.99 |
| Arizona | 16.00 | 39,710 | 0.59 | 1.03 |
| Arkansas | 16.87 | 34,342 | 0.60 | 1.24 |
| California | 14.28 | 50,360 | 0.64 | 1.11 |
| Colorado | 10.36 | 49,877 | 0.59 | 1.04 |
| Connecticut | 8.81 | 62,613 | 0.64 | 1.19 |
| Delaware | 10.23 | 63,123 | 0.56 | 1.04 |
| District of Columbia | 18.48 | 156,401 | 0.62 | 0.91 |
| Florida | 13.19 | 39,544 | 0.66 | 1.01 |
| Georgia | 14.59 | 44,029 | 0.61 | 1.15 |
| Hawaii | 10.72 | 47,303 | 0.56 | 1.02 |
| Idaho | 12.31 | 34,372 | 0.61 | 1.23 |
| Illinois | 11.85 | 50,152 | 0.61 | 1.12 |
| Indiana | 11.57 | 42,015 | 0.57 | 1.60 |
| Iowa | 9.60 | 43,478 | 0.55 | 1.31 |
| Kansas | 11.85 | 42,317 | 0.58 | 1.42 |
| Kentucky | 15.64 | 37,254 | 0.58 | 1.53 |
| Louisiana | 18.01 | 44,826 | 0.62 | 2.03 |
| Maine | 11.54 | 37,335 | 0.56 | 0.95 |
| Maryland | 8.77 | 50,047 | 0.56 | 0.95 |
| Massachusetts | 10.66 | 56,986 | 0.61 | 0.93 |
| Michigan | 12.27 | 40,985 | 0.58 | 1.30 |
| Minnesota | 8.86 | 49,495 | 0.57 | 1.04 |
| Mississippi | 19.22 | 30,641 | 0.61 | 1.34 |
| Missouri | 12.29 | 41,910 | 0.59 | 1.17 |
| Montana | 14.34 | 34,908 | 0.62 | 1.36 |
| Nebraska | 10.28 | 45,982 | 0.59 | 1.35 |
| Nevada | 11.67 | 48,002 | 0.63 | 0.87 |
| New Hampshire | 6.91 | 45,391 | 0.57 | 0.82 |
| New Jersey | 8.90 | 54,893 | 0.60 | 1.16 |
| New Mexico | 18.85 | 39,232 | 0.60 | 1.23 |
| New York | 15.03 | 56,932 | 0.66 | 1.07 |
| North Carolina | 14.74 | 43,294 | 0.58 | 1.37 |
| North Dakota | 11.49 | 43,967 | 0.58 | 1.41 |
| Ohio | 12.40 | 42,964 | 0.56 | 1.20 |
| Oklahoma | 14.19 | 37,013 | 0.60 | 1.37 |
| Oregon | 12.65 | 43,080 | 0.58 | 1.00 |
| Pennsylvania | 11.03 | 43,997 | 0.59 | 1.14 |
| Rhode Island | 11.79 | 44,282 | 0.57 | 0.84 |
| South Carolina | 14.30 | 36,335 | 0.59 | 1.13 |
| South Dakota | 11.89 | 41,410 | 0.61 | 1.28 |
| Tennessee | 15.16 | 40,331 | 0.60 | 1.19 |
| Texas | 16.38 | 46,741 | 0.63 | 1.49 |

**Table 1** (continued)

| State | Poverty rate (%) | Real GDP per capita (2009) | Gini coefficient | FRASE index |
|---|---|---|---|---|
| Utah | 9.20 | 40,785 | 0.58 | 1.09 |
| Vermont | 9.45 | 39,484 | 0.58 | 0.96 |
| Virginia | 9.74 | 49,809 | 0.57 | 1.09 |
| Washington | 10.73 | 51,363 | 0.58 | 1.31 |
| West Virginia | 16.09 | 33,219 | 0.56 | 1.61 |
| Wisconsin | 10.06 | 43,523 | 0.56 | 1.04 |
| Wyoming | 10.38 | 58,184 | 0.63 | 1.99 |

**Table 2** Panel correlation coefficients

| | Log poverty rate | Log output | Log Gini | Log FRASE |
|---|---|---|---|---|
| Log poverty rate | 1.000 | −0.146 | 0.340 | 0.335 |
| Log output | −0.146 | 1.000 | 0.199 | −0.055 |
| Log Gini | 0.340 | 0.199 | 1.000 | 0.227 |
| Log FRASE | 0.335 | −0.055 | 0.227 | 1.000 |

The combined, balanced panel spans the period from 1997 to 2013, and includes all 50 US states plus the District of Columbia (867 observations).[13] Table 1 contains summary statistics for the benchmark dataset by state. The simple average poverty rate across the states between 1997 and 2013 was 12.56%, with the highest average rate equaling 19.22% (Mississippi) and the lowest average rate equaling 6.91% (New Hampshire). The simple average real per capita GDP across the states between 1997 and 2013 was $46,939, with the highest average from the District of Columbia ($156,401) and the lowest average coming from Mississippi ($30,641). Frank's Gini coefficients are quite large, with the average value across all of the states and years equaling 0.59. The lowest average Gini equals 0.55 (Iowa), and the highest average equals 0.66 (both Florida and New York). Finally, the simple average value of the FRASE index across the full sample equals 1.22, which implies that the states, on average, experienced a relative regulatory burden between 1997 and 2013 that was 22% higher than the US average in 1997. The state with the highest average FRASE index is Louisiana (2.03), whereas the state with the lowest average FRASE index is New Hampshire (0.82).

As a preliminary step, we calculate the correlation matrix for poverty, real per capita income, the Gini coefficient, and the FRASE index, all expressed as natural logarithms. The results (see Table 2), though only anecdotal, are consistent with our prior expectations. Specifically, poverty is negatively correlated with log per capita income (−0.146), implying that states with higher mean incomes exhibit less poverty. Likewise, log poverty is positively correlated with the log of the Gini coefficient (0.340), consistent with the notion that as income inequality rises, absolute living standards for the poorest households decline,

[13] Going forward, we will treat the District of Columbia as a state: instead of referring to the "50 US States plus the District of Columbia," we will simply refer to the group as "the states".

**Table 3** Equation 5 estimation results

| Variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Log FRASE | 0.2879*** | 0.2596*** | 0.2504*** | 0.2125** | 0.2373*** |
| | (0.0390) | (0.0170) | (0.0205) | (0.0929) | (0.0903) |
| Log output | −0.2113*** | −0.2224*** | −0.2075*** | −1.0313*** | −0.8060*** |
| | (0.0237) | (0.0241) | (0.0277) | (0.1164) | (0.0684) |
| Log Gini | 1.4849*** | 1.4057*** | 1.6036*** | −0.0543 | −0.0087 |
| | (0.1014) | (0.1368) | (0.1865) | (0.1223) | (0.1037) |
| Time trend | – | 0.0034 | – | 0.0200*** | – |
| | | (0.0037) | | (0.0037) | |
| Fixed state effects | No | No | No | Yes | Yes |
| Fixed period effects | No | No | Yes | No | Yes |
| Observations | 867 | 867 | 867 | 867 | 867 |
| Goodness of fit | 0.222 | 0.224 | 0.277 | 0.837 | 0.860 |

Dependent variable is the log of the poverty rate; intercept included, but not reported; white robust cross-section standard errors in parentheses

***, ** and *Denote 1%, 5% and 10% statistical significance, respectively

thus increasing the poverty rate. Finally, log poverty also is positively correlated with the log of the FRASE index (0.335), implying that states that are effectively more federally regulated also exhibit higher poverty rates.

## 5 Benchmark estimation results

### 5.1 Estimation results for Eq. (5)

Table 3 reports the estimation results for five variants of Eq. (5). In column (1), the log poverty rate is regressed on a pooled constant term (not reported), the log of the FRASE index, log GDP per capita, and log Gini coefficient. In line with prior expectations, the coefficient on the log FRASE index (0.2879) is positive and statistically significant at the 1% level. This finding implies that a 1% increase in federal regulatory restrictions is associated with a 0.2879% rise in the poverty rate.[14] The coefficient on log output has the appropriate sign (−0.2113) and is statistically significant at the 1% level, implying that a 1% increase in output reduces the poverty rate by just over 0.2%. Finally, the coefficient on the logged Gini coefficient is positive and statistically significant at the 1% level (1.4849), implying that a 1% increase in income inequality increases the poverty rate by 1.4849%.

Column (2) is the same as column (1), but includes a time trend, as is common practice in the literature. The estimation results change very little: the coefficient on the logged FRASE index equals 0.2596 and is significant at the 1% level. The coefficients on log output and the logged Gini coefficient are nearly unchanged, and both remain statistically significant at the 1% level. The added time trend is statistically insignificant.

[14] Regulatory restrictions—as explained *supra* 12 and in McLaughlin and Sherouse (2018)—are words in federal regulation that are likely to create an obligation to perform some specific action, or a prohibition from doing so.

**Table 4** Estimation results for Eqs. (6)–(9)

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Δ (log FRASE) | 0.2944** (0.136) | 0.2752** (0.1339) | 0.3169** (0.1315) | 0.2332* (0.1251) | 0.3195** (0.1336) | 0.2338* (0.1267) | 0.2822** (0.1222) | 0.2845** (0.1235) |
| Δ (log output) | −0.1102 (0.1752) | −0.0701 (0.2329) | −0.1035 (0.1871) | −0.0837 (0.1702) | −0.0614 (0.2533) | −0.0693 (0.2322) | −0.1065 (0.1866) | −0.0609 (0.2527) |
| Δ (log Gini) | 0.1825 (0.288) | 0.0071 (0.2840) | 0.0347 (0.2942) | −0.0063 (0.2875) | 0.0348 (0.2937) | −0.0062 (0.2877) | 0.0242 (0.2976) | 0.0242 (0.2971) |
| Δ (log government) | – | 0.0120 (0.1385) | – | – | 0.0522 (0.1397) | 0.0180 (0.1395) | – | 0.0566 (0.141) |
| Δ (log high school) | – | – | 0.5025 (0.5814) | – | 0.5064 (0.5757) | – | 0.4933 (0.5813) | 0.4974 (0.5757) |
| Δ (log agriculture) | – | – | – | 0.0332 (0.0257) | – | 0.0334 (0.0262) | 0.0279 (0.0263) | 0.0284 (0.0269) |
| Observations | 816 | 800 | 750 | 800 | 750 | 800 | 750 | 750 |
| Goodness of fit | 0.114 | 0.111 | 0.118 | 0.112 | 0.118 | 0.112 | 0.119 | 0.119 |

Dependent variable is the first difference of the log poverty rate; period fixed effects and intercept included, but not reported; white robust cross-section standard errors in parentheses

***, ** and *Denote 1%, 5% and 10% statistical significance, respectively

Column (3) is similar to column (2), but fixed period effects replace the time trend. The coefficient on the logged FRASE index is virtually unchanged and remains statistically significant at the 1% level. The coefficient on log output also changes very little and remains statistically significant. The coefficient on the logged Gini coefficient remains significant at the 1% level but increases in magnitude to 1.6036.

Columns (4) and (5) include state fixed effects. The overall goodness of fit of these models ranges from 0.837 to 0.860, much larger than the $R^2$ values reported in the first three columns (ranging from 0.222 to 0.277), which ignore state-specific heterogeneity in the poverty rate. Column (4) includes a time trend, whereas fixed time effects are entered in column (5). In column (4), the coefficient on the logged FRASE index equals 0.2125 and is significant at the 5% level. This finding is similar to that in column (5), in which the coefficient on the logged FRASE index equals 0.2373 and is statistically significant at the 1% level. In both columns (4) and (5), the coefficient estimate on log output is negative and statistically significant at the 1% level, ranging in estimated value from −0.8060 to −1.0313. That finding implies that a 1% increase in the log of per capita output reduces poverty by between 0.8060 and 1.0313%. Finally, the coefficient on the logged Gini coefficient is statistically insignificant in both columns (4) and (5). The coefficient on the time trend in column (4) is positive and statistically significant (0.02), implying that poverty rates are drifting 2% upward every year, all else being equal.

### 5.2 Estimation results for Eq. (6)

Column (1) of Table 4 reports the estimation results for the baseline version of Eq. (6). Because taking the first differences of the model's variables eliminates state heterogeneity, only fixed *period* effects are considered.[15] The coefficient on the first difference of the logged FRASE index (0.2944) is statistically significant at the 5% level and in line with the previous results from Eq. (5), suggesting that a 1% increase in binding regulations is associated with about a 0.3% increase in the poverty rate. The coefficient on the first difference of log output is negative, but statistically insignificant. Likewise, the coefficient on the first difference of the logged Gini coefficient has the expected positive sign, but is statistically insignificant.

## 6 Robustness results

To ensure that our results are robust to the inclusion of other independent variables, we add three additional explanatory variables common to the poverty literature. Regardless of how those additional explanatory variables are entered (individually, in pairs, or as a group), the regulation coefficient is consistent in sign and magnitude, averaging 0.2779, and statistically significant in all cases. In other words, a 1% increase in binding federal regulations is associated with increases in state-level poverty rates of just under 0.28%, which is consistent with our findings from the baseline model.

We also examined whether one particular set of observations—those from the District of Columbia (DC)—could be influencing our results unduly. As shown in Table 1, DC has both a high poverty rate (3rd highest overall) and a large GDP per capita (highest overall). Other states with relatively high poverty rates, such as Mississippi, Alabama, New Mexico and West Virginia tend also to have relatively low GDPs per capita. The presence of the federal government in DC inflates the ranks of the District's professional workers, who apparently are well compensated for their provision of government services and government-related activities, such as lobbying, consulting and advising. We thus re-ran our estimations of Eqs. (5) and (6), while dropping DC altogether from the sample, but found that omitting DC did not materially alter our results.[16] The coefficient estimates on the regulation and Gini variables are very similar in magnitudes and significance when DC is excluded from both sets of regressions. The coefficient estimates on GDP per capita became more negative and significantly significant in the estimations of Eq. (5), but they were essentially unchanged in the first-differenced estimations [Eq. (6)].

### 6.1 Government expenditures

Following Chambers et al. (2008), we entered total public expenditures relative to the size of the state economy as a proxy for the provision of public goods and services and government's overall size and scope within each state economy.[17] The resulting model, which builds on Eq. (6), is specified as follows:

$$\Delta p_{it} = \beta_1 + \beta_2 \Delta y_{it} + \beta_3 \Delta gini_{it} + \beta_4 \Delta frase_{it} + \beta_5 \Delta gov_{it} + \eta_t + u_{it}, \tag{7}$$

where $\Delta gov_{it}$ is the first difference of the log of state government expenditures as a fraction of state GDP and $\eta_t$ is a fixed-effect time dummy. The estimation results are reported in

[15] Any exogenous trend variables become constants.

[16] Our results after excluding DC are not reported here, but are available from the authors upon request.

[17] Government expenditures and state GDP data are obtained from the US BEA.

column (2) of Table 4. Focusing on the variable of interest, the coefficient estimate on the first difference of the log of the FRASE index equals 0.2752 and is statistically significant at the 5% level. That result is quite consistent with the previous estimations and suggests that a 1% increase in binding federal regulations is associated with increases in the state poverty rate of just under 0.28%.

## 6.2 Human capital

Following Chambers et al. (2008), Apergis et al. (2011) and Johnson et al. (2011), we include a measure of educational attainment as a proxy for human capital levels within each state. In principle, states with more human capital should have less structural unemployment, higher labor force participation rates, and higher real earnings.[18] The resulting model, which builds on Eq. (6), is specified as follows:

$$\Delta p_{it} = \beta_1 + \beta_2 \Delta y_{it} + \beta_3 \Delta gini_{it} + \beta_4 \Delta frase_{it} + \beta_5 \Delta education_{it} + \eta_t + u_{it}, \tag{8}$$

where $\Delta education_{it}$ is the first difference of the log of the high school completion rate, given as a percentage of the adult population (age 18 and over), and $\eta_t$ is a fixed time effect. The estimation results are shown in column (3) of Table 4. Again focusing on the variable of interest, we find that the coefficient estimate on the first difference of the log of the FRASE index equals 0.3169 and is statistically significant at the 5% level. This finding is very consistent with the previous estimation results and suggests that a 1% increase in binding federal regulations is associated with increases in the state poverty rate of just under 0.32%.

## 6.3 Agriculture

Following Chambers et al. (2008), we include a measure of the relative size of the agricultural sector within each state. Given that highly agrarian and rural economies have lower wages and greater seasonality in employment patterns, we anticipate a positive relationship between the relative size of the agricultural sector and the poverty rate.[19] The resulting model, which builds on Eq. (6), is specified as follows:

$$\Delta p_{it} = \beta_1 + \beta_2 \Delta y_{it} + \beta_3 \Delta gini_{it} + \beta_4 \Delta frase_{it} + \beta_5 \Delta agriculture_{it} + \eta_t + u_{it}, \tag{9}$$

where $\Delta agriculture_{it}$ is the first difference of the log of the output of the agricultural sector as a percentage of state GDP and $\eta_t$ is a fixed time effect. The estimation results are provided in column (4) of Table 4. Focusing on the variable of interest, we note that the coefficient estimate on the first difference of the log of the FRASE index equals 0.2332 and is statistically significant at the 10% level. That finding is again consistent with the previous estimation results and suggests that a 1% increase in binding federal regulations is associated with increases in the state poverty rate of just over 0.23%.

[18] High school completion rate data are from the US Census Bureau and can be accessed at https://www.census.gov/topics/education/educational-attainment/data.html.

[19] Agricultural output (North American Industry Classification System sector 11) and state GDP data are obtained from the US BEA.

### 6.4 Combined effects

While the preceding robustness checks are based on entering government expenditures, high school completion rates, and the relative size of the agricultural sector in separate exercises, we also include every possible pairing of the those additional explanatory variables in columns (5) to (7) of Table 4. The resulting coefficient estimates on the FRASE index range in value from 0.2338 to 0.3195 and are universally statistically significant. Finally, we include all three of these robustness variables in the augmented model (see column (8) of Table 4). The resulting coefficient on the FRASE index equals 0.2845 and is statistically significant at the 5% level.

## 7 Conclusion

Consistent with economic theory, previous empirical research has documented that regulations reduce real incomes and regressively affect consumer prices, entrepreneurship, and income inequality. Given those demonstrable effects, it is not unreasonable to suspect that regulations also increase poverty rates. However, no study has provided a comprehensive analysis of the impact of regulation on poverty.

This paper fills that gap in the literature by being the first to examine the impact of federal regulations on US poverty across the 50 states and the District of Columbia. Until recently, however, empirically estimating that relationship was impossible because of the unavailability of state-level regulatory data. But we use the FRASE index, which ranks the 51 sub-federal jurisdictions according to how federal regulations affect each of them. Controlling for a large number of other factors known to influence poverty rates, we find a robust, positive and statistically significant relationship between the FRASE index and cross-state poverty rates. Specifically, we find that a 10% increase in the effective federal regulatory burden on a state is linearly correlated with approximately a 2.5% increase in that state's poverty rate. Although our analysis does not necessarily demonstrate a causal relationship, we find the relationship between federal regulation and state poverty rates to be robust to the inclusion of other explanatory variables common to the poverty literature, including government expenditures, human capital, and the relative size of the agricultural sector in each state. Consequently, we argue that a previously neglected and unappreciated connection exists between regulatory policy and poverty rates that policymakers and regulators should consider when drafting new rules.

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