Regulation and Poverty

An Empirical Examination of the Relationship between the Incidence of Federal Regulation and the Occurrence of Poverty across the 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 percent increase in the effective federal regulatory burden on a state is associated with an approximate 2.5 percent increase in the poverty rate. This paper fills an important gap in both the poverty and the regulation literature because it is the first paper to estimate the relationship between these variables. Moreover, our results have practical implications for federal policymakers and regulators, because the increased poverty that results from additional regulations should be considered when weighing the costs and benefits of additional regulations.

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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 this 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 been widely neglected by economists. As such, this paper is the first to examine the relationship between poverty and federal regulations across the states. Although both regulation and poverty are interesting in their own right, we argue that there is an underappreciated connection between them that policymakers should consider when drafting new rules. Empirically estimating this relationship 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 state or district. 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 regulation 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 research the impact of federal regulations at the state level faced a daunting task. The 2016 *Code of Federal Regulations* (CFR), which annually compiles 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 this 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 these restrictions to the four-digit North American Industry Classification System industry codes to which they apply.[3]

Although federal regulation applies 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 this problem, McLaughlin and Sherouse, the makers 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

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

[2] The Mercatus Center estimates that the average reader (reading at a rate of 300 words per minute) would take nearly three years to read the current CFR if 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/.

distribution of income is a reflection of the operation of the market economy, given the initial endowments and preferences of participants and the success or failure of their individual economic decisions. Government policies, such as federal regulations, influence economic winners and thus the resulting income distribution. Higgs (1987) stresses that regulations reduce the sphere of private economic decision-making, because through regulations and restrictions, the government effectively makes choices for the private sector. Given that these predetermined choices are likely to be dynamically inefficient, the result is both reduced freedom and poorer long-run economic performance.

Consistent with these theories, a growing number of recent papers empirically estimate 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 decreased 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, McLaughlin, and Peretto (2016) find that if federal regulations had been frozen in 1980 and subsequently never increased, the US economy would have been approximately 25 percent larger in 2015 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 these impacts affect all income groups proportionately (i.e., there is no change in income inequality), the absolute income levels of low-income individuals would be reduced and there would be more

[4] To put that number into perspective, note that the 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.

people living below any absolute poverty threshold. Unfortunately, recent research finds ample evidence that regulations have regressive effects—that is, that regulations have a disproportionately negative impact on poorer households.

There is a growing body of literature on the regressive effects of regulations. Such effects include costly risk mitigation, higher consumer prices, barriers to entry (such as those created by occupational licensure and startup regulations), and compliance costs and mandates. These 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; and those with less income and political clout. Therefore, it is not unreasonable to hypothesize that greater regulation, 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 higher willingness to pay to mitigate low-probability risks. When federal regulations target low-probability risks—especially those that are expensive to mitigate—all households pay for them in the form of lower wages and higher prices. These costs are disproportionately borne by low-income earners. Chambers, Collins, and Krause (2018) find empirical evidence that the poorest households spend a larger proportion of their income on goods and services that are heavily regulated, suggesting that the regulations have a regressive effect.

Small business owners and would-be entrepreneurs are also disproportionately affected. Crain and Crain (2010) find that small businesses bear most of the costs of regulation. Chambers, McLaughlin, and Stanley (2018) find that countries with more barriers to business entry tend to experience higher levels of income inequality. Chambers and Munemo (2017) find that nations with more startup regulations also have lower rates of entrepreneurship. Bailey, Thomas, and Anderson (2018) find that regulations lead to an increase in the relative demand for compliance-oriented professionals (e.g., lawyers and accountants), which means lower wage growth and fewer job prospects for less educated, noncompliance workers. McLaughlin, Ellig, and Shamoun (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 social mobility and economic advancement, thus stranding many in a life of poverty.

Although the previous literature on regulation has focused on its regressive impact on prices, entrepreneurship, or 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 regressive relationship between regulation and the poverty rate across US states. We find a significant and positive relationship between the FRASE index and poverty levels across states. Specifically, we find that a 10 percent increase in the effective federal regulatory burden on a state is associated with an approximate 2.5 percent 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 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 (ℓ) by way of the following identity:

$$P \equiv f\big(Y, \ell(Y)\big). \tag{1}$$

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. This yields the model below, wherein ε 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 development literature, this equation can easily be adapted to fit a panel framework. For example, Meng, Gregory, and Wang (2005) and Chambers, Wu, and Yao (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; α_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; η_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 ε_{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., β_2), also known as the growth elasticity of poverty. In this strand of the literature (see, for example, Adams 2004, Ram 2007, and Chambers and Dhongde

2011), common practice is to take model (3) and transform it by way of a first difference. This exercise has the advantage of removing both the cross-sectional fixed effects (α_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 burden 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 section 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. This 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 economic winners and losers). The literature also finds empirical evidence that regulations affect the overall level of output of an economy (see Dawson and Seater 2013, Crain and Crain 2014, and Coffey, McLaughlin, and Peretto 2016, among others), which suggests that including both the FRASE index and mean income in a linear regression model will likely introduce some multicollinearity. Although this effect does not bias the

[5] The decomposition of changes in poverty into changes in income distribution (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).

coefficient point estimates, it will inflate standard errors and reduce statistical significance. Adding the FRASE index to equation (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 equation (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, equations (5) and (6) will serve as the benchmark regression models to test the empirical impact of federal regulatory burden upon the poverty rates of states.

4. The 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. For example, in 2016, the poverty line for a four-person family consisting of two adults and two children equaled $24,339.[7] The poverty line does not vary by state, and it is adjusted annually for inflation. The data on mean income are from the BEA and equal the real per capita GDP for each state in chained 2009 dollars.[8] The Gini coefficient panel is an update of the one constructed by Frank (2009), which is derived from individual income tax filings from the Internal Revenue Service.[9]

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[6] Following common practice, we retain the period fixed effect in equation (6) despite its first-difference derivation.
[7] Poverty rates and threshold values can be obtained from the Census Bureau website: http://www.census.gov/topics /income-poverty/poverty.html.
[8] Data on real per capita GDP can be accessed at the BEA website: https://www.bea.gov/regional/.
[9] The Gini panel can be downloaded from Frank's website: http://www.shsu.edu/eco_mwf/inequality.html.

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.[10] 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. 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 result across all industries and scale the resulting score to that of the nation overall.

The result 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 degree that they affect the nation as a whole. A score greater than 1 means that federal regulations have a higher impact on the state than on the nation, whereas a score less than 1 means that they have a lower impact on the state.

The combined, balanced panel spans the period from 1997 to 2013 and includes all 50 US states plus the District of Columbia (867 observations).[11] Table 1 contains summary statistics for the benchmark dataset by state. The simple average poverty rate across the states between 1997 and 2013 equals 12.56 percent, with the highest average rate equaling 19.22 percent (Mississippi) and the lowest average rate equaling 6.91 percent (New Hampshire). The simple average real per

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

[11] 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."

capita GDP across the states between 1997 and 2013 equals $46,939, with the highest average hailing 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 the states and time periods 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 states and time periods equals 1.22, which implies that the states, on average, experienced a relative regulatory burden between 1997 and 2013 that was 22 percent 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).

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
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

Source: Author calculations based on the FRASE index.

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

Table 2. Panel Correlation Table

	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

Source: Author calculations.

5. Benchmark Estimation Results

5.1. Estimation Results for Equation (5)

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

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 log FRASE index equals 0.2596 and is significant at the 1 percent level. The coefficients on the log output and the log Gini coefficient are nearly unchanged, and both remain statistically significant at the 1 percent level. The added time trend is statistically insignificant.

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

Notes: (1) Dependent variable is the log of the poverty rate; (2) intercept included but not reported; (3) White robust cross-section standard errors in parentheses; (4) ***, **, and * denote 1 percent, 5 percent, and 10 percent statistical significance, respectively.

Column (3) is similar to column (2), but fixed period effects replace the time trend. The coefficient on the log FRASE index is virtually unchanged and remains statistically significant at the 1 percent level. The coefficient on the log output also changes very little and remains statistically significant. The coefficient on the log Gini coefficient remains significant at the 1 percent 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 (0.222 to 0.277), which ignore state-specific heterogeneity in the poverty rate. Column (4) includes a time trend, whereas column (5) uses fixed time period effects. In column (4), the coefficient on the log FRASE index equals 0.2125 and is significant at the 5 percent level. This finding is similar to that in column (5), in which the coefficient on the log FRASE index equals 0.2373 and is statistically significant at the 1 percent level. In both columns (4) and (5), the coefficient estimate on the log output is negative and statistically significant at the 1 percent level, ranging in estimated value from −0.8060 to −1.0313. This finding implies that a 1 percent increase in the log per capita output reduces poverty by 0.8060 percent to 1.0313 percent. Finally, the coefficient on the log 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 percent higher each year, all else being equal.

5.2. Estimation Results for Equation (6)

Column (1) of table 4 reports the estimation results for the baseline version of equation (6). Because taking the first difference of the model's variables eliminates state heterogeneity, only fixed *period* effects are considered.[12] The coefficient on the first difference of the log FRASE index (0.2944) is statistically significant at the 5 percent level and in line with the previous results from equation (5), suggesting that a 1 percent increase in binding regulations is associated with an approximate 0.3 percent increase in the poverty rate. The coefficient on the first difference of the log output is negative but statistically insignificant. Likewise, the coefficient on the first difference of the log Gini coefficient has the correct sign but is also statistically insignificant.

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[12] Any exogenous trend variables become constants.

Table 4. Estimation Results for Equations (6)–(9)

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

Notes: (1) Dependent variable is the first difference of the log poverty rate; (2) period fixed effects and intercept included but not reported; (3) White robust cross-section standard errors in parentheses; (4) ***, **, and * denote 1 percent, 5 percent, and 10 percent statistical significance, respectively.

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 these additional explanatory variables are added (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 percent increase in binding federal regulations is associated with increases in state-level poverty rates of just under 0.28 percent, which is consistent with our findings from the baseline model.

6.1. Government Expenditures

Following Chambers, Wu, and Yao (2008), we include the size of public expenditures relative to the size of the state economy as a proxy for the relative provision of public services and public goods and the overall size and scope of government within each state economy.[13] The resulting model, which builds on equation (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 Δgov_{it} is the first difference of the log of state government expenditures as a fraction of state GDP and η_t is a fixed-effect time period dummy. Estimation results are provided in 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 percent level. This is very consistent with the previous estimation results and suggests that a 1 percent increase in binding federal regulations is associated with increases in the state poverty rate of just under 0.28 percent.

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

6.2. Human Capital

Following Chambers, Wu, and Yao (2008); Apergis, Dincer, and Payne (2011); and Johnson, Formby, and Kim (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.[14] The resulting model, which builds on equation (6), is specified as follows:

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

where $\Delta education_{it}$ is the first difference of the log of the high school completion rate (given as a percentage) and η_t is a fixed effect time period dummy. Estimation results are provided in column (3) of table 4. 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 percent level. This finding is very consistent with the previous estimation results and suggests that a 1 percent increase in binding federal regulations is associated with increases in the state poverty rate of just under 0.32 percent.

6.3. Agriculture

Following Chambers, Wu, and Yao (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.[15] The resulting model, which builds on equation (6), is specified as follows:

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[14] 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.

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

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

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 η_t is a fixed effect time period dummy. 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 percent level. This finding is very consistent with the previous estimation results and suggests that a 1 percent increase in binding federal regulations is associated with increases in the state poverty rate of just over 0.23 percent.

6.4. Combined Effects

As a final robustness exercise, we include every pairing of the above explanatory variables (i.e., government expenditures, high school completion rates, and the relative size of the agricultural sector) in columns (5) to (7). 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)). The resulting coefficient on the FRASE index equals 0.2845 and is statistically significant at the 5 percent 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 these 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 this gap in the literature by being the first to examine the impact of federal regulations on poverty within the United States. Until recently, however, empirically estimating this relationship was impossible because of the unavailability of state-level regulatory data. But we use the FRASE index, which ranks the 50 states and the District of Columbia according to how federal regulations affect each state. 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 the poverty rates across states. Specifically, we find that a 10 percent increase in the effective federal regulatory burden on a state is linearly correlated with an approximate 2.5 percent 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 there is a neglected and unappreciated connection between regulatory policy and poverty rates that policymakers and regulators should consider when drafting new rules.

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