Which Policies Reduce Emissions?
Evidence From Agnostically Detected Reductions in State Residential Emissions

by

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Introduction

The unprecedented rise in greenhouse gas emissions in the years post-1900 and especially post-1970 have given rise to forecasts of a consequent warming of the earth's climate, accompanied by a litany of severe threats to the environment and human livelihood, growing in intensity as greenhouse gas emissions continue (IPCC, 2021). Naturally, the severity of the climate change issue has prompted coordinated and committed policy responses across all levels of governance. From the modeling work of the supranational International Panel on Climate Change as well as various international accords negotiated among the world's leading economies, to climate change mitigation programs operated at the subnational and municipal levels, the abatement of greenhouse gas emissions is a widely sought-after policy goal. The desire for a future of 'net zero' emissions in order to limit climate change and its associated costs is well-documented at the level of public policy actors. The future implied in these visions of net zero emissions necessitates emission abatement and/or mitigation across all sectors of the economy, including those with the highest cost to do so.

Standard economic theory has advocated for a policy dynamic whereby emission abatement initiatives are undertaken according to their relative cost-efficiency of emission reduction per dollar spent (Field & Field, 2021). This is the impetus behind 'cap-and-trade' systems of emission reduction such as the EU's Emissions Trading System, which formalize this policy dynamic into legislation. But this economic dynamic can be assumed to operate anywhere people or institutions are seeking to reduce greenhouse gas emissions under constrained resources. This cost-efficiency dynamic has crucial implications for public policy regimes with the goal of net zero emissions: the aggregate emissions mitigation problem gets harder and more costly as time and policy effort go into it, increasing in cost and complexity once the low hanging fruit of cost-efficacious policy has already been undertaken, in sectors of the economy with lower abatement costs.

Taking the United States as our example of a large greenhouse gas emitter, we can see that this is not merely an academic distinction wherein hard-to-abate sectors are marginal to the economy. In 2022, the transportation sector produced 28% of all US greenhouse gas emissions, while the residential and commercial sectors produced 13%, a number that climbs to 30% when accounting for the sector's electricity demands. (EPA, 2021). These two sectors alone therefore account for over half of the US's total emissions. Bringing them to net-zero levels of emissions necessitates tremendous capital investment in both the electrification of emission sources currently reliant on fossil fuels, as well as an overhauling of electricity production infrastructure towards low-emissions sources. In brief, these are precisely the sort of hard-to-abate emissions sources policymakers will need to plan to tackle sooner rather than later if they are serious about meeting net zero goals.

It is this paper's goal therefore to examine emission-reduction policies implemented in the US residential sector, to contribute to the literature on abatement policy in sectors with high abatement costs. Specifically, this paper applies the novel break-detection approach introduced in Pretis (2022) to U.S. state-level residential emissions data, using machine learning to detect breaks in a difference-in-differences model, and attributing these breaks to policy mixes. In this way, questions of policy efficacy are answered in the opposite manner to the standard difference-in-differences approach: As with the methodology of Pretis (2022), this paper does not assess the emission-reduction effectiveness of a particular policy, but rather first detects real emission reductions, after which it can assess the viability of attributing those reductions to contemporaneous policies.

The choice of residential emissions as the specific area of inquiry owes to two principal factors. Firstly, this paper's break detection methodology is now well-documented in handling policy cases concerning general C02 emissions (Pretis, 2022), as well as road emissions in specific (Koch, Naumann, Pretis, Ritter, & Schwarz, 2022). The methodology's application to residential emissions, a large emissions source that is similar to road emissions in its relative level of homogeneity, is a natural point of continuation. Secondly, the focus on residential emissions specifically over a wider focus on building-related emissions from both commercial and residential sectors owes to the tendency of public policy in the US to separate out policies dependent on building use-case, with differing policy regimes for commercial and residential buildings. (DSIRE, 2023) As residential emissions are higher than commercial emissions in the US, residential emissions reduction policy was chosen as the more pressing area of policy and therefore the subject of inquiry. (EIA, 2023)

As this paper aims to exploit state-level variation in residential emissions data to detect state-specific policy-attributable breaks, the following section outlining the policy environment will naturally focus on state-level policy. This is not to discount federal or municipal initiatives, but rather is a concession on the part of the model that the efficacy of federal or municipal initiatives is not something the model directly tests. As this essay centers on a two-way fixed effects model using state-level panel data, federal initiatives affecting all states in the model simultaneously would have their affects absorbed into time fixed effects, and therefore would not be identifiable as breaks. Municipal level policies are not assumed to have an effect size large enough to signal state-level breaks and are better studied with more granular datasets.

The key findings of this essay provide empirical support for Renewable Portfolio Standards (RPS) and interconnection policy in reducing residential greenhouse gas emissions and do so at a higher level of statistical significance than previous assessments in the literature. Policy mixes containing RPS are associated with four high-confidence emission reductions of 16% to 20% which are not explained by the base two-way fixed effects model. North Dakota's 16% reduction in 2010 sees the enaction of RPS policy as the only relevant contemporaneous policy, while three higher magnitude breaks are associated with RPS policy mixes containing only 1-3 other relevant policies. Policy mixes containing interconnection standards are associated with five high-confidence emission reduction breaks beyond the explanation of model fundamentals with effect sizes signifying reductions of 12% to 20%. This includes a 14% reduction in Arkansas in 2003, wherein interconnection standards and associated supplemental policies are the only relevant contemporaneous policies identified. Given the identification of isolated policy effects for RPS and interconnection standards, as well as their broad proliferation across detected emission reduction breaks, this paper supports the conclusion that these policies can be effective at reducing residential emissions at the state-level. Even absent any additional novel policies discovered in the model, RPS and interconnection standards policies receive enough empirical support to encourage emulation from future policy at the state level and above.

Overview of US State-Level Climate Policies and Their Effectiveness

In the realm of residential emissions abatement policy in the US, there exist a handful of favored policies that have received wide adoption among states. Net Metering provisions have been adopted by 46 states as well as the District of Columbia (DC), which allow for residents with renewable energy sources, such as residential-grade solar panels, to provide energy back to the electricity grid in exchange for a commensurate credit on future energy consumption from the grid (DSIRE, 2023). These net metering policies are accompanied by broadly contemporaneous laws which update a state's interconnection guidelines, standardizing and making transparent the technical and economic process of connecting distributed solar installations to the electricity grid. 47 States and DC have implemented broad updates to their interconnection standards, typically in line with net metering initiatives (DSIRE, 2023). 37 states and DC have enacted Renewable Portfolio Standards (RPS) laws, which represent a wide range of policies whose commonality is the setting of official targets such that a certain percentage of energy retail sales within the state be generated by renewable energy sources by a specified year (DSIRE, 2023).

RPS policies can range widely on a number of policy specifics. California's current RPS law requires that 60% of the state's electricity sales come from renewables by 2030, while Ohio's current RPS laws began with a 25% by 2025 target that has since been amended downwards to 8% by 2025 (DSIRE, 2023). Some state RPS policies apply only to the state-owned electricity regulator, while others apply to all retail sales in the state. More variation still lies in source-specific carve-outs that are common in RPS policies, wherein total renewable percent sales targets are segmented by technology, requiring certain percentages from specific favored energy sources, such as solar or offshore wind. (DSIRE, 2023). In addition to the widely adopted Net

Metering and RPS policies, there are a litany of boutique tax credits, subsidies, and government programs enacted by smaller numbers of states. They will be familiar in mechanism amongst each other and when compared to other areas of US policy making, and therefore would be excessive to list in full here. Exceptional policies will be noted in the policy attribution phase of the break detection model, and the broad effects of tax and subsidy policies will be surveyed in the literature where available.

The key findings of RPS literatures on energy creation and emissions will be summarized here. To begin with RPS policy's most direct goal, increasing renewable energy deployment, results have been unpromising at the state level. Studies treating RPS as a homogenous binary variable have predominantly found small negative or nil effects of RPS policy on in-state renewable energy deployment (Shrimali, Jenner, Groba, Chan, & Indvik, 2012). Yin and Powers (2010) implement a measure of RPS policy intensity in attempts to account for variation in RPS policy, and while they do find a significant positive effect of RPS on renewable energy deployment, this effect is not reproducible in datasets from other jurisdictions, nor in direct reproductions of the approach of Yin and Powers with subsets of their data which account for changes in measurement procedure within the initial study's dataset (Shirmali et al., 2012).

Analyses of RPS policy's effect on renewable energy deployment which account for the spatial aspects of electricity grid dynamics have produced more promising results. Shirmali et al. (2012) include metrics of inter-state trade in electricity in their regressions, as well as a control variable indicating if neighboring states have implemented RPS policies. This modeling approach produces weakly robust positive findings for RPS policies encouraging renewable deployment and suggest that RPS-implementing regions may undergo a dynamic whereby renewable energy deployment flows to the least-cost state for its development, regardless of whether that state in particular has enacted an RPS policy. This hypothesis is lent support by Bowen and Lacombe's (2015) empirical assessment of the effects of U.S. RPS policy when observed on the level of electricity sharing regions rather than states, which find robust positive effects on renewable electricity deployment at this higher jurisdictional level.

While regional versus state-level effects can be confounding for precise analysis of RPS policy's effectiveness on renewable energy deployment, the econometric relationship between state-level RPS policy and state-level residential emissions should be more straightforward to estimate. Whether energy comes within or without state bounds makes no difference for emissions accounting, so RPS policies requiring some portion of retail electricity sales be sourced from renewable energy should show up straightforwardly in emissions data. In spite of, or perhaps because of, this theoretically straightforward relationship, there exists markedly less empirical literature estimating RPS policy's impacts on emissions than exists for the aforementioned energy creation metric.

Approaches focusing on theory-based mathematical models tend towards findings that support the economic theory proposition that RPS is a 'second-best' policy option that is higher in cost than approaches that focus on minimizing abatement cost, with inefficiency concerns growing more prevalent in results as RPS policies hew closer to industrial organization policy, with carve-outs favoring specific technologies (Bento, Garg, and Kaffine, 2018; Young, Bistline, 2018). While no empirical studies exist to the author's knowledge focusing on U.S. state-level emissions reduction effects of RPS policy, national-level estimations have placed the effect of U.S. RPS policy at an emissions reduction of 4% nationwide from 1997 to 2010, compared to business-as-usual counterfactuals (Sekar and Sohngen, 2014).

In contrast to RPS policy's focus on the commercial energy grid, other state-level policies focus on encouraging residential-level renewable deployment. Literature on the efficacy of these policies will be summarized here. Major solar incentive policies in wide use comprise net metering and interconnection guideline updates, a variety of tax incentives, and direct subsidies. The small econometric literature on policy efficacy in this space consistently shows that tax incentives, no matter whether they operate through income, sales, or property taxes, are not statistically significant drivers of residential solar deployment. Direct cash or subsidy incentives, which act at the point of purchase and so beneficially bypass the delayed compensation system of tax credit schemes, do see some weak statistical significance in terms of encouraging residential solar installation (Matisoff and Johnson, 2017, Shrimali and Jenner, 2013). Crucially given its widespread adoption, net metering policies also are not found to have statistically significant effects of solar deployment, (Shrimali and Jenner, 2013) but through promising results from interaction terms may be an important prerequisite or amplifier for future solar incentives (Matisoffa and Johnson, 2017). Interconnection standards policies, which tend to be enacted in a broadly contemporaneous manner with net metering initiatives and therefore may potentially benefit from that amplifying effect, present in the data as a weakly statistically significant positive effect on residential solar deployment. (Shrimali and Jenner, 2013)

The remaining sections of this essay are as follows. After an overview of general trends in the data, as well as notes on its usage and limitations, I will outline the econometric methodology used in this essay, elaborating on its practical strengths, technical details, and theoretical motivations. Following this, results of the essay's analysis will be presented and discussed, delving into the notable findings of the model and the policy design repercussions they may indicate. Finally, a concluding section will note key findings and potential areas for future extended research.

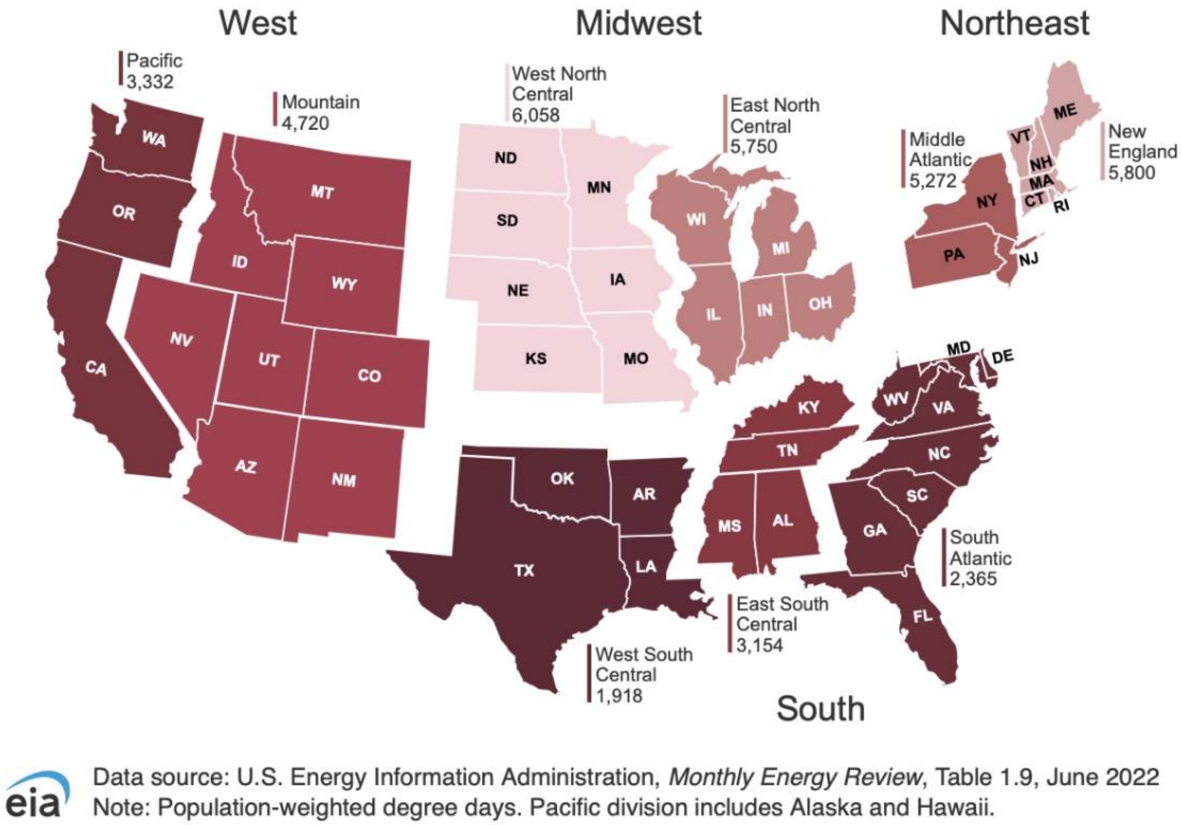
Data

This paper focuses on yearly, U.S. state-level data on residential carbon dioxide emissions which include emissions owing to the energy production demands of households. This data is sourced from the U.S. Energy Information Administration (EIA, 2023), and spans from 1970-2019. Five control variables enter the model to account for underlying non-policy characteristics that may influence emissions. Heating degree days (HDD) and cooling degree days (CDD), also collected from the EIA, act as measures of temperature-driven demand for heating and cooling in residential areas, and thereby predict the energy use associated with cooling and heating functions. Degree days compare mean outdoor temperatures to a standard temperature, usually 65° Fahrenheit in the United States (EIA, 2023).

Degree days are reported by the EIA in nine regional divisions of 3-9 states, rather than on a state-by-state basis. EIA degree day data is an aggregated measure created by weighting degree day observations from weather stations throughout a regional division by that station's associated population, as a percentage of total regional population. In order to cohere with state-level emissions data, the regional average figures for HDD and CDD are assigned to each state in that EIA region. The combining of regional degree day data with state-level data on emissions does introduce some room for error or misattribution. The East South Central region, for instance, includes only Texas, Oklahoma, Louisiana, and Arkansas. Texas is both disproportionately populous and extends substantially further south towards the equator when compared to the other states in the region, and therefore it stands to reason that Texas may bias the data for the more-northern Oklahoma and Arkansas, forcing them to present in the data as having fewer HDD and more CDD than is actually experienced in these states. While state-level fixed-effects could account for an average discrepancy caused by this regional-level data, the model could misrepresent the response of residential emissions to large changes in degree days for certain states. Nevertheless, degree days are a strong determinant of household energy demand and residential emissions, and robustness checks will be performed to ensure any undue effects stemming from regional degree day data are identified. A chart of degree day regions sourced from the EIA is given in Figure 1 below.

A final note on the EIA's degree day data which is made clear by the figure below is that no data is recorded from non-contiguous U.S. states, which removes Alaska and Hawaii from the paper's analysis. To the best of my knowledge, comprehensive and reliable state-level data on degree days is not available for the time period under study. Subsequent studies which are narrower in focused time period or number of states may be able to exploit more precise geographic data on degree days and avoid regional-level degree day data as a source of potential error.

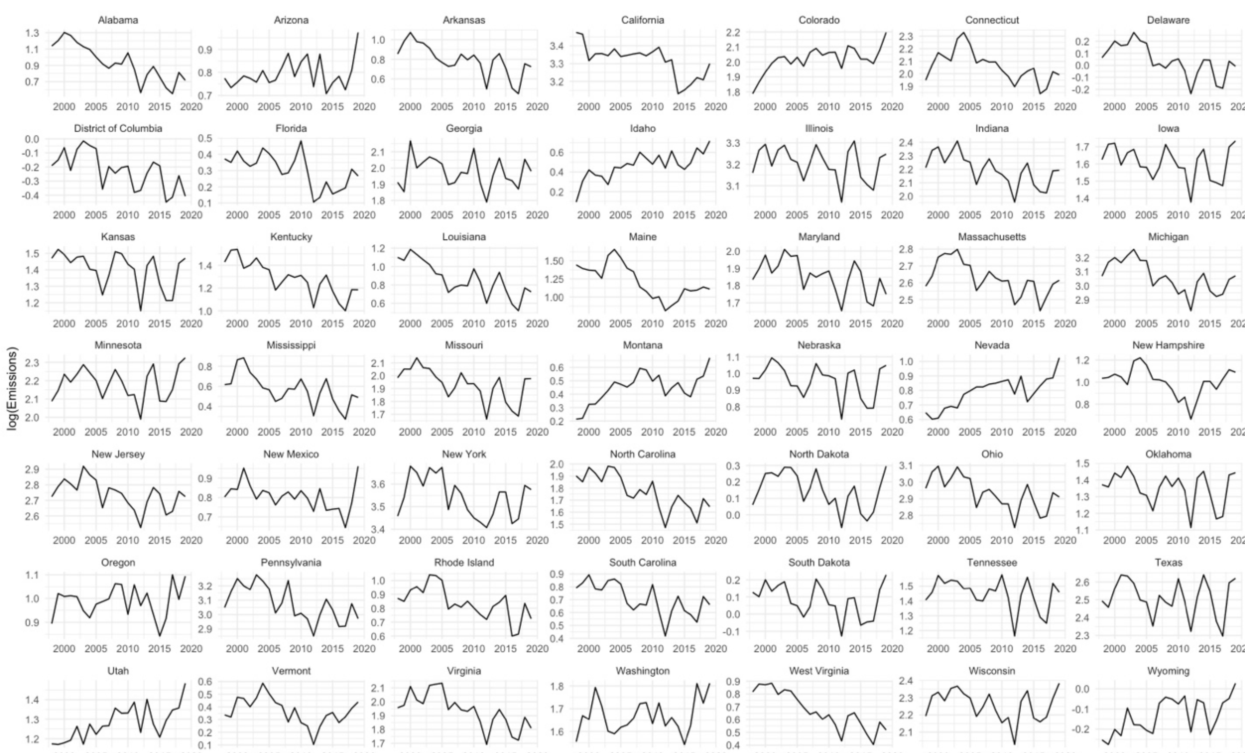
Figure 1 - Heating Degree Days by Region



Continuing with descriptions of control variables and their sourcing, state-level data on population is taken from the U.S. Census Bureau. (U.S. Census Bureau, 2020). State-level data on Gross Domestic Product is sourced from the U.S. Bureau of Economic Analysis (BEA). This GDP data is the limiting factor in terms of the time period able to be assessed, as the BEA's measurement processes for GDP change in the year 1998, and the bureau therefore cautions against combining GDP data pre- and post-1998 (BEA, 2023). The effective time period for which all data is complete and without issue is therefore 1998-2019. Finally, to account for fluctuations in the energy market and the potential substitution effects they may have on residential energy usage and emissions, state-level data on the residential price of natural gas is also collected from the EIA (EIA, 2023).

With all relevant data collected, residential emissions are then log-transformed, along with population, GDP, and the natural gas price. HDD and CDD data are left untransformed. Log-transformation of variables is undertaken so that the interpretation of coefficients and break magnitudes is comparable across states in percentage rather than absolute terms. Figure 2 below provides a time-series graph of the log of residential emissions for the 48 contiguous U.S. states and DC.

Figure 2 - Log(Emissions) by State and Year



The trends present in Figure 2 reveal some key features of the continental U.S.'s residential emissions landscape. Most immediately apparent is the data's high variability on a year-to-year basis. Many states experience their absolute maximum and minimum recorded emissions over the 21-year time period under study within the same five-year span. See Texas from 2012-2017, Washington from 2014-2019, and Illinois from 2010-2015. This variation tends to transcend state boundaries, with extraordinarily high- and low-emission years echoing across geographic regions as well as at the national level, as with the notable dip in emissions in 2012 that appears in the data coast-to-coast, apparent in the trends of Delaware, Florida, and California concurrently, among many other states. Also notable in a visual inspection of the data is that there appears to be no clear trend in residential emissions over time. There is neither a steady increase attributable to rising populations or living standards and an associated increase in demand for residential energy, nor is there any steady decrease in emissions that could be attributed to national-level policies, or broader economic trends such as energy efficiency improvements or a declining price of renewable energy.

Methods

The methods employed in this paper draw from the works of Pretis (2022), Koch et al. (2022), Pretis and Schwarz (2022), using autonomous break detection in panel data models towards the aim of policy attribution and analysis. In this section, I will provide a short overview of the methods of these papers, after which I will detail this essay's application of the methodology to residential emission abatement policy.

Break Detection to Detect Treatment

To begin with, I will summarize here Pretis and Schwartz's (2022) work situating the methodology of the break detection approach within the broader literature on econometric theory and practice. Break detection is in common use in time series analysis of policy impacts. However, it is difficult to assert the causality for detected structural breaks when most time series data is without an effective control group, and/or the super-exogeneity of the policy interventions under study is in question. In the panel data space, there are some existing approaches for the detection of breaks, but Pretis and Schwartz find no scholarship formally considering the link between structural breaks and treatment effects, as attempted in time series work. Wooldridge (2021) showed that heterogeneous and time-varying treatment effects can be consistently identified and estimated in the two-way fixed effects (TWFE) framework, using the interactions of treatment timing and dummy variables. Pretis and Schwartz build on this work, showing that in TWFE settings, treatment dummies are equivalent to structural breaks, taking the form of a step-shift in the individual fixed effects of the panel units. Estimating a TWFE panel model and searching it for potential structural breaks can therefore be interpreted as a search for unknown treatment effects, by the equivalence of fixed effect step-shifts and treatment dummies. This approach contrasts with time series break detection in that units under study without breaks can be used as a control group against which structural breaks can be identified. Finally, a strength of this approach relative to the large existing literature on TWFE policy evaluation is that the reverse-causal estimation strategy can account for previously unknown or unconsidered treatments. The policy attribution process is agnostic to which policies, well-established or novel, are included in attribution. Instead, the process searches for any applicable policies which may explain the unexplained variation of the base model, resulting a greater potential to identify novel treatments than in an effects-of-causes framework (Gelman and Imbens, 2013). This is a boon in the policy area of residential emissions reductions, where a large variety of policies have been tried, but relatively few large reductions in emissions can be seen in the data.

Moving to empirical uses of break detection for policy attribution in a TWFE panel model, this section will now summarize Pretis (2022) and Koch et al. (2022). Pretis (2022) assesses the effectiveness of British Columbia's carbon tax in reducing both sector-specific and aggregate C02 emissions. The well-established difference-in-differences approach is used, with results that are replicated afterwards by the novel break-detection approach. Using both methods, the carbon tax was found to have a statically significant effect only on emissions in certain sectors, while no statistically significant effect was found for aggregate emissions. In addition to replicating the findings of other models, the break detection methodology was able to identify several significant breaks aside from the carbon tax under study, attributable to various restructurings of provincial energy grids.

Koch et al. (2022), in contrast to Pretis (2022), narrows the scope of inquiry purely to road-related C02 emissions, but broadens the policy question being asked to include any policies undertaken in the time frame under study. This broadening of the question is available because of the exclusive use of the aforementioned break-detection methodology, using EU data on road C02 emissions to detect structural breaks at the member state level, after which policy mixes can be attributed to those breaks. Koch et al. (2022) find ten structural breaks in their data, six of which are found at their model's highest targeted significance rate, with an expected false positive rate of 0.1%. A notable benefit of the break detection approach over traditional difference-in-differences methods in the context of Koch et al. (2022) is that break detection allows for the assessment of a variety of policy mixes within the same analysis. This allows not only for comparisons of effectiveness between individual policies, but also provides a view into the potential cumulative effect of multiple policies acting at the same time. Indeed, one central conclusion of Koch et al. is that combinatory policy regimes featuring both carbon, fuel, or road-use taxes as well as taxes or subsidies based on vehicle type appear in the data as the most effective regimes for reducing emissions.

In terms of methodology, Pretis (2022) and Koch et al. (2022) saturate a TWFE panel with a full set of step shifts for every policy jurisdiction at every point in time under study. Variable selection methods from machine learning are used that allow the model to have more candidate variables than observations, which in turn allows the model to identify breaks independently, without the need for knowledge of break timing in advance. In panel data of N policy jurisdictions and T time periods, these new candidate variables add N(T-1) potential break variables, some number of which can be deemed as significant structural breaks depending on model specification. After choosing a targeted significance rate, those break variables that reach the significance threshold remain in the model, while those deemed statistically insignificant are dropped. The remaining significant break variables can then be interpreted as heterogeneous treatment effects, having been estimated through the interactions of unit-fixed effects with treatment timing.

The mechanical process of model creation is similar between Koch et al. (2022) and this essay. Therefore, the following section will summarize the model creation methodology of Koch et al. (2022), detailing how it has been adapted for the purposes of this paper. For this paper, the criteria for model selection and statistical packages used are unchanged in comparison to Koch et al. (2022), but the choice of independent and control variables differ, leading to slightly differing equations. To begin model specification, a TWFE panel model is saturated with a full set of step shifts, represented as:

$$\log(\text{Emissions})_{i,t} = \psi_i + \rho_t + \sum_{j=1}^{N} \sum_{s=2}^{T} \tau_{j,s} \mathbf{1}_{i=j,t \geq s} + x'\beta + \epsilon_{i,t}$$

Where ψ_i and ρ_t denote unit and time fixed effects, and $x_{i,t}$ is a vector of control variables comprising log(population size), heating degree days, cooling degree days, log(GDP) and log(residential price of natural gas). The treatment coefficients $\tau_{j,s}$ are assumed to be sparse with zero coefficients for all but the treated jurisdictions (where treatment is unknown a-priori). Using the machine learning functionality of the R package 'getspanel', and the 'gets' block search algorithm contained within it, we are able to remove all but the breaks with a targeted level of significance. The block search algorithm is preferred over alternative shrinkage-based methods, such as LASSO and its derivatives, due to the ability to target a given level of significance. This allows for a stringently low expected false positive rate, if desired. The breaks which are deemed significant according to the 'gets' algorithm can then signify the presence of true, potentially unknown treatment effects. Letting $\widehat{Tr}$ denote the treated jurisdictions, along with associated treatment timings $\hat{T}$ for each element of $\widehat{Tr}$, the post-algorithm model can be given by:

$$\log(\hat{\text{Emissions}})_{i,t} = \hat{\psi}_i + \hat{\rho}_t + \sum_{j \in \hat{T}r} \sum_{s \in \hat{T}_j} \hat{\tau}_{j,s} \mathbf{1}_{i=j, t \geq s} + x'\hat{\beta}$$

Where coefficients $\hat{\tau}_{j,s}$ denote the estimated heterogeneous treatment effects for the detected treated jurisdictions. These treatment effects are each individually tied to specific states in specific years, denoting time periods in policy jurisdictions where emissions have over- or under-performed the model's fundamentals to a statistically significant degree. For the model's negative breaks, which denote statistically significant and large reductions in emissions, we can observe policy mixes in the break state for the years around the break, and attribute the detected reduction in emissions to said policy mix.

For the sake of attribution, assessing the model's level of certainty as to the timing of breaks is crucial. Rather than treating detected breaks as indelibly associated with the exact year of their detection, the construction of confidence intervals around the detected breaks allows for a fuller and more certain picture of the policy mix associated with the reduction in emissions. Hendry and Pretis (2023) details the process of estimating confidence intervals through the use of the approximate normal distribution of error terms in order to compute the probability of underlying breaks falling within a specified interval around a step-indicator saturated model's breaks. This process is undertaken in this paper through the R package 'getspannel'. The range of dates indicated by these confidence intervals, rather than the model's exact year estimates, will serve as the basis for the policy attribution step.

The attribution step consists of matching state-level policy interventions to the state and year range of the model's detected breaks. Any policy applicable state-level policy interventions implemented within the confidence intervals of a given break are considered, and additionally I allow for a 'grace period' of two years prior to the break range to account for the potentially time delayed effects of many energy policies. Changes to energy grids, or the uptake of residential solar panels in response to policy incentives, for instance, may occur on a larger time frame than a strict year-by-year approach may be able to interpret.

In discussion of policy mix attribution, it should be noted that the break detection approach employed by this paper targets the discovery of sharp, quick discontinuations in emissions. Therefore, the subsequent attribution should also be considered tailored to the discovery of sharp, swift discontinuations in emission reductions policy. This is to the notable exclusion of policies that act gradually or ramp up their effects over time, which is especially notable for emissions policy. A Renewable Portfolio Standard policy that increments its clean energy targets by 1% each year, for instance, may never reach the required drop in emissions within an isolated yearly data point to be considered a break in the model, but may nonetheless be effective in reducing emissions over the long term. However, the model is able to detect discontinuities in such long-form policies, detecting significant shifts in emissions after an RPS policy is amended to shift future targets upwards, for instance. In exploiting these discontinuities, the model is able to assess the effectiveness of these long-term policies, given that those long-term policies are widely spread and long lasting enough to have received updated legislation in enough jurisdictions to draw meaningful statistical conclusions from. Some long-term emissions reduction policies without a substantial number of step-shift breaks in their policy, however, may elude detection in the model.

Policy Database for Ex-Post Attribution of Detected Breaks

The Database of State Incentives for Renewables and Efficiency (DSIRE), compiled by North Carolina State University, is the most comprehensive source on policies in support of clean energy generation and energy efficiency in the United States, and acts as the policy attribution database for this paper (DSIRE, 2023). All state-level policies within the DSIRE relating to residential emissions for a given break state and within the year range specified by the model or the two years immediately prior to the break range will be noted in break attribution. As a final note on methodology, the results of some standard robustness checks for this paper's model can be found in the appendix. These include running the model with robust standard errors, as well as checks for the consistency of breaks and coefficient estimates as the model changes in variable specification. Based on these checks, the results of the model are considered sufficiently robust for the purposes of this paper, those being break detection and subsequent policy mix attribution.

Results and Discussion

Regression

Table 1 - Regression Summary, 0.1% Targeted Significance Level

	State Residential Emissions
Population	0.837^{***}
	(6.63e-2)
HDD	1.47e-4***
	(7.65e-6)
CDD	4.54e-6
	(1.69e-5)
GDP	0.131^{***}
	(4.14e-2)
Natural Gas Price	-0.159^{***}
	(2.07e-2)
Observations	1078
Cross-Sections (N)	49
Time Periods (T)	22
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$	

A regression summary for the model is provided in Table 1 above. The characteristics of the regression model will be assessed before analyzing detected breaks and their coefficients, which are reported later in the results section. Table 1's regression coefficients are in line with conventional theoretical models of residential emissions intensity. The population of a state, its level of wealth as measured by GDP, and the demand for heating in heating degree days are all statistically significant drivers of aggregate emissions levels. Interestingly diverging from heating degree days, cooling degree days are not statistically significant drivers of emissions in the model. This may be a result of drawing data from each state in the contiguous U.S. as the base dataset, which will necessarily include many states for which air conditioning or other energy-intensive cooling devices are not widely proliferated. It is entirely possible that a subset of warmer states in the southern parts of the U.S. would yield a statistically significant coefficient for cooling degree days, but this effect is crowded out by its lack of effect in more northern states with less cooling demand.

Representing the potential substitution effects brought about through increasing energy costs, the price of natural gas enters with strong statistical significance as the only negatively correlated control variable in the model. Some of the empirical literature on RPS policy indicates increasing energy prices as a key emission-reduction mechanism for RPS policy, and that the modeling of energy prices can attenuate the observed effects of RPS-related emissions reductions (Sekar and Sohngen, 2014). To account for this, the model has also been re-run absent natural gas prices as a control variable. The regression and break results of this model are listed in the appendix and will be summarized here. The effects of removing natural gas prices on the model is minimal. When compared to the base model at the highest target significance level, 0.1%, the model without natural gas increments break effects and regression coefficients up or down by 0.01 or 0.02 log points, and renders a break in Florida in 2012 significant in the 0.1% targeted false positive rate model, rather than only in models at a 1% or 5% targeted false positive rate. As these are the sum total of changes in results between models, for discussion and analysis or results the full model with the included effect of natural gas prices will be used.

Breaks

The model finds twelve negative emission breaks at the lowest (most conservative) targeted level of significance, a false positive rate of 0.1%. As noted in Koch et al. (2022), one concern with the break detection model is that an agnostic detection approach may neglect some real treatments which are lesser in effect than the most stringent breaks. To allay this concern, the model is run again at two higher (less conservative) target significance levels, 1% and 5%, yielding two novel negative breaks of small magnitude in the 1% model, and seven such novel breaks in the 5% model. The 1% model additionally splits a 2006 break in North Carolina into two separate breaks in 2006 and 2008, but this is not replicated in either the 0.1% or 5% model, and as such is not considered a novel break. A summary of the negative breaks found in all three models are detailed in Table 2 below with information on break magnitude, standard errors, the year of the break, and 99% confidence intervals around the break years. The model also finds a variety of positive emissions breaks in the data. However, for the sake of containing the scope of this essay to the topic of effective emission reduction policies, these positive breaks will not be listed in the table below, or analyzed in detail. For reference on effect scale, emissions are logged in the model, and so the effect of breaks can be seen as logged differences in emissions, approximating percent reductions for small values.

Table 2 - Summary of Negative Breaks Detected Across Models

State		Targeted Significance Level		
		5%	1%	0.10%
Alabama	Effect Size	**-0.184**	**-0.184**	**-0.190**
(1st Break)	Standard Error	-0.026	-0.028	-0.025
	Year	2003	2003	2003
	99% CI	±1	±1	±1
Alabama	Effect Size	**-0.138**	**-0.142**	**-0.142**
(2nd Break)	Standard Error	-0.023	-0.024	-0.025
	Year	2012	2012	2012
	99% CI	±2	±2	±2
Arkansas	Effect Size	**-0.129**	**-0.14**	**-0.142**
(1st Break)	Standard Error	-0.024	-0.025	-0.027
	Year	2003	2003	2003
	99% CI	±2	±2	±2
Arkansas	Effect Size	**-0.059**		
(2nd Break)	Standard Error	-0.029		
	Year	2017		
	99% CI	±11		
Delaware	Effect Size	**-0.114**	**-0.124**	**-0.112**
	Standard Error	-0.022	-0.023	-0.024
	Year	2006	2006	2006
	99% CI	±3	±3	±4
DC	Effect Size	**-0.177**	**-0.216**	**-0.198**
	Standard Error	-0.028	-0.028	-0.029
	Year	2016	2016	2016
	99% CI	±1	±1	±1
Florida	Effect Size	**-0.106**	**-0.119**	
	Standard Error	-0.021	-0.023	
	Year	2012	2012	
	99% CI	±4	±3	
Indiana	Effect Size	**-0.091**		
	Standard Error	-0.022		
	Year	2004		
	99% CI	±5		
Kentucky	Effect Size	**-0.142**	**-0.159**	**-0.162**
(1st Break)	Standard Error	-0.029	-0.03	-0.033
	Year	2001	2001	2001
	99% CI	±2	±2	±2
Kentucky	Effect Size	**-0.061**		
(2nd Break)	Standard Error	-0.026		
	Year	2016		
	99% CI	±10		
Louisiana	Effect Size	**-0.153**	**-0.151**	**-0.164**
	Standard Error	-0.024	-0.025	-0.027
	Year	2003	2003	2003
	99% CI	±2	±2	±2
Maine	Effect Size	**-0.347**	**-0.349**	**-0.291**
	Standard Error	-0.027	-0.029	-0.026
	Year	2008	2008	2008
	99% CI	±0	±0	±0

*(Maine has a positive break of (+0.179, +0.178, +0.174) in 2015)

State		Targeted Significance Level		
		5%	1%	0.10%
Mississippi	Effect Size	**-0.101**		
	Standard Error	-0.024		
	Year	2003		
	99% CI	±4		
North Carolina	Effect Size	**-0.215**	**-0.138**	**-0.207**
(1st Break)	Standard Error	-0.021	-0.039	-0.024
	Year	2007	2006	2006
	99% CI	±1	±2	±1
North Carolina	Effect Size		**-0.098**	
(2nd Break)	Standard Error		-0.038	
	Year		2008	
	99% CI		±5	
North Dakota	Effect Size	**-0.108**	**-0.149**	**-0.155**
(1st Break)	Standard Error	-0.029	-0.026	-0.028
	Year	2009	2010	2010
	99% CI	±3	±2	±2
North Dakota	Effect Size	**-0.079**		
(2nd break)	Standard Error	-0.03		
	Year	2013		
	99% CI	±7		
South Carolina	Effect Size	**-0.129**	**-0.135**	**-0.122**
	Standard Error	-0.021	-0.022	-0.023
	Year	2007	2007	2007
	99% CI	±2	±2	±3
South Dakota	Effect Size	**-0.081**		
	Standard Error	-0.023		
	Year	2004		
	99% CI	±6		
Texas	Effect Size	**-0.085**	**-0.093**	
	Standard Error	-0.023	-0.025	
	Year	2004	2004	
	99% CI	±6	±5	
Virginia	Effect Size	**-0.136**	**-0.135**	**-0.129**
	Standard Error	-0.02	-0.021	-0.023
	Year	2008	2008	2008
	99% CI	±2	±2	±3

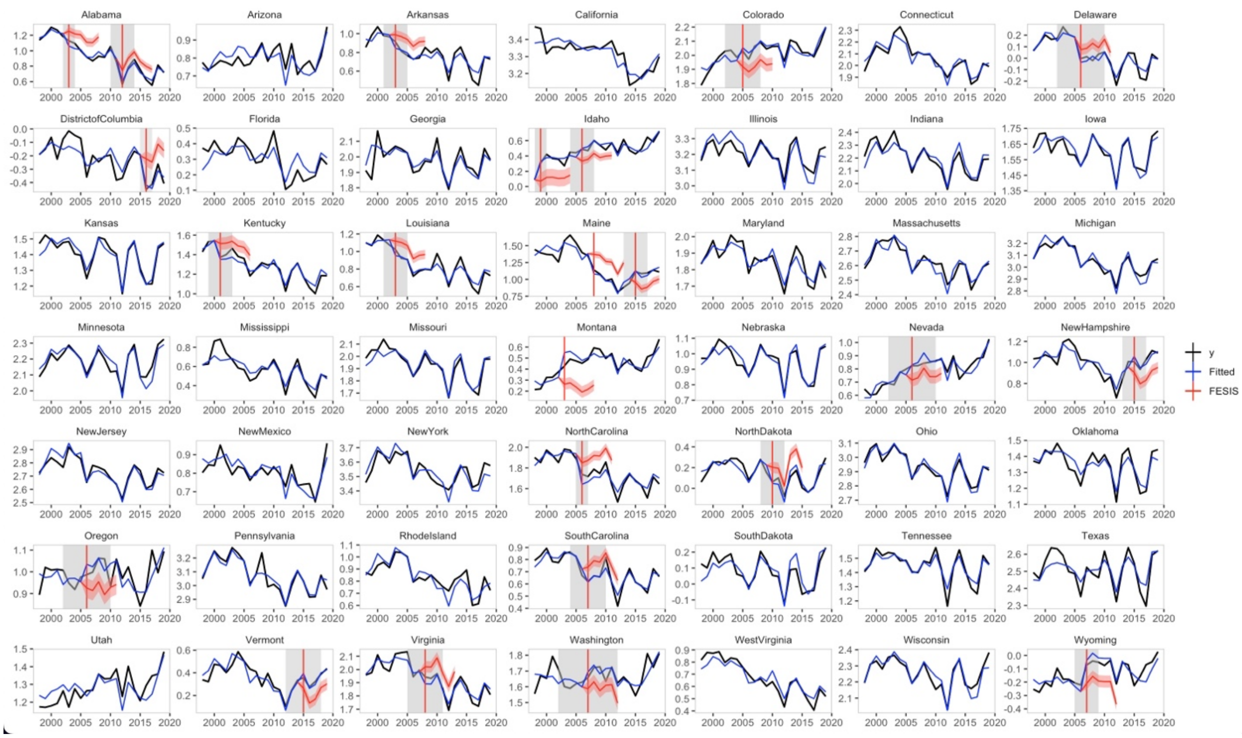
The effect size for breaks in the most stringent 0.1% model tend to fall within the bounds of 0.10 and just above 0.20 log point reductions. A notable exception to this trend is Maine, with its 2008 break reaching an effect size of -0.291 in the 0.1% model, which only grows greater in magnitude in lower stringency models. This is the greatest single-year reduction break observed in the model, but this outlier is tempered by a subsequent positive break in Maine in 2015, with a magnitude of +0.174. Combining these effects yields a value of -0.117, which is within the normal range of break effect sizes. Given this complication, Maine should not be considered the high watermark for emissions reduction in the model. Maine has notably caused outlier data issues in similar studies, owing to the small size of its electricity grid rendering objectively small changes in grid structure as uncharacteristically large shocks in relative data. (Shrimali et al., 2012)

Leaving aside Maine as an outlier, the remaining highest reduction breaks belong to North Carolina in 2007 (-0.207), DC in 2016 (-0.198), and Alabama in 2003 (-0.190). Louisiana, with its 2003 break of magnitude -0.164, and Kentucky, with a 2001 break of magnitude -0.162 comprise the following batch of effect size. North Dakota's 2010 break has a magnitude of -0.155, which marks the final standout data point among the breaks, with the remaining five breaks in the 0.1% significance model ranging in effect size from -0.112 to -0.142. Throughout the model, confidence interval ranges have a general trend of increasing as effect sizes decrease.

As expected, the 1% targeted significance model adds breaks which are smaller in magnitude and less certain in year specification. Florida's 2012 break has a magnitude of -0.119, with a confidence interval range of ±3 years. Texas's 2004 break has a magnitude of -0.093, with a range of ±5 years. While these breaks provide a reasonable if non-ideal window for policy mix attribution, the same cannot be said for many of the breaks detected in the 5% target significance model. The 5% model detects seven breaks in total, although none of these breaks bear the level of statistical confidence necessary for use in policy mix attribution, for reasons which will be elaborated on here. The 5% model finds novel second breaks in North Carolina and North Dakota's, but these breaks land within the confidence intervals of the original breaks identified in more stringent 1% and 0.1% models. The effects of these supposed 'second breaks' are therefore not statistically distinguishable from these states' original breaks, as is evidenced by the fact that the first breaks' effect sizes are attenuated in the 5% model. Novel second breaks are also detected in Arkansas and Kentucky, but while these breaks exist outside of the confidence intervals of these states' higher-scrutiny first breaks, the confidence intervals of their novel breaks are too large to yield workable policy mix results, at plus or minus 11 and 10 years respectively, so these breaks are also excluded from consideration. The three remaining novel breaks found in the 5% model are lesser in effect size magnitude than any break in the 0.1% model which serves as a base, and so given their appearance only in models with high false positive rates, they will also be excluded from policy analysis.

As a final presentation of model fit before moving to policy mix attribution, Figure 3 below plots the fitted values of the most conservative break model in blue over the previous data summary plot of Figure 2, plotted in black. Additionally, breaks are identified with red vertical lines at their break year. The shaded grey areas surrounding these break indicators represent the breaks' associated 99% confidence interval ranges. Counterfactuals representing estimated emissions in absence of the treatment effect of breaks are given by the red plots diverging from break years. For the sake of a more complete presentation of the model and its fit, all detected emission breaks are present, which includes many positive changes in emissions which have not been relevant to this essay's focus on effective emission reduction policies.

Figure 3 - Model Fit, Break Detection, and Counterfactual Emissions by State and Year

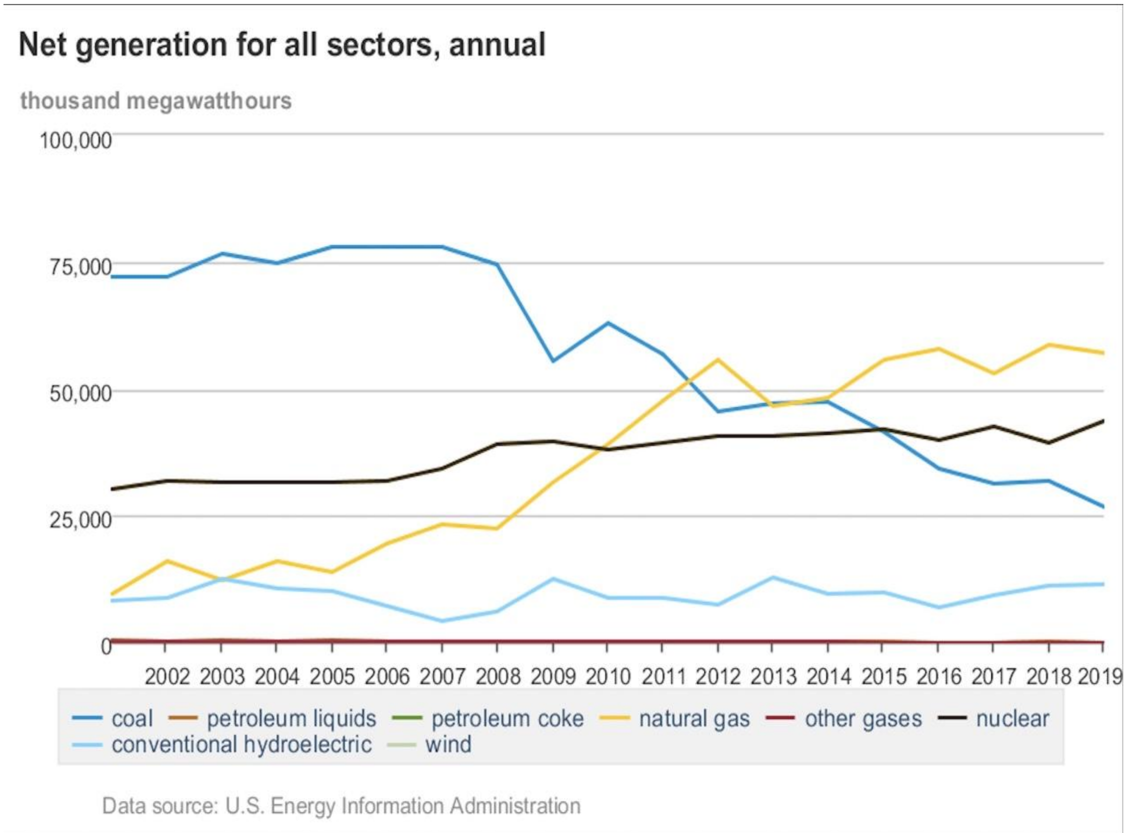


The previously noted year-to-year volatility in emissions data is captured well by the control variables of the fitted model. This is attributed primarily to the inclusion of Heating and Cooling Degree Days, which operate at the regional and national level in contrast to the other strictly state-level control variables, and appear to account for supra-state trends in emissions which might otherwise interfere with break detection. Estimated counterfactual pathways may appear visually steeper than their true values in cases where uncertainty around break timing is high. Certainty on counterfactual emissions pathways rises in tandem in with certainty around break timing and effect size.

In total, analysis of the models will attempt to match policy mixes focusing on the 12 breaks detected in the 0.1% model, with supplemental, weaker evidence being garnered from policy mix matches from the two breaks of the 1% model. These 14 breaks will be sorted by effect size and subsequently linked to policy mixes enacted during their associated break intervals. Not all breaks detected in the model, however, are able to be matched to state-level policies. Alabama's 2003 and 2012 breaks, as well as Kentucky's break in 2001 are without any state-level policies listed in the DSIRE within their break windows. These three breaks are therefore the most demanding of discussion, in that assessments of these breaks' validity has important bearing on the validity of policy-attributable breaks, and therefore on the policy conclusions that can be drawn from their analysis. If Alabama's large 2003 break is attributable to some general factor that may affect another state with equal likelihood, for instance, then the certainty of policy effects weakens. Attaining some certainty as to the mechanisms of these non-policy breaks is therefore crucial to assessing the strength of the model's findings for policy consideration.

On the level of electricity management, Alabama is an atypical state. Alabama is the second largest exporter of power within the U.S., exporting 45 million MWh in 2019, while only 15 of the lower 48 states exported 10 million MWh or above. (EIA, 2023). Given Alabama's abnormally large role in the trade of power, it might be assumed that Alabama would react to changes in energy demand differently from the average state, as is represented by the effects of the fitted model against which breaks are drawn. Degree day data for 2003 and 2012 in Alabama's region show surprise drops of more than 300 CDD in 2003 and nearly 500 HDD in 2012 when compared to their preceding years, representing a fall in domestic energy demand far above usual year-on-year ranges observed elsewhere in Alabama's data. It is possible that when Alabama 'over-performs' the emission reduction predictions of the model, what is being captured in the model is that the energy dynamic in Alabama for the 1998-2019 time period relies on the state's carbon-intensive fuels like coal in years of high domestic energy demand, but tends to export that coal in large amounts when domestic energy demand is low. In these low-demand years, Alabama may rely instead on its nuclear and natural gas power in place of coal. This may lead to a less carbon-intensive energy mix than would be seen either in Alabama’s usual years, or in other states’ low-demand years, wherein they simply use less coal energy in aggregate, but retain the same energy mix on a MWh-by-MWh basis. A more complete analysis of the energy dynamics at play in Alabama throughout the early twenty-first century is left for more specialized sources, but for the purposes of model analysis in this paper, it suffices to identify that Alabama is a unique state in terms of its energy management and trade behavior, its detected breaks occur at periods of unusually low domestic energy demand, and therefore the model may be detecting real reductions in emissions which nonetheless are not attributable to policy mixes, as they may be a result of economic factors unique to Alabama which lay beyond policy. The energy trade dynamic is given as one of many potential causes of the detected breaks but is not meant to be an exhaustive examination of the phenomenon.

Figure 4 - Alabama Net Generation by Source



Given in Figure 4 above is a graph of Alabama's mix of energy production for the time period under study (EIA, 2023). Notable in explaining Alabama's breaks is the large shift away from coal production and into natural gas as an energy source within the state. This trend finds a notable local maximum in 2012, the year of Alabama's second break. This corroborates attribution of Alabama's breaks to energy mix factors, and also denotes a responsiveness in Alabama's grid makeup to wider factors affecting the economic viability of potential energy sources. This makes for a potent link to the literature on RPS policy which notes that RPS implementation sees its strongest energy creation effects at the regional level, encouraging development in least-cost regional areas (Bowen and Lacombe, 2015). As Alabama already stands out as a hub for energy generation as signaled by its strong energy exporting behavior, then the observed policy-naive reductions in Alabama's residential emissions may be a result of the changing regional energy demands of a market becoming more saturated with RPS-affected jurisdictions. This phenomenon may assist in explaining some trends in Figure 4, such as the cyclical peaks in hydroelectricity production and the 2008 increase in nuclear power.

The case of Kentucky's 2001 break is less clearly attributable to consequential and unique factors of the state, but rather lends itself more in explanation to the limitations of the data. Data on heating and cooling degree days are pulled at the regional level, and as noted in Figure 2's rendering of degree day regions, Kentucky is the northernmost state in a four state block principally situated along the U.S.'s southern border. Examinations of available state-level data on degree days reveals a notable difference in the climate experienced in the East South Central region's southern states of Mississippi and Alabama, compared against the more northern climate of Kentucky (NCEP, 2023). As noted in the earlier section of the paper detailing data limitations, this situation of a small state encountering a climate substantially different from the bulk of the populated area of its degree day region is a situation ripe for data distortions, and has a strong potential to lead to unsubstantiated breaks. When running the break detection model absent degree day data, Kentucky is one of only two states to see their detected breaks removed, the other being Delaware in 2006, which is in a similar regional geographic position, as the small northernmost state of a region spanning disparate climates. Given the strong theoretical backing for data distortion, these results caution against interpreting Kentucky's 2001 data as a relevant break, and provides pause for interpretation of Delaware's 2006 break as well, despite a litany of policy efforts within the state at the time available for attribution. Conversely, that the 10 other breaks in the 0.1% model remain even when absenting degree days does well to assuage concerns that other states may be experiencing similar ghost effects as seen in Kentucky, as well as providing indication of general model robustness. With this and the above analysis, the conclusion is reached that the three policy-lacking breaks do not represent a generalizable issue in model specification.

With model concerns addressed, attribution of detected emission reductions to policy mixes can begin. What follows in Table 3 below is a list of all examinable breaks, sorted first by the highest statistical stringency of model in which they are detected, and then sorted within those groups by the effect size of their break. To the right of the table is a list of all policies relating to residential energy and emissions that have been identified within the timeline of the break's confidence interval range, with an additional lead time of two years previous to the break to allow for a delay in policy goal achievement. Policies that have received some support for emission reduction potential in previously surveyed empirical analysis are given in bold. Policies which have, to the knowledge of the author, not yet been assessed empirically for efficacy in the literature are given in underline. Policies such as net metering or income tax incentives, which have been assessed in the surveyed literature as having no statistical effect on green energy creation or emissions, are left as plain text.

Table 3 - Emission Break Policy Mix Attribution

State, Year (99% CI)	Approximate Effect Size	Year	Policy
0.1% Targeted Significance ***			
Maine, 2008 (2008-2008)	-29%	2006	**RPS increases targets**
* Net effect accounting for subsequent positive break places Maine 2nd to bottom	(-12% net 2015 break)	2006	"Efficiency Maine" Trust established
North Carolina, 2006 (2005-2007)	-20%	2005	Net Metering
		2005	**Interconnection Standards**
		2007	**RPS established**
		2007	Solar Rights - Permitting
District of Columbia, 2016 (2015-2017)	-20%	2015	Solar Energy Tax Credit
		2016	**RPS increases targets**
Alabama, 2003 (2002-2004)	-19%	2002-2004	No State-Level Policies
Louisiana, 2003 (2001-2005)	-16%	2003	Net Metering
		2003	Solar Property Tax Incentive
		2004	**Interconnection Standards**
		2005	Home Energy Loan Program: $6000 for energy efficiency upgrades
Kentucky, 2001 (1999, 2003)	-16%	1999-2003	No State-Level Policies
* Break Is not robust to removal of Degree Day climate data			
North Dakota, 2010 (2008-2012)	-16%	2007	**RPS established**
Alabama, 2012 (2010-2014)	-14%	2010-2014	No State-Level Policies
Arkansas, 2003 (2001-2005)	-14%	2001	Net Metering
		2002	**Interconnection Standards**
Virginia, 2008 (2005-2011)	-13%	2003	**Interconnection Standards**
		2007	Sales Tax Incentive - Energy Efficiency
		2007	Mandatory Green Power Option for Utilities
		2008	Solar Rights - Permitting
		2008	Energy Efficiency Property Tax Incentive
		2010	Income Tax Deduction - Energy Efficiency
		2011	RPS-like Energy Efficiency Resource Standard
		2011	Solar and Wind Permitting Standards
South Carolina, 2007 (2004-2010)	-12%	2006	Renewables Tax Credit
		2006	Energy Efficient Manufactured Homes Sales Tax Incentive
		2007	**Interconnection Standards**
		2008	Net Metering
		2008	Energy Efficient Manufactured Homes Tax Incentive
Delaware, 2006 (2002-2010)	-11%	2000	Net Metering
* Break Is not robust to removal of Degree Day climate data		2000	Delmarva Green Energy Fund Created
		2001	**Direct Subsidy - Green Power**
		2002	**Interconnection Standards**
		2005	**RPS established**
		2007	Sustainable Energy Utility Foundation (SUEF) established
		2009	Wind Power - Permitting
		2009	Solar Rights - Permitting
		2009	SUEF increases stringency
		2010	RPS-like Energy Efficiency Resource Standard
1% Targeted Significance **			
Florida, 2012 (2009-2015)	-12%	2008	Net Metering
* Break Is not robust to removal of Degree Day climate data		2008	**Interconnection Standards**
		2010	RPS-like Energy Efficiency Resource Standard
Texas, 2004 (1999-2009)	-9%	2000	**RPS established**
		2000	Property Tax Incentive - Renewables
* Break Is not robust to removal of Degree Day climate data		2002	**Interconnection Standards**

The results of the policy attribution table are consistent with established empirical literature on renewable energy creation. Policies which have received empirical support for their renewable energy creation effects are well-represented in breaks' policy mixes. RPS policy or derivatives thereof are present in 8 of the 11 policy-attributable breaks. Pure RPS policy accounts for 6 of these breaks, while the RPS-derivative Energy Efficiency Resource Standard (EERS) accounts for 3 breaks, with one overlapping break between EERS and RPS. Interconnection standards are present in a separate but overlapping subset of 8 of the 11 breaks. Taken as a whole, policy mixes containing one or both of pure RPS policy and interconnection standards account for all 11 policy-attributable breaks. While novel policies do appear in the data, the overwhelming impression relates to the extreme prevalence of RPS and Interconnection policy as the clear connective tissue between policy-attributable breaks.

The table's highest strength breaks, chronicling emissions reductions of 20% to 16%, are especially strong indicators of the strength of RPS policy for emissions reduction. RPS policy is involved in the policy mixes of three of these four policy-attributable breaks, as well as in Maine's massive but questionably short-lived 29% reduction in 2008. Isolating evidence indicating RPS policy's emissions-reduction efficacy can be found in North Dakota's impressive 16% reduction, for which RPS is the only policy within the policy attribution window. Additionally, DC's 20% reduction is attributed to only one policy other than the twelve percentage point increase in its RPS targets. This additional policy is a solar tax credit, a policy form with little empirical support in the broader literature for its efficacy in promoting energy grid changes or emission reductions. RPS policy is also linked to Texas's -9% 2004 break, as well as Delaware's -11% 2006 break, although these breaks are both smaller in magnitude and more complex in terms of policy mix when compared to the previously discussed breaks. Additionally, breaks in Delaware and Texas notably are not robust to the removal of degree day climate data, and so act as supplemental evidence to the more robust and precisely indicated findings above.

Interconnection standards also demonstrate a strong link to residential emission reduction, being the most widely identified policy in break-attributable policy mixes. Compared to RPS, interconnection standards are more spread out among policy mixes contemporaneous with both large and small emission reductions. The only three policy mixes that do not contain interconnection standards are Maine, (-29%/-12%) DC (-20%), and North Dakota (-16%). While these breaks are high in magnitude as a group when compared to the rest of the table, this is not to indicate that interconnection standards cannot be a strong driver of emission reductions. Arkansas's policy mix includes interconnection standards and associated net metering policy as the only relevant emission reductions policy during the break interval for its substantial -14% break, while Louisiana's -16% break has interconnection standards and accompanying net metering initiatives as two of only four policies. Interconnection standards are indicated in two of the top three emission reduction breaks in the model, when discounting Maine's emission drop to account for its subsequent positive shock. As such, interconnection standards are considered in the findings of this paper to have been effective emission reduction policy for the residential sector.

Moving to policies which have yet to be discussed in the surveyed literature, there are a number of unique policies which recur in the data, or which are noteworthy for their inclusion in policy mixes related to strong emission reduction numbers. One such notable policy is the RPS-derivative Energy Efficiency Resource Standards (EERS) scheme. EERS policies operate by the same mechanism as RPS policy, but focus on energy use reductions through efficiency upgrades as their targeted metric of choice, rather than measures of renewables penetration in a state's electricity sales. EERS is given in underline in the table above because despite EERS being an offshoot of RPS policy, it is uncertain whether the empirical findings detailing RPS policy's emissions reduction effects can be carried over to the similarly structured but significantly altered EERS policy.

EERS policies are part of three policy mixes attributed to emission breaks, while RPS-specific policies can be found in six. A lessened popularity alone is not reason enough to believe EERS policy is less effective than RPS policy, but EERS policy presents with less strong emission reduction behavior than its parent policy of RPS. EERS is found exclusively in emission reduction breaks of 13% or smaller effect size, and of its three attributed breaks, two of them are not robust to the removal of degree day data. Additionally, attempting to isolate for the effects of EERS policy is difficult, as it does not appear in any policy mix absent interconnection standards, which is already expected to have an emissions reduction effect based on surveys on the literature and isolated findings within this paper's data. At a minimum, these results do not indicate that EERS policy is a substantially stronger pathway for emissions reduction policy than the already existing and well-tested RPS framework.

Solar and wind permitting measures are found in three attributable policy mixes. Two of these breaks occur near the bottom end of break effect size, and due to either policy fervor in the case of Virginia or an exceptionally large confidence interval range in the case of Delaware, are stranded in policy mixes containing eight or more separate policies, which cautions against extrapolating out a large effect of these permitting laws on emissions. Solar permitting reform in the case of North Carolina's impressive -20% break should appear more promising, as the policy mix for that break contains only four policies, but two of those are interconnection standards and RPS, both of which have already proven their effectiveness. The data does not support solar or wind permitting reform as a substantial reducer of residential emissions.

Finally for novel policies observed in policy mixes, there is Louisiana's Home Energy Loan Program, which provides loans of up to $6000 for residential energy efficiency upgrades. This policy exists in a policy mix in which only interconnection standards is a proven policy, with net metering and a property tax incentive being the only other policy explanations for Louisiana seeing the highest percentage reduction in emissions for states not implementing an RPS policy, at -16% compared to the next highest -14%. It is feasible therefore that the Home Energy Loan Program could be responsible for this two percentage point gap. While these results alone are not conclusive enough to point to the efficacy of this loan policy, it does point to the Home Energy Loan Program as a potential area of further study.

Also in the realm of potential areas of further studies are unique and tangentially related policies out of Maine and Delaware, what will be termed here as 'efficiency trusts'. The establishment of the Efficiency Maine trust, as well as the creation of Delaware's Sustainable Energy Utility Foundation (SUEF) act as in-house expertise on energy efficiency incentives, programs, and best practices. The data does not provide any isolating policy mixes to assess their efficiency here, but the establishment of a new quasi-governmental agency to implement policies and build knowledge is a bold and uncommon step in comparison to other policies. That two such organizations appear in a small number of break confidence intervals may point to some efficacy in these setups worthy of investigation.

An analysis of state-level policy mixes contemporaneous with large, autonomously-detected reductions in residential emissions confirms the positive findings of the econometric literature, and also indicates why previous findings in this policy sphere have been so weakly statistically supported. Emission reduction breaks are strongly associated with interconnection standards legislation, which points to a successful policy lever states may have access to in meeting their climate goals. But the eight successfully identified interconnection standards policies belie the 39 other interconnection standards laws passed in the contiguous U.S. which were not identified in the model. The same worrying inconsistency shadows the six successfully-identified RPS policy interventions compared against 31 such policies that were not identified by the emissions break model. The lack of any other consistently identified workhorse policies which could lower emissions if passed in other jurisdictions leaves state policymakers either back at the drawing board entirely, or left to tinker with established RPS and interconnection standards policies, adapting them in the style of more successful peer states' policies. The notable lack of a downward trend in residential emissions data across the U.S. highlights a general lack in effective residential emissions reduction policy in the 1998-2019 time period, not only at the state level, but at the regional and federal level as well. The passage of 2022's Inflation Reduction Act after the time period under study, with its substantial clean energy investments, may represent a stronger emissions-reduction policy pathway for the future. The results of this analysis of state-level policy indicates that the residential emissions issue may be acted upon most effectively not at the level not of the state, but rather of the regional electricity grid and higher still with nationwide initiatives.

Conclusion

Residential emissions comprise a significant portion of the total emissions owing to large greenhouse gas emitting nations like the United States, and as such these emissions will need to be reduced in order to meet climate targets. Using the novel TWFE break-detection approach seen in Pretis (2022) and Koch et al. (2022), this essay examines the efficacy of state-level emissions-reduction policies within the contiguous U.S. through a 'causes-of-effects' framework. First, large reductions in residential emissions are detected in panel data through an autonomous machine learning process, after which these large reductions can be assigned to contemporaneous policy mixes, in efforts to identify common effective policies.

Fourteen such breaks were identified in this paper's model as suitable candidates for policy mix analysis, of which eleven were matched with contemporaneous policy mixes. Strong support was found for both Renewable Portfolio Standards (RPS) and Interconnection Standards as emission reduction policies, both of which individually were present in over half of the policy-relevant breaks. These findings confirm the results of previous assessments in the literature, and to a stronger degree of statistical significance. In general, however, the results of this analysis may serve as evidence against state-level policy being an effective jurisdictional level for residential emission reduction policy, as much of those emissions are determined by regional electricity grids which transcend state boundaries. Despite state-level emission reduction policy being fertile ground wherein many disparate policies are attempted, and isolated policies can be shown to have desirable effects, the aggregate picture is one of stagnant outcomes. Even the proven-effective Renewable Portfolio Standard and Interconnection Standard policies have large majorities of their state-level implementations go entirely undetected in the model, indicating a small average effect size. This, combined with a lack of empirically effective novel emission reduction policies detected through autonomous breaks, leads to a dour assessment of state-level residential emission reduction policy, in line with the literature surveyed.

Further research in the area may wish to focus on policy comparisons of break jurisdictions with non-break jurisdictions, identifying the particulars of effective policy at the state-level. Addressing the limitations of regional level climate data, additional statistical work may be performed on a more narrow band of jurisdictions that allows for more fine-grained control of climate-related variation in emissions.

Pessimism importantly does not characterize this paper’s overall findings on residential emission reduction policy. Emission reductions of up to 20% were credibly detected in the model, indicating a strong possible effect size for top-performing emission reduction policies when implemented effectively. The breaks states identified may be able to serve as examples of effective implementations of RPS or interconnection standards policies, for use in peer jurisdictions or indeed in higher levels of U.S. governance more in line with the jurisdictional areas that determine residential emissions. The wide variety of identified breaks in the model, as well as the consistency of identified policy in the greatest effect size emission reductions indicate that there do exist credible policy pathways to reduce residential emissions for large emitters like the United States. The 'laboratories of democracy', as state level policy may aspire to be, have yielded impressive results in isolated form, even if not in aggregate. While there is indication that state-level policy alone may not be sufficient or optimal in tackling the issue of residential greenhouse gas emissions, the results here exhibit successful policy mixes worthy of emulation for subsequent policy in peer jurisdictions at the state level and above.

Appendix

Table A 1 - Regression Summary and Break Detection by Varying Model Specification

	Model		
Variable	(1)	(2)	(3)
Population	0.837^{***}	0.888^{***}	0.621^{***}
	(6.63e-2)	(6.81e-2)	(7.70e-2)
HDD	$1.47e\text{-}4^{***}$	$1.55e\text{-}4^{***}$	
	(7.65e-6)	(7.74e-6)	
CDD	4.54e-6	9.69e-6	
	(1.69e-5)	(1.72e-5)	
GDP	0.131^{***}	0.158^{***}	0.294^{***}
	(4.14e-2)	(4.23e-2)	(4.75e-2)
Natural Gas Price	-0.159^{***}		-0.217^{***}
	(2.07e-2)		(2.46e2)
Observations	1078	1078	1078
Cross-Sections (N)	49	49	49
Time Periods (T)	22	22	22
	Note: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

Negative Break	(1)	(2)	(3)
Alabama 2003	-0.190	-0.203	-0.188
	(0.029)	(0.030)	(0.035)
Alabama 2012	-0.142	-0.155	-0.137
	(0.025)	(0.026)	(0.030)
Arkansas 2003	-0.142	-0.147	-0.152
	(0.027)	(0.027)	(0.032)
Delaware 2006	-0.112	-0.129	
	(0.024)	(0.025)	
DC 2016	-0.198	-0.193	-0.203
	(0.029)	(0.030)	(0.035)
Kentucky 2001	-0.162	-0.174	
	(0.033)	(0.033)	
Louisiana 2003	-0.164	-0.166	-0.174
	(0.027)	(0.027)	(0.032)
Maine 2008	-0.291	-0.298	-0.414
	(0.026)	(0.026)	(0.037)
North Carolina 2006	-0.207	-0.208	-0.212
	(0.024)	(0.024)	(0.028)
North Dakota 2010	-0.155	-0.164	-0.195
	(0.028)	(0.028)	(0.033)
South Carolina 2007	-0.122	-0.136	-0.123
	(0.023)	(0.024)	(0.028)
Virginia 2008	-0.129	-0.122	-0.144
	(0.023)	(0.023)	(0.027)

Table A 2 - Regression Summary and Break Detection, State Cluster-Robust Standard Errors

	State Residential Emissions
Population	0.837***
	(1.44e-1)
HDD	1.47e-4***
	(9.15e-6)
CDD	4.54e-6
	(1.70e-5)
GDP	0.131**
	(6.60e-2)
Natural Gas Price	-0.159***
	(3.60e-2)
Observations	1078
Cross-Sections (N)	49
Time Periods (T)	22
Note: *p < 0.1; **p < 0.05; ***p < 0.01	
Negative Break	
Alabama 2003	-0.190
	(7.86e-3)
Alabama 2012	-0.142
	(7.62e-3)
Arkansas 2003	-0.142
	(8.70e-3)
Delaware 2006	-0.112
	(1.69e-2)
DC 2016	-0.198
	(1.46e-2)
Kentucky 2001	-0.162
	(1.09e-2)
Louisiana 2003	-0.164
	(1.15e-2)
Maine 2008	-0.291
	(8.91e-3)
North Carolina 2006	-0.207
	(1.53e-2)
North Dakota 2010	-0.155
	(2.69e-2)
South Carolina 2007	-0.122
	(1.42e-2)
Virginia 2008	-0.129
	(9.77e-3)

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