Inframarginal Investments with Clean Energy Subsidies: Evidence from the Inflation Reduction Act

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Abstract

Subsidies are popular tools to promote socially beneficial behavior, including in the energy sector for addressing climate change and innovation externalities. However, there is concern that subsidy-based instruments could reward inframarginal firms and households that would have adopted these technologies anyway, which has been challenging to account for in policy analysis. This paper uses a stylized static model combined with empirical analysis and detailed numerical modeling to assess the extent of inframarginal investments for power sector tax credits, which have been augmented in the U.S. Inflation Reduction Act (IRA). Our empirical analysis indicates that a third of wind capacity additions and a half of solar additions are inframarginal in U.S. states without binding renewable portfolio standards (in contrast to states with mandates, where all subsidies are inframarginal). Numerical modeling suggests 28-72% of investments would occur without IRA's power sector credits. Analysis that treats all recipients as additional would underestimate the fiscal costs of tax credits, which are about two times higher for power sector credits. While this inframarginal participation increases abatement costs compared to previous analysis, the average abatement cost (\$96/t-CO_2) remains below recent social cost of carbon estimates (\$100-360/t-CO_2).

Keywords: Tax credits, energy subsidies, instrument choice, climate policy

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1. Introduction

Subsidy-based approaches such as tax credits, loans, and grants are popular tools to address externalities. In particular, subsidies have been used to encourage clean energy adoption, which can lower greenhouse gas (GHG) emissions, encourage innovation, and decrease energy expenditures for consumers. For instance, the U.S. Inflation Reduction Act (IRA) of 2022 was billed by supporters as an "historic commitment to build a new clean energy economy, powered by American innovators, American workers, and American manufacturers, that will create good-paying union jobs and cut the pollution that is fueling the climate crisis and driving environmental injustice" (White House, 2023). While Pigouvian taxes have been widely studied as emissions policies (Gillingham and Stock, 2018), there is comparatively limited evidence of the cost-effectiveness of clean energy subsidies (Newell et al., 2019).

Although tax credits have been popular with policy-makers, there is concern that subsidy-based instruments could reward inframarginal firms and households, raising questions about the extent of recipients who would have adopted with lower incentives or even in the absence of policy. Compensation for non-additional actions creates windfalls without accompanying behavior change, which decreases cost-effectiveness by increasing fiscal costs to the government without emissions reductions.[1] The non-excludability of tax credits, where it may not be possible to prohibit new projects from claiming subsidies, means that credits apply to all projects, allowing recipients to free ride by not taking additional effort beyond levels without subsidies.[2] However, it is challenging to

[1]This paper uses terms "inframarginal" and "non-additional" interchangeably to refer to subsidies and investments that would have occurred in the absence of subsidies.

[2]Non-additionality and inframarginal rents are issues for other policies such as subsidies for carbon offsets, energy efficiency, and alternative-fuel vehicles (Joskow and Matron, 1992; Bento et al., 2015; Huse and Lucinda, 2014), and economists have long been concerned about non-additional participants/free-ridership (Löfgren et al., 2002). Non-additionality is also a feature in debates about the effectiveness of other clean energy policies, including whether portfolio standards have increased renewable generation or whether they reflect trends that would have lead to deployment without standards. Feldman and Levinson (2023) find that the effects of renewable portfolio standards to date are small once endogenous non-additionality and interstate trading are taken into account.

assess an appropriate counterfactual without policy, especially with contemporaneous changes over time from other policies, technology cost declines, and other market drivers.

While there is a growing literature on instrument choice for clean energy policy and specifically on tax credit design and impacts (Newell et al., 2019; Bistline and Wolfram, 2024), these papers do not typically compare the extent of inframarginal investment or compare incentives across sectors. Boomhower and Davis (2014) summarize the additionality literature for energy subsidies and other public policies that incentivize socially beneficial actions. Most papers in the literature are focused on demand-side credits (Berkouwer and Dean, 2023; Boomhower and Davis, 2014). For instance, several ex-ante and ex-post studies find that between 40% and 77% of passenger vehicle tax credits in the U.S. go to households that would purchase an electric without a subsidy (Allcott et al., 2024; Cole et al., 2023; Xing et al., 2021).

To understand the extent to which different subsidies can reward firms and consumers for investments that would have occurred in the absence of policy, this analysis contributes to the literature on instrument choice and specifically the cost-effectiveness of clean energy subsidies for addressing emissions and innovation externalities (Sallee, 2011; Boomhower and Davis, 2014; Xing et al., 2021; Mignone et al., 2022; Bistline et al., 2023b). This paper provides a stylized static model (Section 2) combined with empirical modeling (Section 3) and detailed numerical modeling (Section 4) to assess the extent of inframarginal investments for power sector tax credits, comparing responses and non-additionality in these different settings. Empirical analysis can estimate the historic sensitivity of firms and consumers to all-else-equal changes in revenues and costs. The dynamic structural modeling can systematically investigate issues related to supply substitution and demand for clean energy that reduced-form methods cannot, including simulations of adoption with and without subsidies to quantify inframarginal investment. We apply both empirical and structural approaches to understand the IRA, the largest legislative climate policy in U.S. history, which offers a range of tax credits for zero-emitting electricity supply, end-use electrification, energy storage, carbon capture, clean hydrogen production, and others (White House, 2023).

This analysis finds potentially large shares of inframarginal recipients and non-additional investments for power sector tax credits. Inframarginal shares are linked to supply elasticities for supply-side-targeted subsidies and demand elasticities for subsidies that target the demand, with less (more) elastic demand implying lesser (greater) additional adoption from subsidies. Using data on locational marginal prices (LMPs) for wholesale electricity generation and utility-scale wind and solar capacity additions from 2010 to 2019, we estimate that about one-third of wind additions and one-half of solar in states without binding renewable portfolio standards (RPS) are inframarginal. Theory predicts, and our estimates fail to reject, that all IRA subsidies in states with binding RPS policies go to projects that would have been built without them. Building on the empirical results, our numerical structural modeling show how inframarginal rents can impact cost-effectiveness: Analysis that treats all recipients as additional underestimates fiscal costs of clean electricity tax credits by a factor of two for IRA's power sector credits. Average abatement costs of IRA's power sector credits (\$96/t-CO_2) are generally lower than recent social cost of carbon estimates, which range from \$100-360/t-CO_2 depending on the assumed discount rate (Rennert et al., 2022). Results suggest how policy design can target participants that have lower probability of being inframarginal.

2. Model

This section introduces stylized models to illustrate drivers of clean energy adoption and substitution in the power sector, which is the second largest emitting sector in U.S., and inframarginal investments. We begin with a simple model of a renewable energy investment decision (Section 2.1) that builds to a static supply model (Section 2.2), which forms the basis of the empirical analysis in Section 3. We then consider a social welfare model (Section 2.3) that motivates the detailed numerical modeling in Section 4.

2.1. Model of Investment Decisions

We begin with a model of renewable energy investment decisions that captures the key economic factors driving project development. The fundamental condition for investment is that expected discounted net private benefits must be positive:

$$0 < \pi_i = \int_0^T \Big(\underbrace{q_i f_i \mathbf{E}(p_t + \sigma_{q_t})}_{\text{revenue}} - \underbrace{q_i \big((k_{q_i} - \sigma_{k_t}) m(r,T) + k_{u_i} \big)}_{\text{cost}} \Big) e^{-\delta t} dt \tag{1}$$

where π_i represents the expected discounted net private benefits for project i over its lifetime T. Project revenue is determined by four factors: installed capacity (q_i), capacity factor (f_i), expected electricity prices ($\mathbf{E}p_t$), and output subsidy level (σ_{q_t}). Costs comprise two components: capital costs (k_{q_i}) adjusted by a loan repayment scalar $m(r,T)$ that depends on the bank rate r, and non-financeable costs (k_{u_i}) such as transmission interconnection, permitting, and land rental payments. The latter are typically unobservable to researchers (at least not directly) and likely spatially correlated. Financed capital costs may also be reduced by a capital subsidy σ_{k_t}.

Assuming that electricity prices follow a random walk with drift such that $\mathbf{E}p_t = p_0 + t\Delta_p$, where p_0 is the initial wholesale price, and that subsidies are constant, we can simplify the investment condition to:

$$0 < \phi_i = \zeta(p_0 + \sigma_q) f_i - \zeta(k_{q_i} - \sigma_k) m(r,T) - \zeta k_{u_i} - f_i \Delta_p \big(e^{\delta T} - \delta T - 1 \big) \tag{2}$$

where $\zeta \equiv \big(e^{\delta T} - \delta \big)$ and ϕ_i is proportional to π_i.

This formulation yields several key insights about the investment sensitivity to market conditions. First, the effect of initial electricity prices on project viability is:

$$\frac{\partial \phi_i}{\partial p_0} = \frac{\partial \phi_i}{\partial \sigma_q} = \zeta f_i \tag{3}$$

showing that higher-quality resources (i.e., higher f_i) amplify the impact of price changes on investment decisions. Second, the sensitivity to interest rates is:

$$\frac{\partial \phi_i}{\partial r} = -\zeta (k_{q_i} - \sigma_k) \frac{\partial m}{\partial r} \tag{4}$$

where $\frac{\partial m}{\partial r} = \frac{e^{rT}(-rT+e^{rT}-1)}{(e^{rT}-1)^2}$. This relationship is particularly important, because while we lack identifying variation to directly estimate interest rate effects, understanding their magnitude is crucial given the significant interest rate changes that coincided with recent policy shifts.

This framework provides the theoretical foundation for our empirical analysis in Section 3 by identifying the key variables affecting investment decisions and their interactions. It also highlights the challenge of separating policy impacts from concurrent macroeconomic changes, particularly in interest rates, which we address in our empirical strategy.

2.2. Supply Model

Building on our microeconomic investment model, we develop a static supply framework that aggregates individual project decisions into market outcomes. The total supply of renewable capacity is determined by summing across all potential projects that meet the investment criterion:

$$S = \sum_i \mathbf{1}(\phi_i(p_0, f_i, k_{q_i}, k_{u_i}) > 0) \tag{5}$$

where each project's characteristics—resource quality (f_i), capital costs (k_{q_i}), and unobservable costs (k_{u_i})—are treated as random variables. This static framework implicitly assumes that unobserved project costs vary over time and that the pool of potential projects is not exhausted.

To make this model empirically tractable, we aggregate potential projects to the location level (specifically, counties in the contiguous United States). This aggregation yields:

$$S_l = a_l + \beta_1(\bar{f}(p_{l_0} - \sigma_q) + (\bar{k}_{ql} - \sigma_k)m(r) + \bar{k}_{u_l}) + \beta_2\bar{f} + \varepsilon_l \tag{6}$$

where bars denote location-level averages and a_l captures location-specific time-invariant heterogeneity. This specification allows us to estimate the relationship between local market conditions and renewable energy development while controlling for time-invariant location characteristics.

2.3. Stylized Model of Social Welfare

To motivate the numerical analysis in Section 4, this section provides intuition about the benefits and costs of subsidies, including transfers to inframarginal participants. Here, "inframarginal share" refers to the fraction of adoption that would have occurred without subsidies to the total deployment with subsidies, where higher shares indicate more inframarginal adopters and greater subsidy outlays to firms and households.

Consider a static model, where the quantity of clean energy $q(\sigma)$ is increasing in the subsidy σ, with private benefits $u(\cdot)$ and private costs $c(\cdot)$.[3] The planner has a welfare function:

$$[u(q(\sigma)) + mq(\sigma)] \; - c(q(\sigma)) - (\eta - 1)q(\sigma)\sigma \tag{7}$$

Private benefits of clean energy adoption are lower than social benefits due to the marginal external benefit m, which can represent climate benefits, improvements in air quality, as well as induced

[3]This section follows the general approach of Boomhower and Davis (2014) but extends the framework to a supply-side technology subsidy. Demand for clean electricity is downward sloping and represents the aggregation of price-responsive loads and substitution from emissions-intensive generation (i.e., $u(\cdot)$ is residual demand after accounting for the contribution of fossil-fueled generation). The private marginal cost curve $c(\cdot)$ is upward sloping due to the heterogeneity in regional costs.

technical change.[4] The last term represents general equilibrium effects, where η is the net cost of tax interactions and revenue financing (i.e., $\eta = 1$ without pre-existing distortions). Total subsidy payments are $q(\sigma)\sigma$.

The change in welfare for an increase in subsidy is:

$$\frac{dW}{d\sigma} = \frac{dq}{d\sigma}\left[u'(q(\sigma)) + m - c'(q(\sigma)) - (\eta - 1)\sigma\right] - (\eta - 1)q(\sigma) \tag{8}$$

where $dq/d\sigma$ is the subsidy-induced change in clean energy deployment for a marginal increase in σ. The term in braces represents the welfare benefit of increased adoption at the margin, and $(\eta - 1)q(\sigma)$ is the cost of payments for inframarginal investments. Therefore, welfare impacts of increases in the subsidy σ depend on the extent of inframarginal investments. Efficiency costs become more important with greater η and relative share of non-additional subsidized investments, which weakly increases in σ.

There is an extensive literature related to η on efficiency costs of tax interactions and revenue financing. Overall, the effects of revenue financing tend to exceed tax interactions for subsidies, which implies that optimal subsidy levels are positive but lower than marginal external benefits (Parry, 1998), which is why η is called an efficiency cost.

The inframarginal share also depends private benefits function $u(\cdot)$ in Equation 8. The clean energy investment response to changes in σ can be decomposed into substitution and production scale effects.[5] As shown in Casey et al. (2023), the substitution effect links to the elasticity of substitution between clean and dirty energy. However, this substitution elasticity is difficult to estimate, and there is considerable disagreement across literature (Golosov et al., 2014; Papageorgiou et al.,

[4] m is assumed to be constant in this stylized model. Note that analysis in Section 4 only accounts for climate benefits, which makes estimates lower bounds on external benefits.

[5] Taxes and subsidies both lower the relative price of clean energy, thus causing substitution. However, taxes and subsidies have opposite signs for scale effect, as taxes decrease production while subsidies can increase production.

2017) due to part to simplifications in aggregate elasticities across sectors, firms, and technologies.

3. Empirical Analysis

3.1. Data

We focus our empirical analysis on land-based wind and solar in the contiguous United States. For our empirical analysis, our primary dependent variables—utility-scale wind and solar electricity generating capacity additions—come from the Energy Information Administration's (EIA) Form 860 survey This annual survey captures detailed information on utility-scale generating units, including technology type, capacity, location, and operational date. The spatial distribution of these capacity additions within counties is illustrated in Figures D.9 and D.10.[6]

We obtain LMPs from Lawrence Berkeley National Laboratory's Renewables and Wholesale Electricity Prices tool (Millstein and O'Shaughnessy, 2024). These data provide annual averages for electricity market nodes (Figure D.11). For counties containing multiple nodes, we compute the county-level average. For counties without nodes, we assign prices from the nearest node within the same state to the centroid of the county. Figure D.12 displays the resulting annual average LMPs by county. For our control function approach, we use Henry Hub natural gas spot prices from the EIA to instrument for LMPs. All price data are converted to 2023 dollars using the GDP Implicit Price Deflator from the U.S. Federal Reserve (U.S. Bureau of Economic Analysis, 2024).

Federal support for wind and solar has historically taken two forms—the Production Tax Credit (PTC), which provides a fixed subsidy per unit of electricity generated, and the Investment Tax Credit (ITC), which subsidizes a percentage of equipment and construction costs. Both policies were in force for many years before the IRA. Prior to the IRA, commercial wind projects were only eligible for the PTC, while commercial solar projects could only access the ITC. For this reason,

[6]Capacity of solar PV throughout the paper is generally expressed in nameplate gigawatt AC terms (GW_{AC}) unless otherwise noted.

we add the PTC to LMP for wind but not for solar in the regressions that follow. Between 2017 and 2020, both subsidies underwent a planned phase-out, which Congress temporarily rolled-back during the COVID-19 pandemic. The IRA subsequently restored both programs to their inflation-adjusted 2016 levels, and technology-neutral credits allow both wind and solar projects to choose between either the PTC or ITC. Our empirical analysis currently focuses exclusively on the PTC.

While our primary objective is to analyze subsidy effects, PTC variation alone is insufficient to estimate these effects. We elaborate on this limitation in the following section. As illustrated in Figure 1, which compares PTC levels to the national average LMPs over time, the magnitudes of these two measures were comparable before 2020—our primary estimation period. However, in recent years, the PTC has comprised a smaller share of per-MWh revenue as wholesale electricity prices have risen.

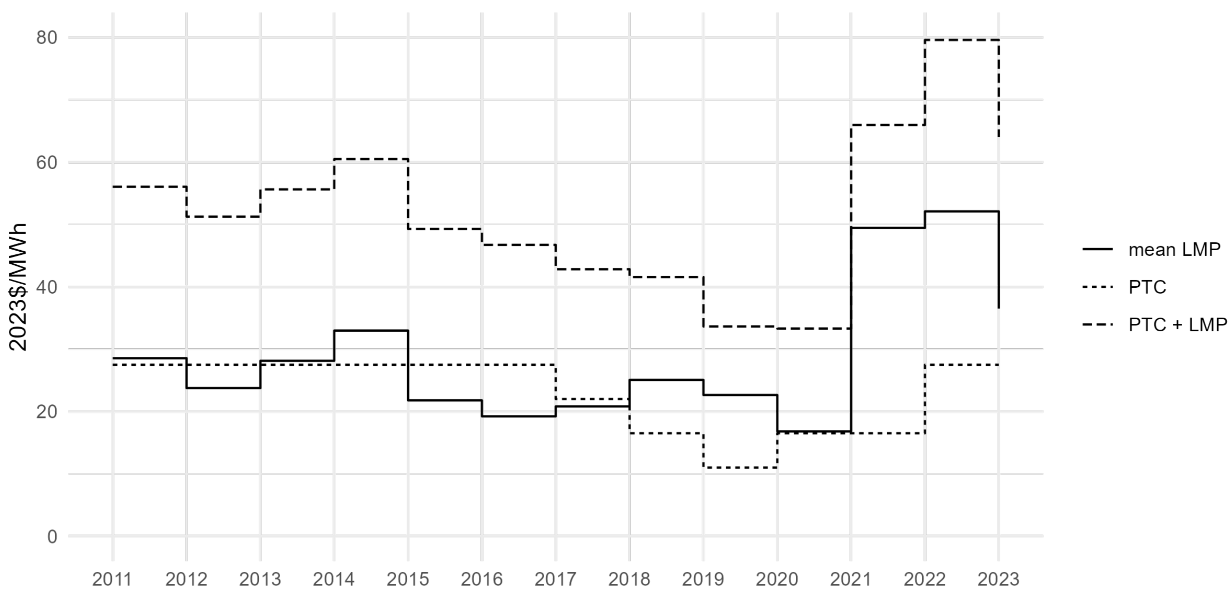

Figure 1: Production tax credit and mean locational marginal prices

Lawrence Berkeley National Laboratory's interconnection queue database (Rand et al., 2024) provides comprehensive information on utility-scale project applications, including submission dates and queue outcomes (withdrawal or interconnection agreement). Figures D.15 and D.16 show the total capacity remaining in state-level queues at the start of each year for wind and solar projects, respectively. The average queue duration by state is displayed in Figures D.13 and D.14.

We measure renewable resource quality using data from two sources. Wind resource data from the Global Wind Atlas 2024 provides capacity factors for a generic class III wind turbine. Solar resource potential comes from the EIA Energy Atlas, which provides average global horizontal irradiance that can be readily converted to capacity factors.

Below, we conduct separate analyses for wind and solar technologies, further subdividing our sample based on state RPS status. This separation reflects the different market dynamics in states with and without binding renewable generation requirements. In states with binding standards, renewable generation decisions are primarily driven by regulatory compliance rather than wholesale electricity prices, though some substitution between technologies may occur under technology-neutral standards due to the shifting relative profitability of technologies, which is not the focus of this paper. The analysis defines RPS states as those with standards greater than 25% of total electricity generation in 2023. Non-RPS states are those without standards or with long-run standards that are less than 25% of generation, which are likely to be non-binding. Future work can test for robustness to alternate RPS definitions and refine this distinction by observing which states have renewable energy credit prices that are larger than transaction costs in a given year.

Table 1: Summary statistics

	Wind		Solar	
	non-RPS	RPS	non-RPS	RPS
N counties	293	113	660	401
N projects	477	213	1,421	2,300
GW	66.8	15.8	21	47
Mean capacity factor	0.49	0.43	0.19	0.18
Mean price ($/MWh)	22.95	23.82	25.95	26.71
Mean years in queue	2.5	1.7	0.2	0.2
Mean GW in queue	23.4	5.8	3.3	3.0
States included	AZ CO ID IN IA KS MO MT NE NC ND OH OK OR PA SD TX UT WA WV WI WY	CA CT IL ME MD MA MI MN NV NH NJ NM NY RI VT	AL AZ AR CO FL GA ID IN IA KS KY LA MS MO MT NE NC OH OK OR PA SC SD TN TX UT WA WV WI WY	CA CT DE DC IL ME MD MA MI MN NV NH NJ NM NY RI VT VA

Note: Mean years in queue and gigawatts (GW) in the queue are means of state totals but weighted by the number of counties in each sub-sample, which are the unit of observation in later regressions. The sums and averages are for the time period 2010–2019.

Table 1 presents summary statistics for our four sub-samples—wind and solar in both RPS and non-RPS states. Each sample is restricted to counties that have installed the relevant technology at least once during our study period. Because we will later be using Poisson quasi-maximum likelihood estimate (MLE) with multiplicative county fixed effects, counties with no observations would provide no information. The table summarizes the total number of counties, number of projects, and capacity additions. It also provides mean capacity factors, LMP, years in queue, and capacity in queue. While the queue variables are measured at the state level, these means are weighted by the number of counties in the sub-sample.

3.2. Empirical Strategy

Our identification strategy relies on variation in LMPs to estimate the impact of increased revenue on renewable capacity additions. With the assumption that all dollars are treated equally regardless if they are from tax credits or changes electricity market prices, this strategy allows us to estimate the effect of subsidies, which provides sufficient variation to causally identify an effect. However, this approach requires several assumptions for us to interpret estimates as we would like.

A crucial identifying assumption is that potential wind and solar investors expect LMPs to follow a random walk, potentially with drift. Further, the subjective expectations of the drift term remain constant or change independently of price shocks. Under these assumptions, observed price shocks shift expectations of future prices by an equivalent amount across all future periods.

The constant or independent drift assumption is most defensible during our primary study period of 2010–2019, characterized by relatively stable macroeconomic conditions. However, this assumption becomes less tenable starting in 2020, when the COVID-19 pandemic, global supply chain disruptions, and the expansion of the Russo-Ukrainian War led to large energy price fluctuations, all which may have been seen as temporary. If prices are seen to be driven by supply disruptions or temporary demand shocks, then the expectation of future trends is likely to be negatively correlated with the direction of the shock, making identification difficult if not impossible. This is the primary reason for estimating the supply response to revenue changes on data to a period that ends before the IRA was passed.

The source of our identifying variation are within-county shifts in LMP. We use one-year lagged LMPs for three reasons: 1. Using the LMP from the year before the operational date avoids simultaneity; 2. Wind and solar projects become operational throughout the calendar year, so annual the average LMP includes prices after the projects are operational; and 3. The final decision to invest is more likely to have taken into account the previous year's prices because of the time it takes to build projects.

Working from Equation 6, we specify the estimating equation as an exponential mean model. Without detailed information on project capital costs, we allow costs to be captured by time trends. An exponential mean model provides a couple benefits: 1. It models a non-negative dependent variable while allowing for zeros; and 2. Its coefficients are easily interpreted as average partial effects in percent changes by multiplying the coefficient by 100.

The baseline model is:

$$\mathbf{E}\left[\mathrm{MW}_{jt}\right] = \exp\Big(\beta_1 p_{j,t-1} + \beta_2 t + \mathbf{X}_{j,t-1}\gamma\Big)\alpha_{1_j} \tag{9}$$

where j indexes counties, t indexes years, MW_{jt} are megawatts of capacity additions for a given technology, and α_j are county fixed effects. β_1 is the coefficient of interest, estimating the multiplicative change in capacity additions for a dollar increase in the wholesale electricity price. In our preferred specification below, we allow the time trend to vary by state.

Our empirical strategy uses several controls. County fixed effects control for time-invariant local characteristics that might influence renewable energy development. We include time trends to capture both the secular decline in renewable energy capital costs and allow for state-specific time trends, in our preferred specification, to capture local conditions and evolving attitudes toward renewable projects.

We include identical analyses for RPS states to serve a falsification test for our identification strategy. We distinguish between binding and non-binding RPS states, defining non-binding states as those with standards of 25% or less as of 2023, based on Lawrence Berkeley National Laboratory data. In states with binding RPS requirements, we expect wholesale electricity prices to have no impact on capacity additions, as these additions are driven by regulatory compliance.

We consider potential threats to identification and employ multiple strategies to address them:

Measurement error: Annual averaging of LMPs may be a concern for solar, which produces energy only in daylight, and to a lesser extent wind, due to diurnal and seasonal variation. It is possible that the subset of prices that are relevant to the investment decision diverge from annual averages. While this is likely to be the case in the future, we show in Figure Y (forthcoming) that the price difference between night and day have remained mostly stable during the study period.

Time-varying local market conditions: Time-trends may fail to capture idiosyncratic time-varying differences across markets and lead to imprecise estimates of our coeffiecnt of interest. There is particular concern about the congestion of the interconnection queue, as discussed above. We include additional controls for the average time in the interconnection queue and the total capacity in the interconnection queue, which are aggregated at the state level. Further, we control for lagged solar and wind capacity additions, which account for potential complementarity or substitution effects between and among the technologies.

Endogeneity: While lagged prices ought to remove concerns of simultaneity and county fixed effects ought to take care of correlation between LMPs and time-constant idiosyncratic errors, endogeneity may sneak in through correlation of LMPs with time-varying idiosyncratic errors. To address potential endogeneity in LMPs, we implement an IV-like error correction model following (Lin and Wooldridge, 2019), using Henry Hub natural gas spot prices as an instrument. This approach allows us to test for and correct any remaining endogeneity in our price measure.

To test and correct for endogeneity, we follow Lin and Wooldridge (2019) using a control function approach that is conceptually similar to two-stage least squares (2SLS) IV estimator. In the first stage, we estimate the linear model with OLS:

$$p_{jt} = \delta_1 \text{HH spot}_t + \mathbf{X}\rho + \alpha_{2_j} + e_{jt} \tag{10}$$

where HH spot_t is the Henry Hub natural gas spot price, which we argue is likely exogenous. We use the same controls as the second stage and linear (instead of multiplicative) county fixed effects, α_2. The residuals $\hat{e}_{jt}$ are then used in the second stage:

$$\mathbf{E}\left[\text{MW}_{jt}\right] = \exp\Big(\beta_1 p_{j,t-1} + \beta_2 t + \beta_3 \hat{e}_{j,t-1} + \mathbf{X}_{j,t-1}\gamma\Big)\alpha_{1_j} \tag{11}$$

The significance of $\hat{\beta}_3$ tests for endogeneity compared the the null hypothesis of no endogeneity and the assumption that the instrument is exogenous.

We considered, and rejected, several alternative empirical approaches that seem less suitable than our price variation strategy. First, we evaluated the possibility of implementing a regression discontinuity design exploiting IRA's bonuses for projects sited in energy communities. Three key limitations made it unsuitable: 1. The extremely short post-treatment period; 2. The restricted geographic scope around boundary regions; and 3. Concerns about strategic project relocation across boundaries that would bias estimates.

We also considered the "blatantly-inframarginal" approach of Calel et al. (2024), which identifies inframarginal projects by comparing profitability indicators across subsidized and unsubsidized projects. In this approach, a subsidized project is classified as inframarginal if its profitability indicators strictly exceed those of unsubsidized projects built in the same year and region. However, two factors made this approach unsuitable for our analysis. First, since IRA applies nationally, we could only examine either the additional energy community credits (which falls outside our scope) if comparing projects built in the same year. Second, we ruled out cross-year comparisons due to large macroeconomic shifts discussed above.

Finally, we explored an event study framework using time-series variation in renewable energy subsidies. This approach faced two significant challenges—the difficulty of accounting for policy expectations in an environment where changes are often anticipated years in advance, and the relatively small magnitude of actual subsidy changes during our study period. These limitations led us to favor our primary identification strategy using variation in wholesale electricity prices.

3.3. Empirical Results

Tables 2 and 3 show the results for wind and solar, respectively, for states without binding RPS targets. Each regression table presents four model specifications of increasing complexity. Column 1 is the baseline specification, which is estimated by quasi-MLE Poisson regression with county fixed effects and a time trend. Column 2 incorporates time-varying state-level market controls, including interconnection queue capacity for wind and solar at the start of the calendar year, mean duration in the queue in years at the start of the calendar year, and lagged capacity additions. Column 3, our preferred specification, allows for state-specific time trends. Column 4 adds residuals from a first-stage control function, discussed above, to test for potential endogeneity in lagged LMPs, though these prove not significant for both wind and solar.

Table 2: Regression results for MW wind capacity additions in non-RPS states

	(1) Poisson FE	(2) + market controls	(3) + state trends	(4) + control function
lag elec. price + PTC ($/MWh)	0.095*	0.080**	0.075**	0.095*
	(0.039)	(0.027)	(0.023)	(0.040)
first stage resid.				−0.055
				(0.083)
wind in queue (GW)		−0.117+	−0.255*	−0.239*
		(0.067)	(0.107)	(0.106)
solar in queue (GW)		0.105+	0.255**	0.241**
		(0.055)	(0.087)	(0.084)
avg. years in queue, wind		−0.268	3.155	3.311
		(0.886)	(2.732)	(2.631)
avg. years in queue, solar		−2.305	−9.272*	−8.598*
		(2.778)	(3.914)	(3.899)
wind_{t-1} (MW)		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
solar_{t-1} (MW)		0.017*	0.018*	0.017+
		(0.008)	(0.008)	(0.009)
year	0.439***	0.597+	−0.452	−0.475
	(0.094)	(0.313)	(0.939)	(0.912)
num. obs.	802	802	802	802
R2 adj.	0.384	0.435	0.459	0.461
first stage F-stat				59.2
PTC avg. partial eff.	261%	220%	205%	261%
county FE	X	X	X	X
year×state			X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable is capacity additions in megawatts by county and year. The time period spans from 2010 through 2019. PTC avg. partial eff. computes the average partial effect of a $27.5 per MWh production tax credit. Non-RPS states includes states without any renewable standard and those with standards below 25% in 2023. Standard errors are clustered by county in all models.

Table 3: Regression results for MW solar capacity additions in non-RPS states

	(1) Poisson FE	(2) + market controls	(3) + state trends	(4) + control function
lag elec. price ($/MWh)	−0.001	0.013	0.028*	0.030*
	(0.024)	(0.015)	(0.013)	(0.013)
first stage resid.				0.034
				(0.021)
wind in queue (GW)		0.161	0.139	0.106
		(0.104)	(0.121)	(0.114)
solar in queue (GW)		−0.031	−0.151	−0.178+
		(0.067)	(0.121)	(0.096)
avg. years in queue, wind		−0.021	−0.647	−0.408
		(0.411)	(0.491)	(0.516)
avg. years in queue, solar		−6.529***	−5.717***	−5.605***
		(1.552)	(1.736)	(1.640)
wind_{t-1} (MW)		−0.011*	−0.013*	−0.013**
		(0.005)	(0.005)	(0.005)
solar_{t-1} (MW)		−0.003	−0.004	−0.004
		(0.003)	(0.003)	(0.003)
year	0.306***	1.142***	1.631**	1.566**
	(0.052)	(0.238)	(0.601)	(0.602)
num. obs.	1124	1099	1099	1048
R2 adj.	0.548	0.621	0.641	0.628
first stage F-stat				6.8
PTC avg. partial eff.	-2%	36%	77%	82%
county FE	X	X	X	X
year×state			X	X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
The dependent variable is capacity additions in megawatts by county and year. The time period spans from 2010 through 2019. PTC avg. partial eff. computes the average partial effect of a $27.5 per MWh production tax credit. Non-RPS states includes states without any renewable standard and those with standards below 25% in 2023. Standard errors are clustered by county in all models.

For wind power, the coefficient of interest is statistically significant across all four specifications, ranging from 0.075 to 0.095. When translated to the context of production-based tax credits, these coefficients imply substantial average partial effects for wind capacity ranging from 205% to 261%.[7] In our preferred specification, this suggests an inframarginal share of approximately one-third for wind capacity.

Solar exhibits sensitivity to specification. Only in Columns 3 and 4 is the coefficient of interest statistically different than zero, with point estimates of 0.028 and 0.030 with state-specific trends and control function, respectively. Our preferred specification indicates that a PTC would increase solar capacity by 77%, corresponding to an inframarginal share of 56%.

Finally, we examine states with a binding RPS target (Tables C.6 and C.7). As expected, we find no significant relationship between locational marginal prices and capacity additions for either wind or solar across all model specifications, consistent with the binding nature of RPS requirements.

4. Numerical Modeling

4.1. Detailed Energy System Models and Scenario Assumptions

The stylized analysis in Section 2.3 indicated that inframarginal investments under clean energy policies depend critically on cross-price and own-price elasticities of demand. There are empirical estimates of these parameters in the literature (Golosov et al., 2014; Papageorgiou et al., 2017); however, there are questions about how future responses could differ given rapid technological change, different characteristics of adopters, and changes in overlapping policies. In addition, earlier research assumed relatively stylized production functions that may not replicate key sectoral dynamics. For instance, the power sector is characterized by dynamic optimization with vintaging, heterogeneity of renewable resources and interfuel substitution, strong regional differences in resource endowments

[7]This is done by multiplying the coefficient by 27.5, the amount of the PTC per MWh in 2023 dollars.

and market structure, and simultaneous impacts of energy storage and transmission (Atkeson and Kehoe, 1999; Fabrizio et al., 2007; Fowlie, 2010; Bushnell and Wolfram, 2012; Gowrisankaran et al., 2016; Bistline et al., 2021).

Given these simplifications, the analysis in this section shows that intuition from the stylized model holds with more detailed dynamic structural modeling and provides numerical estimates of inframarginal shares for a prominent climate policy—the U.S. IRA. The analysis compares results from 11 models that evaluate potential impacts of IRA—6 energy system models and 5 partial equilibrium models of the power sector. A motivation for using structural models is to construct credible counterfactuals without policy and to simulate system responses of subsidies over time. For the power sector, these capacity planning models simultaneously optimize firm entry and exit decisions for generation, energy storage, and transmission while jointly representing system dispatch.[8]

This section primarily focuses on IRA's power sector production and investment tax credits to align with the empirical analysis in Section 3, though we contrast supply-side subsidies with demand-side ones and provide more detail on passenger vehicle inframarginal shares in Appendix B. Model details are compared in Appendix A, and scenarios are discussed in detail in Bistline et al. (2023a).

To assess the model-specific shares of investment that are inframarginal under IRA incentives, this analysis uses a two-scenario design:

- **Reference:** This counterfactual scenario without IRA includes other on-the-books federal and state policies and incentives through mid-2022 when IRA was enacted, including the Bipartisan Infrastructure Law, state emissions policies, and renewable/clean portfolio standards.

[8] The power sector capacity planning problem is often operationalized by minimizing the net present value of system costs, which endogenously accounts for investment costs, operational costs, and marginal revenues discounted across the time horizon, though there is variation across models in their degree of foresight (Bistline et al., 2024; Merrick et al., 2021).

- **IRA:** This scenario uses central estimates of IRA's core climate and energy provisions. Coverage and implementation vary by model (as shown in Figure A.5 in Appendix A), depending on the model's scope and resolution.

Power sector IRA incentives generally include technology-neutral PTC and ITC for zero-emitting electricity, cross-sector credits for carbon capture and storage (CCS), and clean hydrogen production tax credits. The clean electricity PTC and ITC are technology-neutral starting in 2025 and allow zero-emitting generation options to select between these credits with bonuses for meeting labor, energy community, and domestic content requirements. These incentives can continue after 2032 until electric sector CO_2 emissions are 25% of their 2022 levels.[9]

4.2. Numerical Modeling Results

There is cross-model variation in the extent of clean electricity capacity investment, including renewables, CCS-equipped capacity, nuclear, and energy storage (Figure 2). IRA incentives increase deployment of these low-emitting technologies, which average 23-117 GW/yr through 2035 with IRA subsidies compared with 13-61 GW/yr in the counterfactual reference without IRA. These results imply that significant shares of electricity capacity additions could be inframarginal, ranging from 28-72% across models, but also that investments are still price responsive. In general, inframarginal shares are lower (i.e., higher additionality from IRA subsidies) for models with greater IRA-induced solar capacity, which tend to have lower assumptions for the cost of capital.[10]

Another metric to assess the elasticity of demand for clean electricity deployment is annual investments in dollar terms (Figure 2, bottom panel). Inframarginal shares through 2035 in invest-

[9] See White House (2023) and Bistline et al. (2023b) for summaries of IRA's climate provisions. The clean vehicle credit may be up to $7,500 per vehicle, depending on whether critical minerals sourcing, battery components, and domestic assembly requirements are met alongside price- and income-based eligibility limits.

[10] Bistline et al. (2024) analyze drivers of model-specific differences in power sector investments, including the role of input assumptions (e.g., financing, capital costs of technologies) and model structure (e.g., temporal resolution for intra-annual system dispatch).

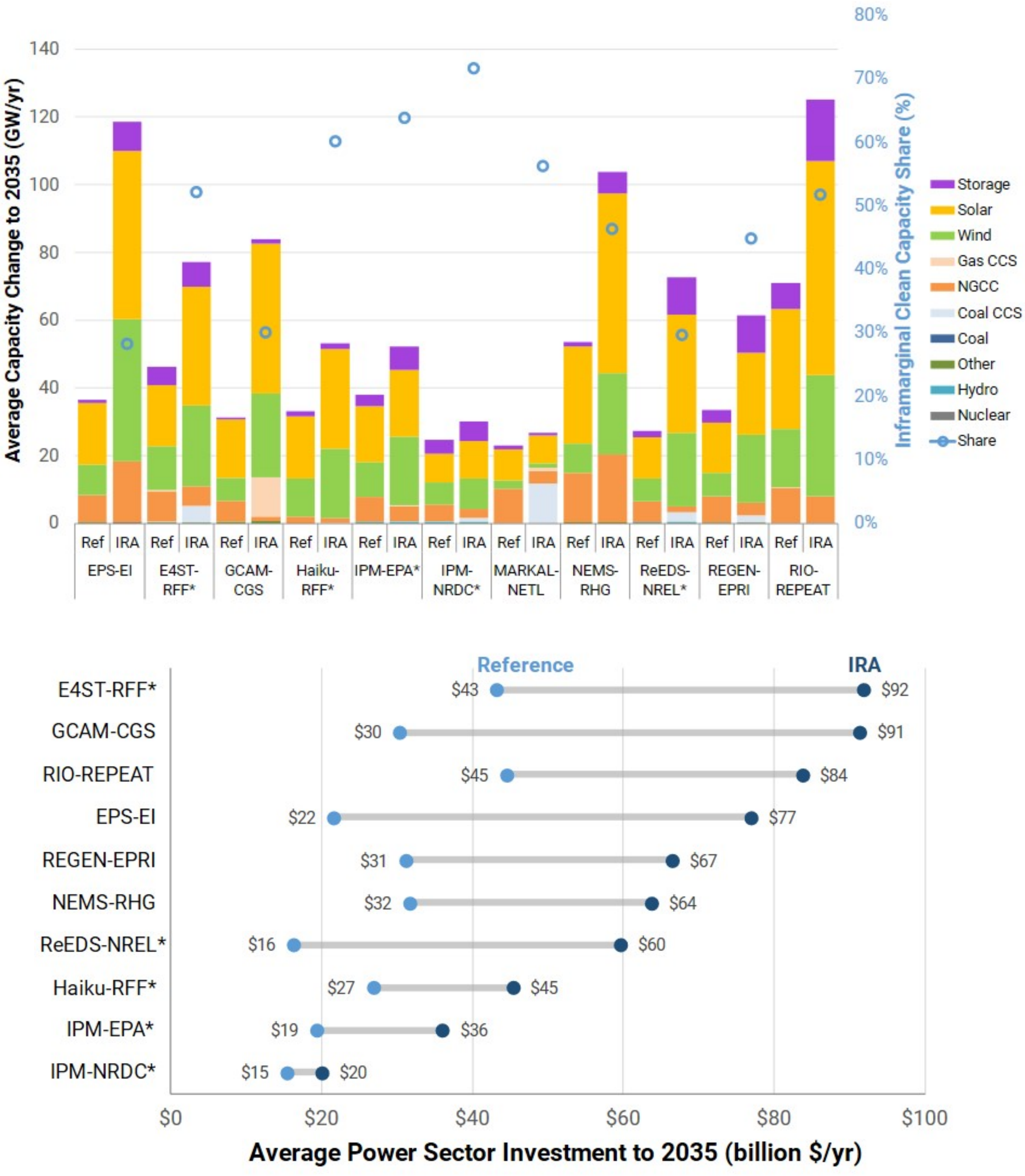

Figure 2: Power sector investments with and without IRA in capacity terms (top panel) and investment terms (bottom panel) across models to 2035. The inframarginal share is the fraction of adoption that would have occurred without subsidies to deployment with subsidies. "Clean" includes renewables, CCS-equipped capacity, nuclear, and energy storage. Partial equilibrium models that represent the power sector only are designated by an asterisk. Investment in the bottom panel is shown in real 2020 dollar terms. Model descriptions are provided in Appendix A, and associated data come from Bistline et al. (2024).

ment dollar terms (27-77%) generally track capacity shares (28-72%), despite differences in capital costs across technologies. These inframarginal shares are generally consistent with the findings from the empirical analysis in Section 3, though the higher numerical shares could be linked to models that include lower bounds on near-term additions to reflect projects under construction, which would be included even in scenarios without subsidies.

Technology-specific inframarginal shares are shown in Figure 3. Solar generally has higher inframarginal shares than wind, though both have considerable cross-model variation. In contrast, the analysis suggests that CCS-equipped capacity is largely additional with IRA incentives, which partially reflects lower deployment in the reference without IRA (Figure 2, top). Figure 3 also compares numerical model results with the empirical analysis in earlier sections. The empirical inframarginal share is limited to states without binding RPS constraints. If inframarginal investments in binding RPS states were also included, the empirical estimates would be higher and align more closely with the numerical modeling.

Appendix B discusses numerical modeling for IRA's passenger vehicle credits. This analysis implies that 67-93% of electric vehicle (EV) investments over the next decade may have occurred without IRA subsidies (Figure B.6). These higher inframarginal shares are due to the relative cost-effectiveness of EV adoption before subsidies owing to their lower total cost of ownership for some households. These ex-ante estimates of IRA's inframarginal shares align with early ex-post microeconomic analysis of IRA's EV credits, which indicate 67-77% of EV credits are inframarginal (Allcott et al., 2024).

The implications of non-additionality on the cost-effectiveness of emissions reductions are summarized in Table 4. Average abatement costs are higher for transport tax credits (\$98-420/t-CO_2) vis-à-vis power sector credits (\$34-170/t-CO_2). Higher abatement costs for IRA's passenger transport tax credits are due in part to their greater shares of inframarginal participants. Although

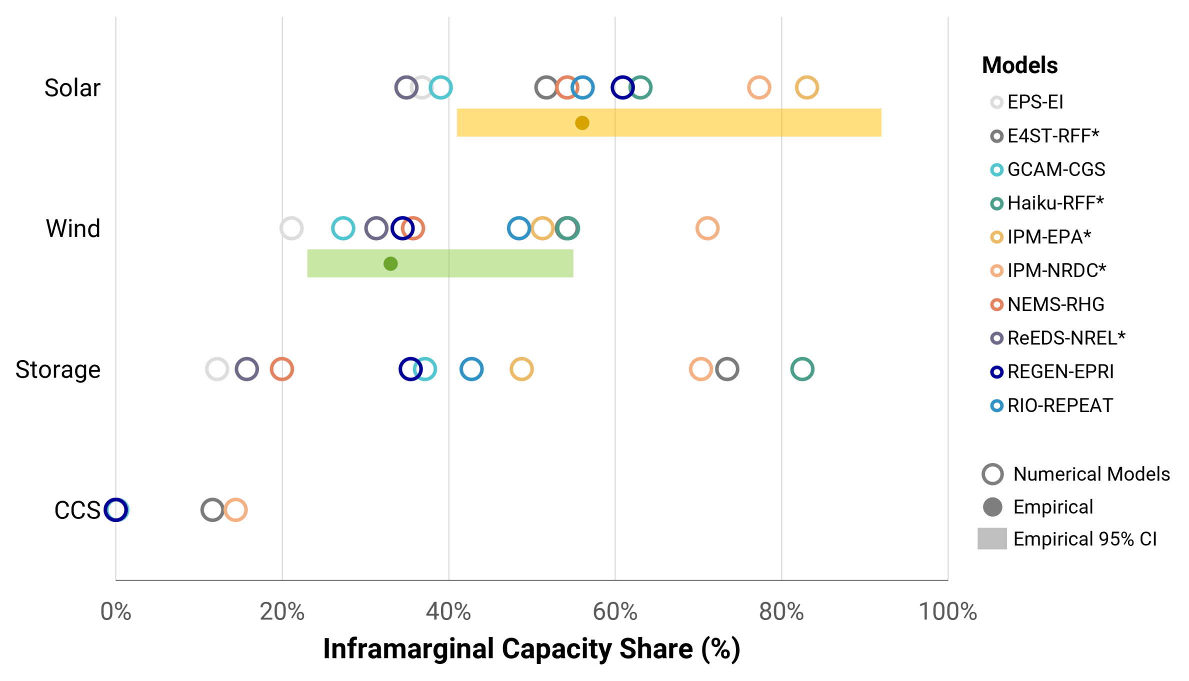

Figure 3: Power sector inframarginal capacity shares by technology. Circles show total inframarginal shares for numerical models from Section 4. Dots with bars show empirical inframarginal shares of wind and solar capacity in non-RPS states from Section 3, where ranges show the 95% confidence intervals.

abatement costs are higher for transport credits, cumulative fiscal costs are generally higher for power sector credits, given their scope, timing, credit magnitudes, and available bonuses.[11]

Analysis that treats all recipients as additional would underestimate the tax credits' fiscal costs. For instance, the average subsidy amount for qualified zero-emitting resources across models is \$23/MWh in 2035. However, the payment per induced output of clean electricity once non-additional participants are taken into account is \$48/MWh when averaged across models, which means that fiscal costs are roughly twice as large. Per-vehicle passenger transport subsidies are nearly three times as large when non-additional purchasers are accounted for, increasing from an average of \$5,980 across models to \$23,700 per induced EV.

Despite these higher costs with inframarginal participation, power sector abatement costs are

[11]Unlike transport tax credits and other IRA provisions that expire after 2032, the power sector PTC and ITC can remain in place at their full value until power sector CO_2 reaches 25% of 2022 levels. 8 of 11 models in the Bistline et al. (2024) multi-model analysis indicate that this emissions threshold will not be reached by 2035.

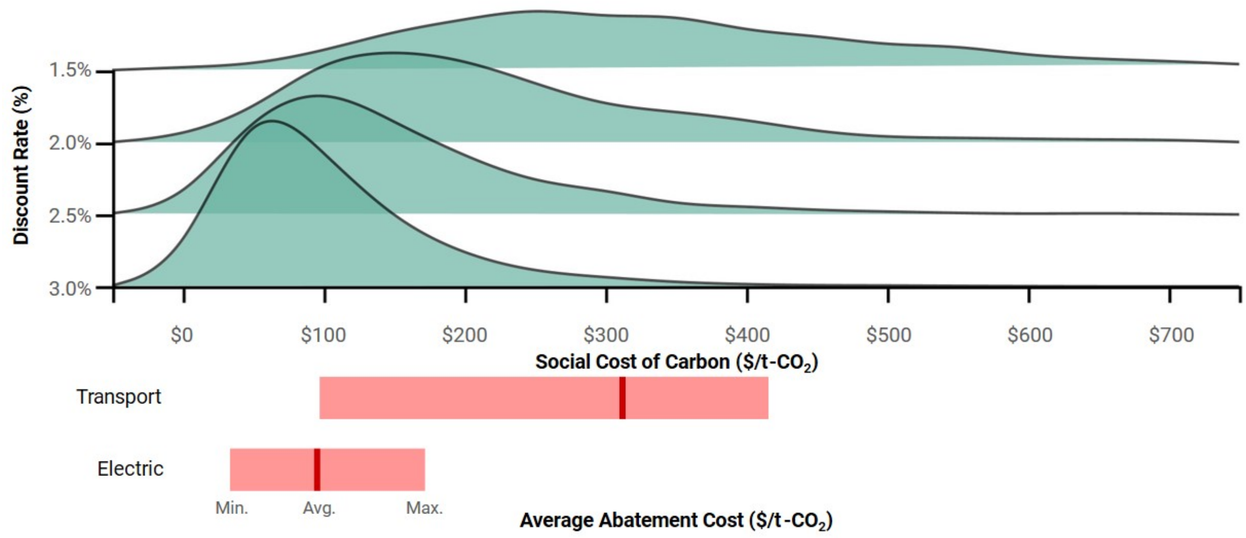

Figure 4: Distributions of the social cost of carbon versus average abatement costs for electric and passenger transport IRA tax credits (in real 2020 dollar terms). Average abatement costs are shown as the minimum, average, and maximum values across models in Bistline et al. (2023a). Social cost of CO_2 distributions across different near-term discount rates come from Rennert et al. (2022) and reflect uncertainty in climate model, sea-level model, and climate damage parameters in the GIVE model.

generally less than recent social cost of carbon estimates for 1.5-3.0% discount rate distributions (Figure 4). The average abatement cost of \$96/t-CO_2 for power sector credits (Table 4) is lower than means for all distributions of the social cost of carbon across discount rates, which range from \$100/t-CO_2 (3.0% rate) to \$360/t-CO_2 (1.5% rate) based on Rennert et al. (2022). In contrast, the average abatement cost of IRA's transport credits of \$310/t-CO_2 is higher than the means for all discount rates except for the 1.5% rate distribution (\$360/t-CO_2).

Table 4: Summary of inframarginal shares, abatement costs, and fiscal costs across models

Metric/Sector	Min.	Avg.	Max.
Inframarginal Share (%), Power Sector Capacity	28%	49%	72%
Inframarginal Share (%), Transport Electric Vehicle Sales	67%	81%	93%
Average Abatement Cost (\$/t-CO_2), Power Sector	\$34	\$96	\$170
Average Abatement Cost (\$/t-CO_2), Transport	\$98	\$310	\$420
Cumulative Fiscal Costs (billion \$ through 2035), Power Sector	\$180	\$450	\$820
Cumulative Fiscal Costs (billion \$ through 2035), Transport	\$120	\$420	\$750

Note: The inframarginal share is ratio of investment without IRA to investment with IRA (cumulative \$ through 2035). Average abatement costs are the change in discounted resource costs over the change in undiscounted emissions relative non-IRA counterfactual through 2035, which is the same definition used in Bistline et al. (2024). Cumulative fiscal costs are shown in nominal dollar terms. "Power sector" includes investment and production tax credits. Calculations are based on model outputs from Bistline et al. (2023a) and Bistline et al. (2024).

5. Conclusions

The extent of inframarginal investments shown here in the context of clean energy subsidies illustrate more general challenges with incentivizing for pro-social behavior. These incentives must implicitly balance false positives (i.e., giving subsidies to non-additional investments) and false negatives (i.e., not providing subsidies to projects and households that would lead to additional adoption), especially where inframarginal adopters are difficult to determine ex ante or cannot be excluded from receiving incentives. Estimates of non-additional investments such as those in this paper can inform future program design, including federal tax credits and localized subsidies. Such estimates of inframarginal investments also can inform projections for emissions reductions, capacity deployment, and fiscal costs. Programs can target incentives for high-value participants rather than providing uniform subsidies that do not account for heterogeneity in price elasticities across firms and households (Allcott et al., 2014). Non-uniform subsidies could, in theory, pay recipients only the amount required for adoption, but several concerns make that approach less workable in practice, such as imperfect information, policy and legal constraints, as well as equity concerns (Newell et al., 2019). Spatially differentiated subsidies are more cost-effective than uniform ones in applications such as tax credits for renewables, given the regional heterogeneity in wind and solar resources, which leads to spatial variation in their competitiveness (Rose and Molar-Cruz, 2023).

Even in cases where policies subsidize inframarginal investments, these incentives may have supplementary rationales. For instance, tax credits for low-emitting electricity may lower wholesale and retail electricity prices for firms and households. These lower energy service costs may, in turn, help to increase political support for future policy, achieve distributional goals, and encourage end-use electrification (i.e., switching from fossil fuels to electricity in transportation, buildings, and industry) beyond the level without accounting for external damages, though the efficacy of subsidies in achieving these goals vis-à-vis other approaches is subject to debate (Hahn and Metcalfe, 2021;

Burgess et al., 2024; Bistline et al., 2023b).

This analysis suggests several areas for future analysis. We intend to refine our empirical analysis to include the investment tax credit (ITC) and the optimal choice of either the ITC or PTC, calculations of inframarginal electricity generation (not just capacity additions), and compare the magnitude of the IRA with interest rates and the effect of interconnection queues. For the numerical simulations, we have yet to fully explore drivers of difference across numerical models in their inframarginal shares, which exhibit notable variation in trends with and without tax credits. Although earlier work discusses how differences in structural features and input assumptions can lead to variation in model outputs (Mai et al., 2018), it is unclear how the relative magnitudes of drivers alter projected inframarginal shares.

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Declaration of Interests

The authors declares no competing interests.

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Appendix A. Numerical Modeling Background

For the detailed numerical modeling in Section 4, results are taken from recent model intercomparisons of IRA's potential impacts (Bistline et al., 2023a, 2024). Model intercomparisons help to assess the role of structural and parametric uncertainties in policy analysis and to identify which insights are robust and which are more uncertain. These studies include 11 energy-economic models—6 models of the full energy system and 5 partial equilibrium models of the power sector only. As shown in Figure A.5, models vary in their implementation of IRA provisions, given differences in model structure and coverage.

Key characteristics for the models used to inform the analysis are summarized in Table A.5.

Table A.5: Energy-economic models used in Section 4.2 and their key characteristics. Models from Bistline et al. (2023a) include the model abbreviation, model name, analysis institution, model type, geographic coverage, and temporal resolution of power sector modeling.

Abbr.	**Model(s)**	**Institution**	**Model Coverage**	**Geo. Coverage**	**Temp. Resolution**
EPS-EI (E-E)	Energy Policy Simulator (EPS)	Energy Innovation	Energy systems	50 U.S. states and D.C.	Seasonal
E4ST-RFF (E-R)	Engineering, Economic, and Environmental Electricity Simulation Tool	Resources for the Future	Electric sector	Contiguous U.S. and Canada	52 segments
GCAM-CGS (G-C)	Global Change Analysis Model for AP	UMD-CGS	Energy systems	50 U.S. states and D.C.	4 segments
Haiku-RFF (H-R)	Haiku Power Sector Model	Resources for the Future	Electric sector	Contiguous U.S.	24 segments
IPM-EPA (I-E)	Integrated Planning Model	EPA	Electric sector	Contiguous U.S.	72 segments
IPM-NRDC (I-N)	Integrated Planning Model	NRDC	Electric sector	Contiguous U.S.	24 segments
MARKAL-NETL (M-N)	MARKet Allocation	NETL DOE	Energy systems	Contiguous U.S.	12 segments
NEMS-RHG (N-R)	National Energy Modeling System	Rhodium Group	Energy systems	50 U.S. states and D.C.	9 segments
ReEDS-NREL (R-N)	Regional Energy Deployment System	NREL	Electric sector	Contiguous U.S. here	17 segments
REGEN-EPRI (R-E)	Regional Economy, Greenhouse Gas, and Energy	EPRI	Energy systems	Contiguous U.S.	120 segments
RIO-REPEAT (R-R)	RIO (supply), EnergyPATHWAYS (demand)	EER/ZERO	Energy systems	Contiguous U.S.	1,080 segments

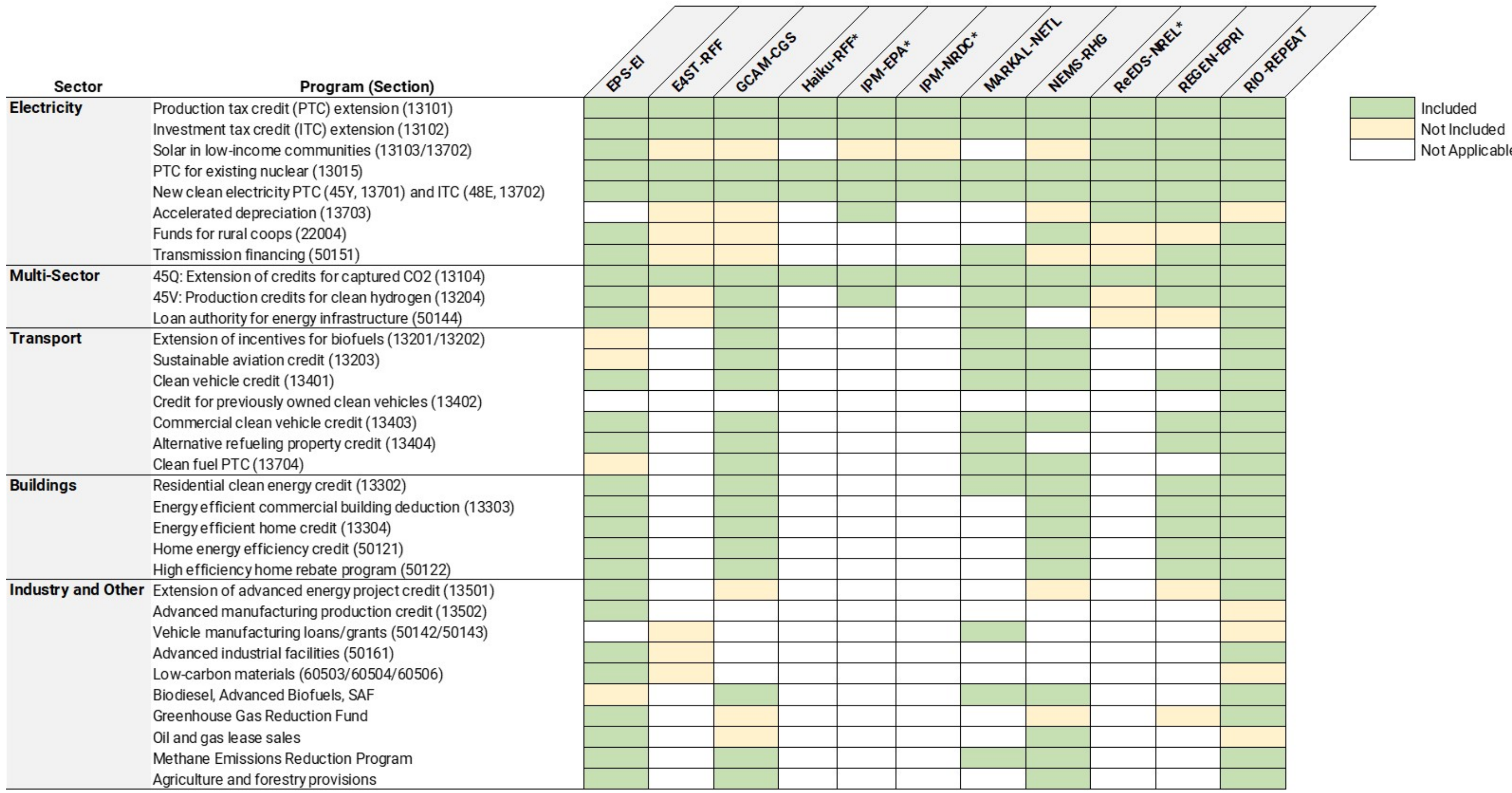


Figure A.5: Summary of energy-economic models and coverage of IRA incentives. Partial equilibrium models that represent the power sector only are designated by an asterisk.

Appendix B. Numerical Modeling Results: Passenger Transport

For a simplified static model of demand-side adoption, consider a discrete choice model of passenger vehicle adoption. In this stylized logit framework similar to Train and Winston (2007), households make new vehicle purchase decisions across across several vehicle types, including an EV with subsidy σ. Xing et al. (2021) show how the change in the inframarginal share N for a marginal change in subsidy relates to the EV own-price demand elasticity ϵ, where the quantity of EV adoption $q(\cdot)$ also depends on the size of the subsidy relative to the pre-subsidy EV price p. A back-of-the-envelope calculation using the own-price elasticity of -2.67 from Xing et al. (2021) implies an inframarginal share of 84%, which suggests large inframarginal rents going to households that would have adopted EVs even without subsidies.[12]

Five numerical energy systems models in Table A.5 analyze IRA's passenger vehicle credits. Models vary in their passenger vehicle frameworks, though many approaches are based on discrete choice models of vehicle demand.[13]

Modeling results suggest that IRA's EV incentives modestly increase passenger EV sales shares[14] (Figure B.6, top)—22-43% of households purchasing a vehicle in 2030 would purchase an EV even without IRA subsidies, which increases to 32-52% with IRA tax credits of up to $7,500 per vehicle. For IRA scenarios, models generally increase at slower rate between 2030 and 2035 after subsidies expire after 2032.

Inframarginal passenger vehicles investments in dollar terms span span 67-93% across models (Figure B.6, bottom). The ordering across models is similar in IRA and non-IRA scenarios. These

[12]The analysis also assumes an average vehicle purchase price of $40,000 per vehicle from Orvis (2022), IRA incentives (σ) of $7,500, and a 50% share of the pre-subsidy vehicle price as a share of the total cost of ownership.

[13]For instance, passenger transport decisions in EPRI's US-REGEN model are based on a nested logit framework that represents household heterogeneity through structural classes such as access to charging, driving intensity, number of vehicles owned, and building type (EPRI, 2023). Such discrete choice models assess purchase probabilities for each consumer class and are rooted in random utility maximization (Train and Winston, 2007; Ramea et al., 2018).

[14]New sales shares of passenger EVs include battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs).

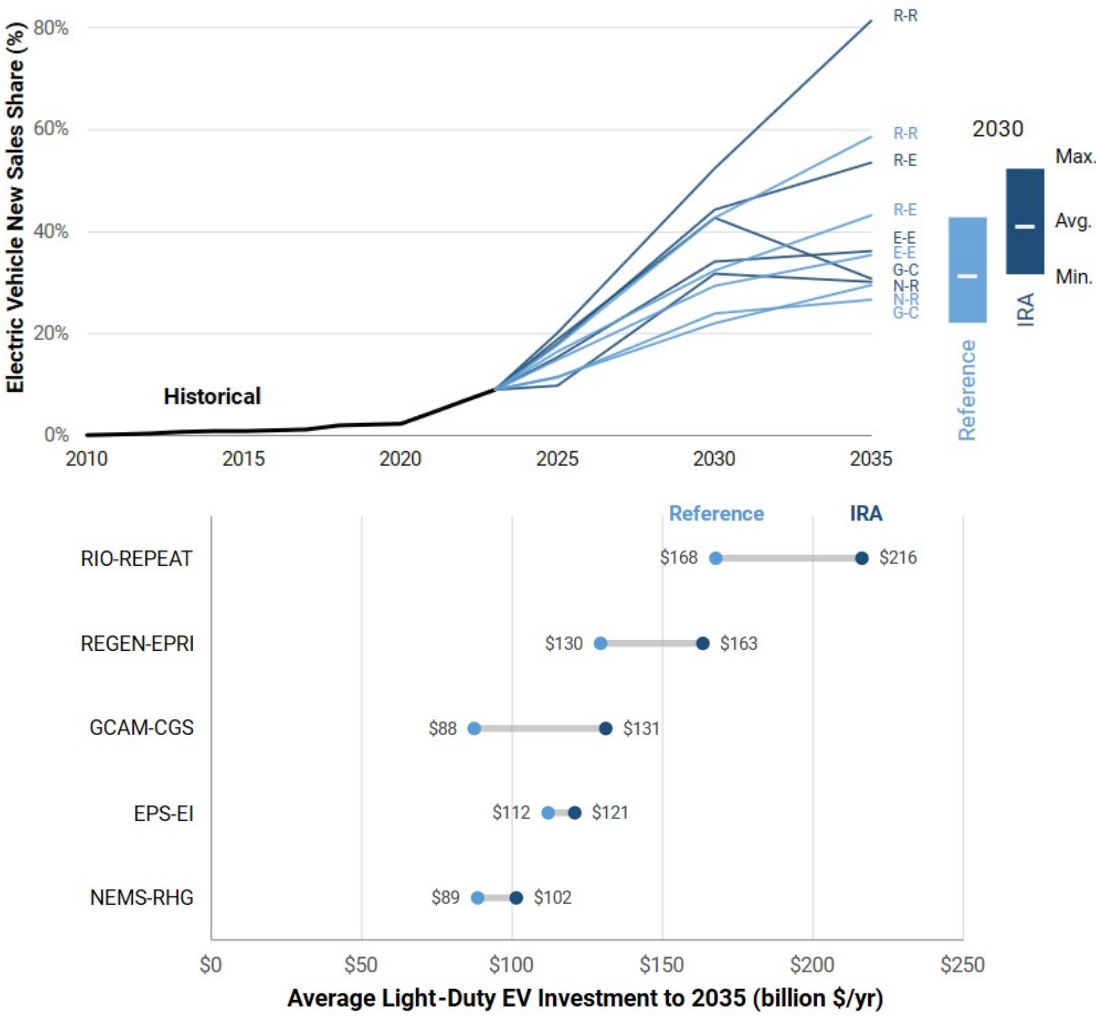


Figure B.6: Passenger EV sales (top panel) and investments (bottom panel) across models. Investment in the bottom panel is shown in real 2020 dollar terms. Model descriptions and abbreviations are provided in Appendix A, and associated data come from Bistline et al. (2023a).

inframarginal shares are broadly similar to other studies of U.S. passenger vehicle subsides. For ex-ante modeling, Bistline et al. (2023b) indicate that 73% of EVs sold in 2030 would have occurred in the counterfactual without IRA incentives, and Cole et al. (2023) find inframarginal EV shares could be 40-57%. For empirical analysis, Xing et al. (2021) conclude that 70% of tax credits go to households that would have bought an EV regardless, and Allcott et al. (2024) indicate 67-77% of EV credits are inframarginal.

Figure B.7 illustrates the range of fiscal costs of IRA's transport credits across models. Cumulative fiscal costs span $120-750 billion across estimates ($420 billion average). These are roughly an order of magnitude higher than the initial score by the Congressional Budget Office (CBO) and Joint Committee on Taxation (JCT), which was $36 billion, though the updated score from February 2024 increases the estimate of these credits to nearly $200 billion. The broad range of estimates reflects differences in projected EV deployment, in average credit value across different vehicles, in the scope of credits modeled, in macroeconomic forecasts, and in whether values represent revenue estimates or tax credit expenditures (JCT, 2023; Bistline and Wolfram, 2024).

In general, inframarginal shares for passenger transport (67-93% across models) exceed power sector shares (27-77%) due to the competitiveness of vehicle electrification even without subsidies and to the magnitude of the credit relative to total lifetime costs in the counterfactual reference.

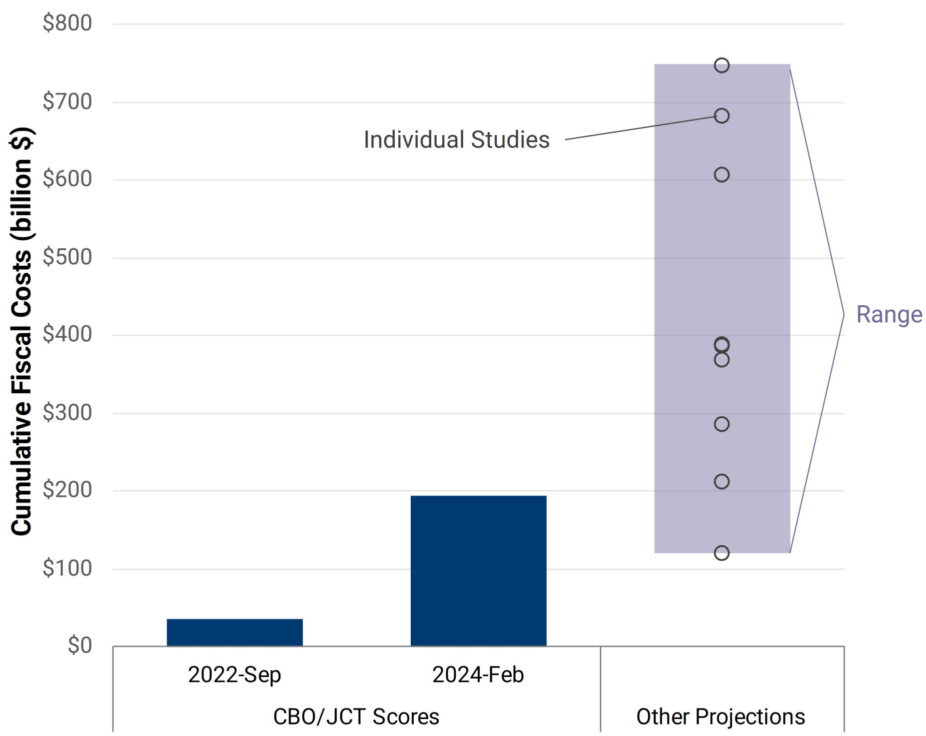


Figure B.7: Cumulative fiscal costs of IRA's transport tax credits (nominal dollar terms). Left bars compare CBO/JCT scores of the transport credits, and the right bar shows other projections of IRA's transport credits, where the bar illustrates the range and circles individual studies (Bistline et al., 2023a; Cole et al., 2023; Bistline et al., 2023b, 2024). The lowest and highest values from Cole et al. (2023) are shown and represent light-duty vehicles only. Multi-model results from Bistline et al. (2023a) are converted into nominal dollars and represent changes in tax expenditures with and without IRA.

Appendix C. Additional Tables

Table C.6: Regression results for MW wind capacity additions in RPS states

	(1)	(2)	(3)	(4)
	Poisson FE	+ market controls	+ state trends	+ control function
lag elec. price + PTC ($/MWh)	-0.144*	-0.028	-0.009	-0.004
	(0.065)	(0.058)	(0.083)	(0.087)
wind in queue (GW)		0.097	0.051	0.050
		(0.132)	(0.156)	(0.159)
solar in queue (GW)		0.389	-0.204	-0.204
		(0.414)	(0.630)	(0.645)
avg. years in queue, wind		0.617	5.196	5.419+
		(0.978)	(3.532)	(3.201)
avg. years in queue, solar		-1.655	-0.870	-1.080
		(2.183)	(7.889)	(8.400)
wind_{t-1} (MW)		-0.002	-0.001	-0.001
		(0.002)	(0.002)	(0.002)
solar_{t-1} (MW)		0.029	0.026	0.025
		(0.054)	(0.065)	(0.067)
year	-0.369*	-0.408	-1.150***	-1.149***
	(0.175)	(0.328)	(0.228)	(0.233)
num. obs.	133	133	133	133
R2 adj.	0.303	0.390	0.443	0.443
first stage F-stat				31.6
PTC avg. partial eff.	-396%	-77%	-25%	-10%
county FE	X	X	X	X
year×state			X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable is capacity additions in megawatts by county and year. The time period spans from 2010 through 2019. PTC avg. partial eff. computes the average partial effect of a $27.5 per MWh production tax credit. Non-RPS states includes states without any renewable standard and those with standards below 25% in 2023. Standard errors are clustered by county in all models.

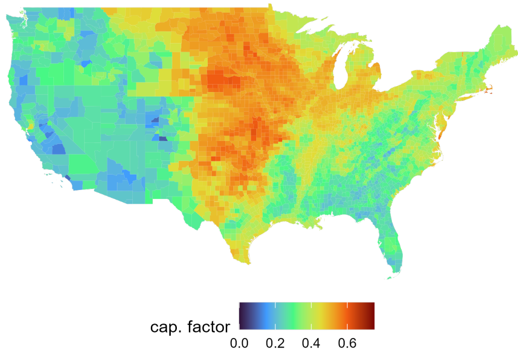
Table C.7: Regression results for MW solar capacity additions in RPS states

	(1)	(2)	(3)	(4)
	Poisson FE	+ market controls	+ state trends	+ control function
lag elec. price ($/MWh)	−0.085	−0.038	0.012	0.008
	(0.054)	(0.050)	(0.052)	(0.058)
wind in queue (GW)		0.168	−0.129	−0.156
		(0.151)	(0.213)	(0.200)
solar in queue (GW)		−0.077	0.094	0.066
		(0.118)	(0.291)	(0.260)
avg. years in queue, wind		1.314	8.415	10.426*
		(2.494)	(5.529)	(4.196)
avg. years in queue, solar		−4.002+	−14.733***	−16.260***
		(2.230)	(3.657)	(3.608)
wind_{t-1} (MW)		0.013***	0.012***	0.012***
		(0.003)	(0.004)	(0.004)
solar_{t-1} (MW)		−0.040***	−0.048***	−0.048***
		(0.009)	(0.009)	(0.008)
year	0.528***	1.050**	0.854***	0.863***
	(0.084)	(0.332)	(0.222)	(0.185)
num. obs.	437	437	437	437
R2 adj.	0.545	0.596	0.626	0.629
first stage F-stat				31.6
PTC avg. partial eff.	-235%	-105%	33%	22%
county FE	X	X	X	X
year×state			X	X

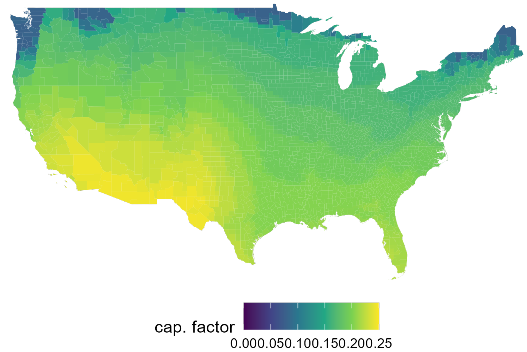
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable is capacity additions in megawatts by county and year. The time period spans from 2010 through 2019. PTC avg. partial eff. computes the average partial effect of a $27.5 per MWh production tax credit. Non-RPS states includes states without any renewable standard and those with standards below 25% in 2023. Standard errors are clustered by county in all models.

Appendix D. Additional Figures



(a) Wind



(b) Solar

Figure D.8: Average capacity factors of wind and solar resources by county

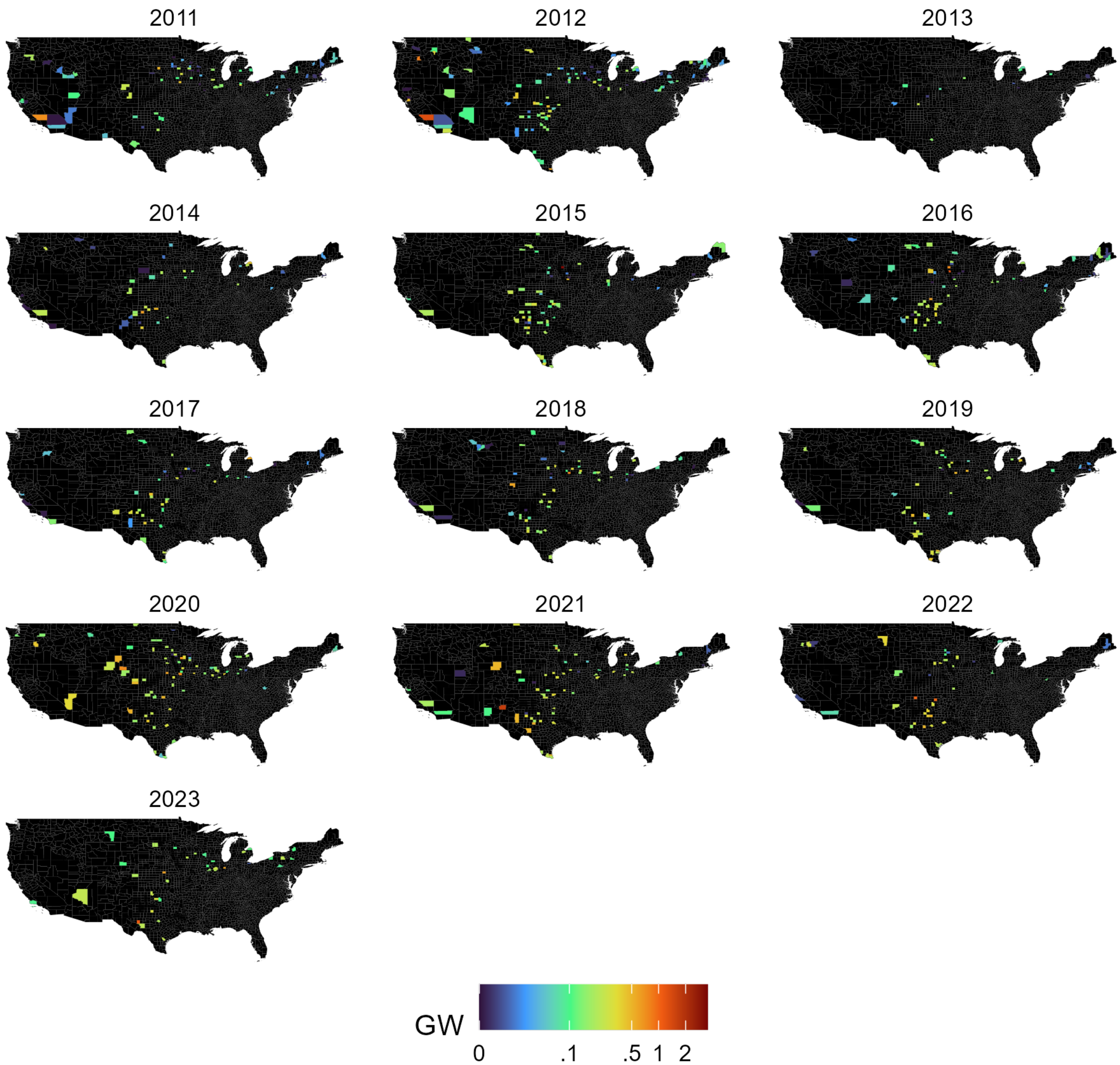


Figure D.9: Land-based wind capacity additions (GW) by county and year

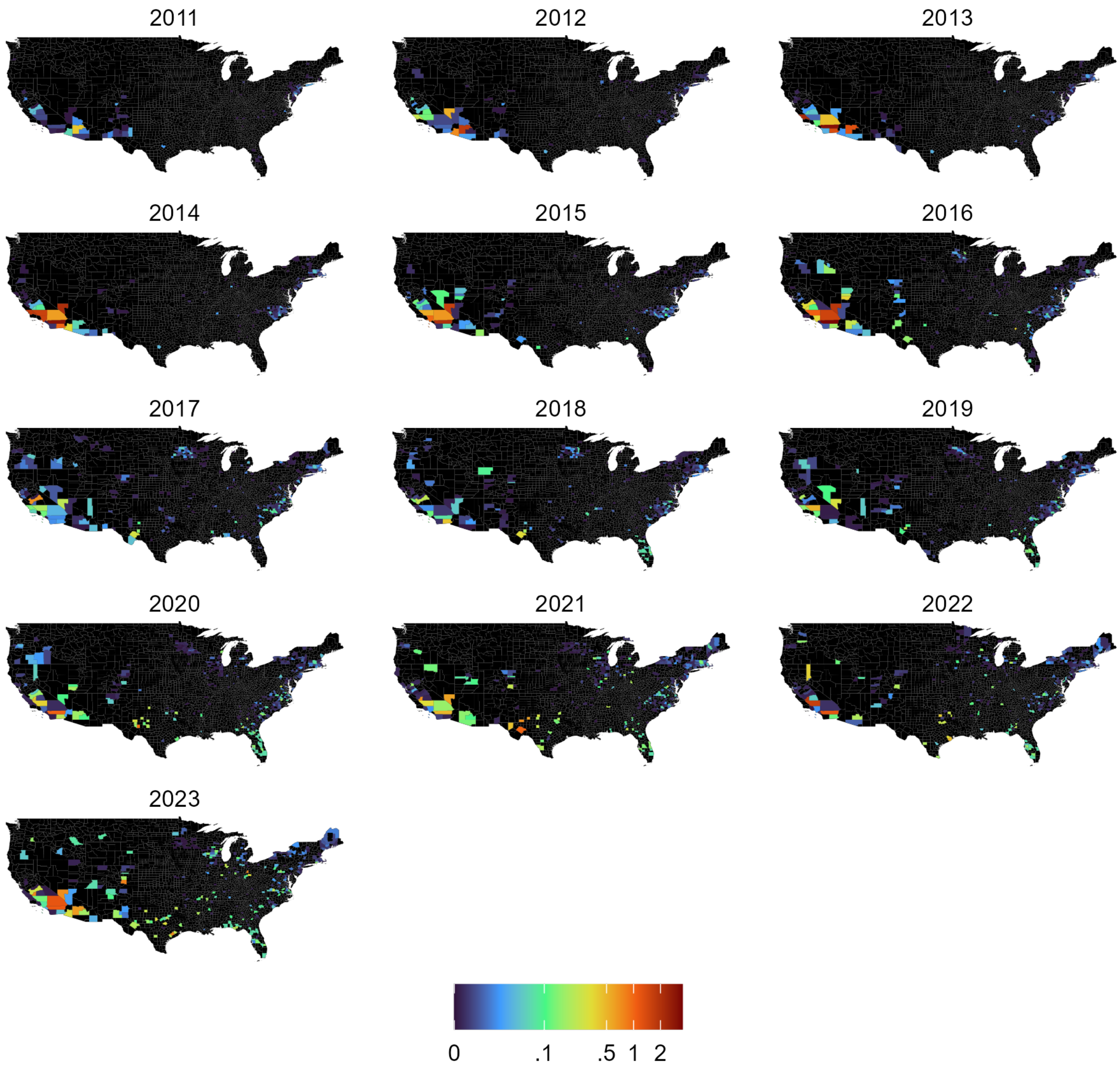


Figure D.10: Utility-scale solar capacity additions (GW_{AC}) by county and year

Figure D.11: Locational marginal price nodes in 2011 and 2019

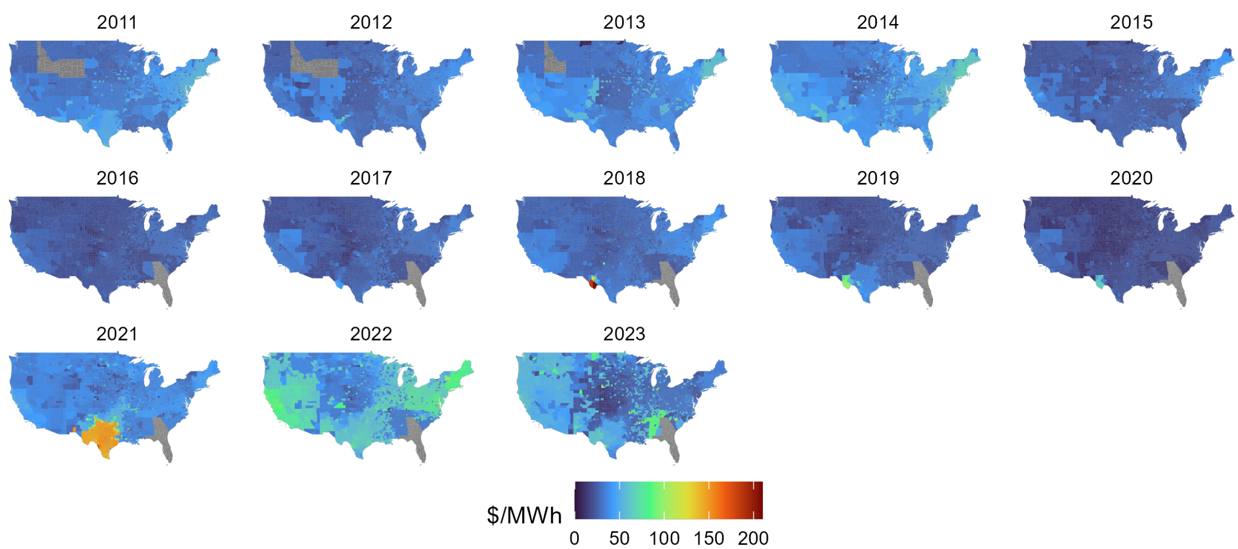


Figure D.12: County average locational marginal price by year

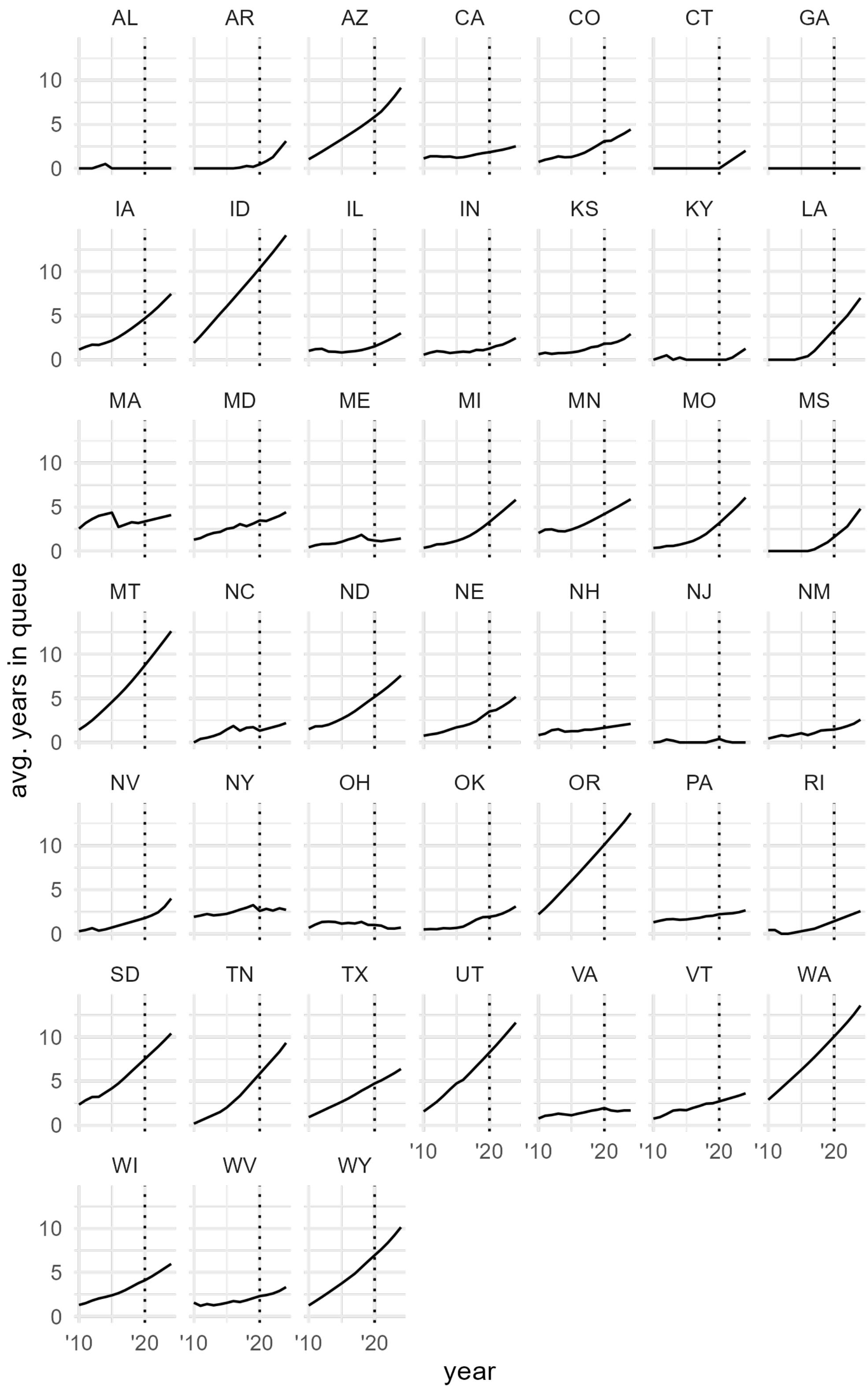


Figure D.13: Mean years in interconnection queue for land-based wind projects under review

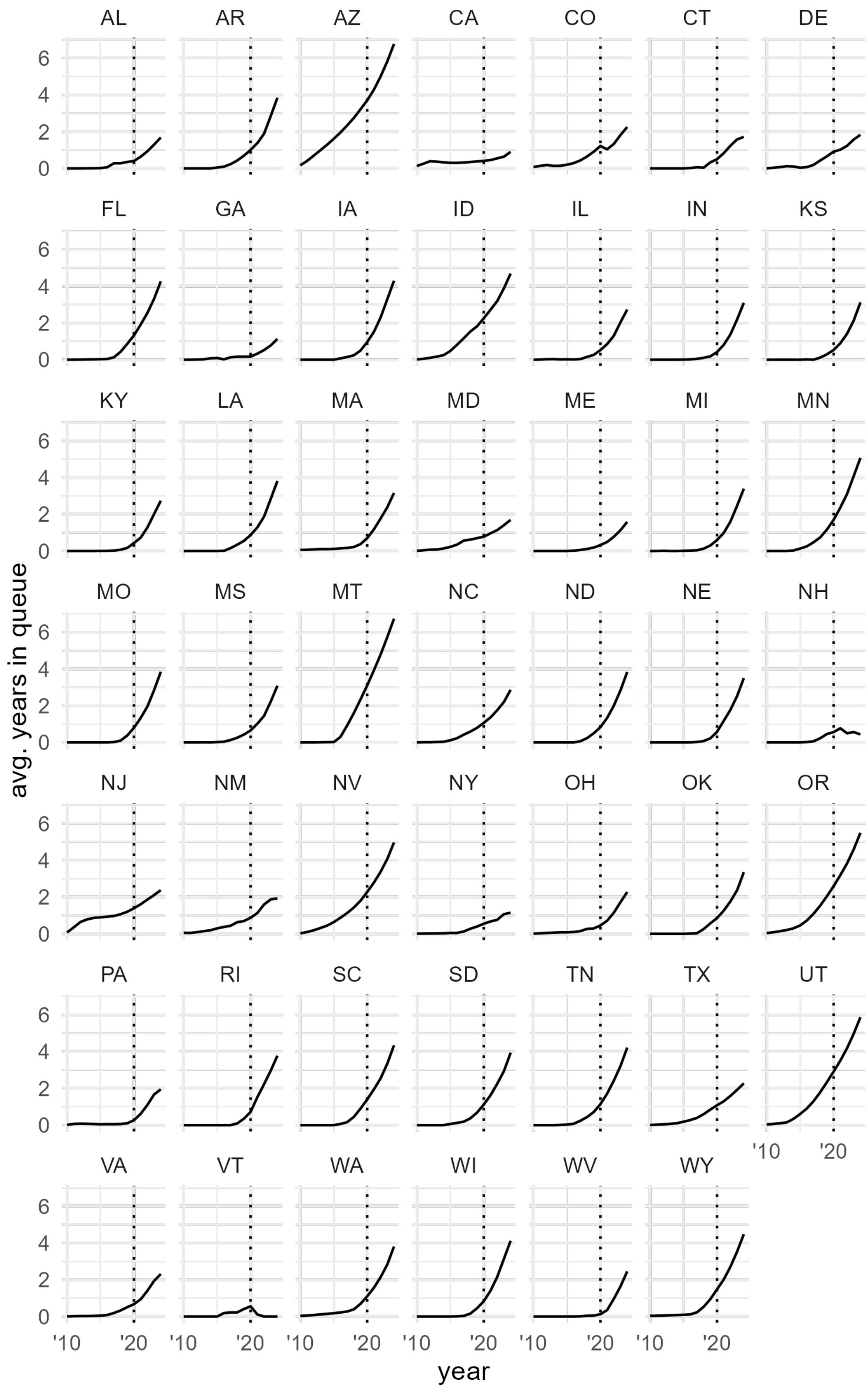


Figure D.14: Mean years in interconnection queue for solar projects under review

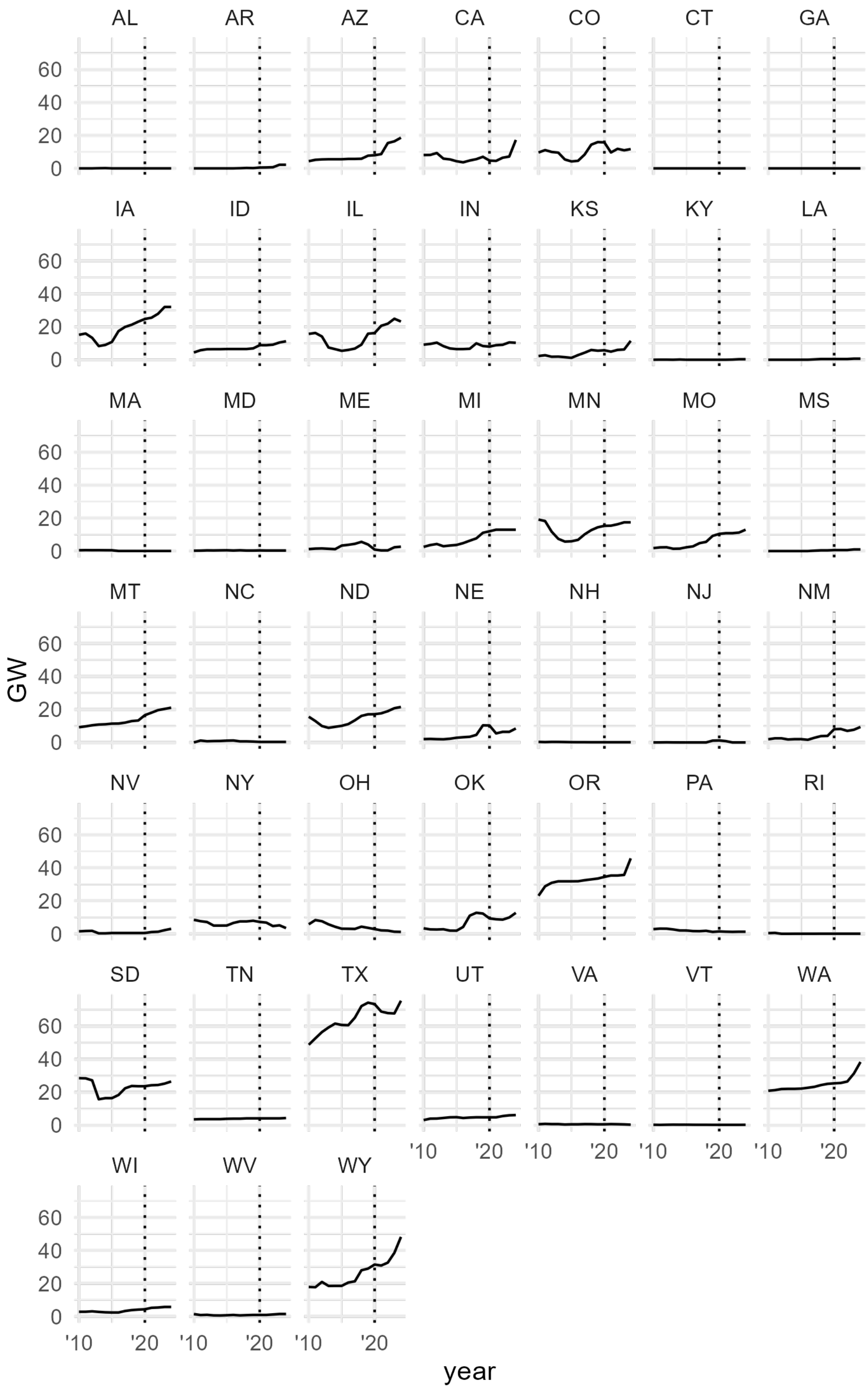


Figure D.15: Capacity (GW) in interconnection queue for land-based wind projects under review

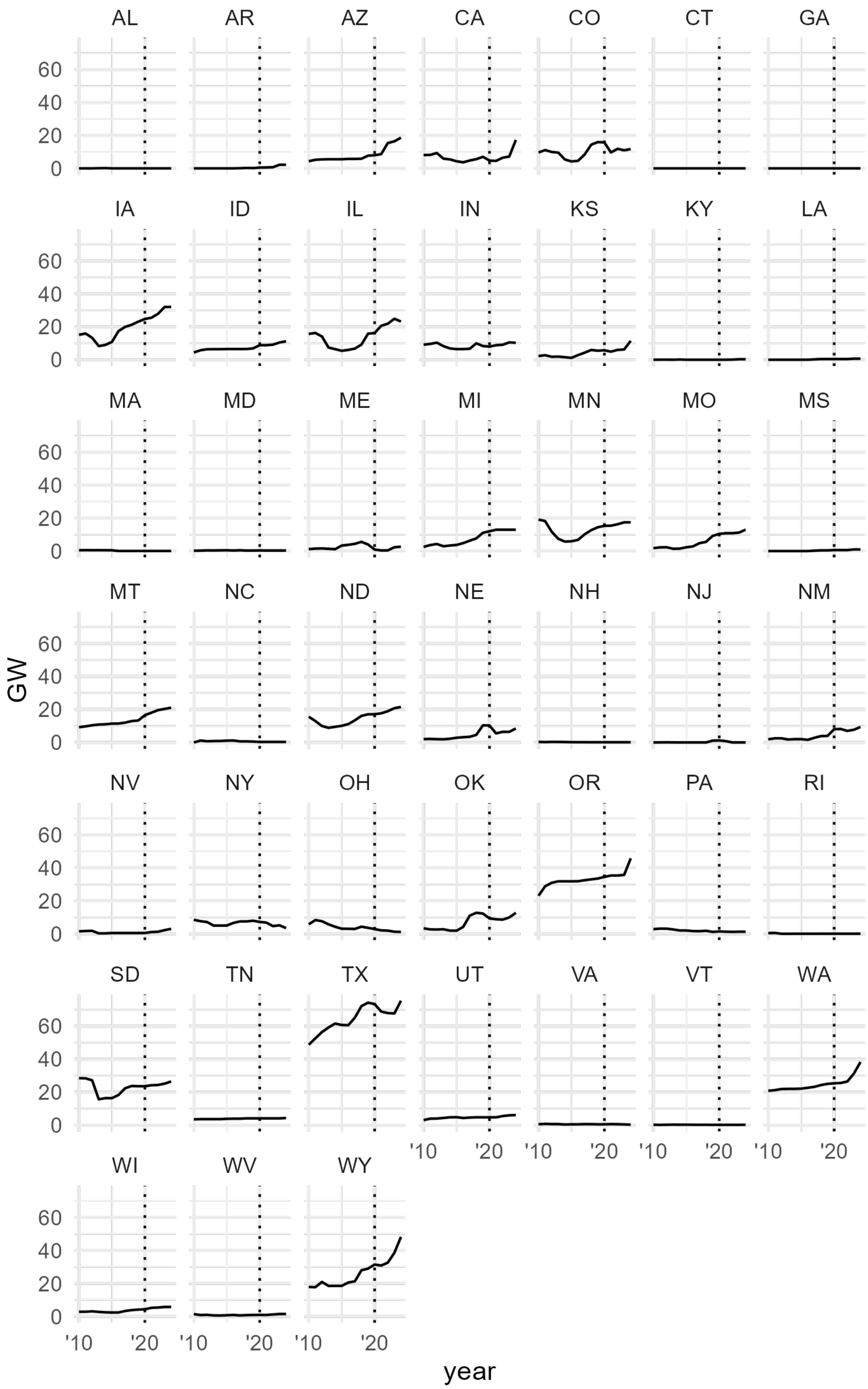


Figure D.16: Capacity (GW_{AC}) in interconnection queue for solar projects under review