Title:

Growth and competition in renewable energy industries: Insights from an integrated assessment model with strategic firms

Author:

Benjamin D. Leibowicz ¹

Affiliation:

¹ Management Science and Engineering Department, Stanford University

Abstract:

This article describes the development, implementation, and application of an integrated assessment modeling framework featuring renewable technology markets with producers engaged in Cournot competition. Scenario results reveal how climate policy and inter-firm learning spillovers interact with market structure to affect wind and solar PV prices, adoption, producer profits, and carbon emissions. Competitive markets yield consistently lower markups than concentrated markets, leading to significantly more adoption and lower emissions. Widespread solar PV adoption is a key component of the largest emissions reductions, but this requires substantial price reductions that only occur if the solar PV market is competitive and learning spills over across producers. Whether a leading firm has a profit incentive to facilitate or obstruct learning spillovers depends on the availability of cost-competitive substitute technologies. If such a substitute exists, the firm prefers strong spillovers that help its industry compete against the substitute; if not, the firm prefers weak spillovers that prevent competitors in its industry from seizing market share. The relationship between price and cumulative capacity is endogenous in the modeling framework. Regression analysis of scenario results yields price learning rates which are similar to unit production cost learning rates in competitive markets, but substantially lower – even negative – in concentrated markets.

Keywords: technological change; market structure; integrated assessment; renewable energy; learning by doing

Corresponding Author:

Benjamin D. Leibowicz
Huang Engineering Center
475 Via Ortega
Office 253A
Stanford, CA 94305 (USA)
Email: bleibowicz@stanford.edu
Phone: 1-516-458-4960
Fax: 1-650-725-5362

1 Introduction

1.1 Clean Energy Technology Growth

Current and anticipated climate change mitigation policies have produced substantial enthusiasm, incentives, and even mandates for adoption of clean energy technologies. Two industries that have grown rapidly as a result are wind and solar photovoltaics (PV). Global capacities of wind and solar PV respectively reached 318 GW and 139 GW in 2013. These totals represent remarkable growth; nearly a third of total solar PV capacity was installed in that year alone, and annual expansion of wind capacity has averaged more than 21% since 2008 (REN21, 2014). While emissions abatement measures are the primary impetus for rapid wind and solar PV diffusion, energy security concerns, scarcity of conventional fossil alternatives, and air quality initiatives serve as additional motivations.

The two technologies are similar in several key respects. They operate with essentially no GHG emissions, have cost structures dominated by capital cost, are land-intensive (or surface-intensive for solar PV), and suffer from intermittent resource availability that presents grid integration challenges. Due to the similarities between wind and solar PV, they are often thought of as together constituting one technology group that can be deployed in response to climate policy (Kanudia et al., 2013; Kriegler et al., 2014). The intermittency challenge in particular distinguishes wind and solar PV from other technology groups, as this is not an obstacle facing nuclear, bioenergy, or fossil fuel with carbon capture and storage (CCS) technologies. Despite these similarities, notable differences between the two technologies merit consideration. Compared to wind, solar PV is characterized by smaller unit scale, larger manufacturing scale, higher levelized cost, and greater potential for continuing efficiency and cost improvements.

In the immediate future, wind will remain a less costly generation alternative than solar PV. The EIA (2014) estimates levelized costs of \$80/MWh and \$130/MWh for wind and solar PV plants entering service in 2019, respectively¹. According to these figures, wind is already cost-competitive with conventional coal (\$96/MWh) and conventional natural gas-fired combined cycle (\$66/MWh) (EIA,

¹ The underlying calculations incorporate active tax credits through their expiration dates. Levelized costs vary across regions due to differences in capacity factors. These EIA estimates are based on 34% and 25% wind and solar PV capacity factors, respectively.

2014). Although wind is the more cost-competitive technology at present, projections agree that solar PV offers more opportunities for further cost reductions. In a report for NREL, Black & Veatch(2012)project that wind capital cost will remain constant through 2050 while utility-scale solar PV capital cost will decline by almost 50%.Based on an expert elicitation, Anadon et al.(2011) forecast a 60% reduction in solar PV module cost by 2030 in the business-as-usual case, with even lower costs possible under expanded RD&D funding. Baker et al.(2009) consider solar PV levelized cost scenarios that settle in the \$29–50/MWh range by the middle of this century. These forecasts largely reflect observed trends in wind turbine and PV module prices since the turn of the millennium (see Figure 1).

Future growth of the wind and solar PV industries will depend on a number of factors and how these evolve over time. As the following subsection describes, some of these factors, such as climate policy, technology costs, and technology performance, receive a great deal of attention in modeling efforts that project the future composition of the energy system. Other important factors, such as market structure and industry competition, have proven more difficult to include in a systems modeling approach and are therefore frequently omitted.

1.2 Integrated Assessment Models

Energy analysts can assess the influence of climate policy, technology costs, and technology performance on technology adoption and carbon emissions using the constellation of integrated assessment models (IAMs) researchers have developed to evaluate the costs and benefits of climate change mitigation measures. Climate policies can be imposed, such as a carbon tax that raises the relative cost of generating electricity from dirty rather than clean sources, or a binding constraint that places an upper bound on emissions or on atmospheric GHG concentrations. Parameter assumptions governing future technology costs and efficiencies can be varied. In models where costs are assumed to evolve exogenously, this means modifying the assumed time path of future costs; in models with an endogenous cost structure (e.g. a learning by doing formulation), this means modifying the relevant technology supply parameter (e.g. the learning rate) or technology demand parameter (e.g. further changes in relative prices

caused by a higher carbon tax). The models generally include rich sets of technology options², so wind and solar PV compete with other technologies (and with one another) for market share.

On a general level, IAMs produce some robust insights. All agree that achieving cost-effective climate stabilization at an atmospheric GHG concentration of 450 or 550 parts per million carbon dioxide equivalent (ppm CO₂e) will require a major transformation of the energy system featuring fast decarbonization of the electricity sector (Kriegler et al., 2014). However, technology-specific findings are far less robust. Examining the results of the Energy Modeling Forum (EMF) 27 study, Luderer et al. (2013) observed that projections for adoption of renewables – particularly wind and solar PV – vary widely across models. For example, under the 450 ppm stabilization target, the MESSAGE model indicates that solar might become the largest source of electricity generation in North America by 2050. In sharp contrast, the MERGE model suggests that solar will not be deployed at all. Luderer et al. (2013) identify three key determinants of wind and solar PV adoption in the models: technology costs, resource availability, and grid integration constraints. Technology cost assumptions appear to play the most crucial role. For example, MESSAGE suggests significantly more solar PV adoption than MERGE primarily because the average 2050 levelized cost is assumed to fall below \$50/MWh in the former and stay close to \$150/MWh in the latter.

1.3 Market Forces

Regardless of whether the models feature exogenous or endogenous representations of technological change, they overwhelmingly exclude market forces that have a significant influence on the wind turbine and PV module prices available to electricity sector project planners. These omitted market forces include market structure, pricing strategy, and competition among firms. Empirical research has revealed that the effects of market dynamics on prices and adoption can be significant. Nemet (2006) showed that changes in the two most important factors driving solar PV cost reductions – plant size and module efficiency – are only weakly explained by cumulative capacity growth,

² In this context, use of the term IAM excludes highly aggregated cost-benefit models of climate change and mitigation that do not represent technologies explicitly, such as the DICE, FUND, and PAGE models.

with market forces playing a more significant role. For example, in its 1970s formative phase, the solar PV industry transitioned from a niche market with only a few price-insensitive customers (e.g. the military and NASA) to a larger, more competitive market structure with greater price sensitivity. Sizable profit margins declined, implying that a standard price-based experience curve analysis, which inherently assumes margins are approximately zero and constant over time, would overestimate the rate of technological progress. Nemet recommends that market dynamics be incorporated into predictions of technological change, such as by allowing variations in market structure to influence prices. Bolinger and Wiser (2011) showed that market forces have had a strong influence on wind turbine prices. While learning curve theory would have predicted a 30% decrease in turbine prices from 2004 to 2009, in reality prices roughly doubled over this period (see Figure 1). This drastic divergence of prices from the learning curve trajectory has several explanations, including labor and materials costs, but also increasing profit margins enabled by rising demand. Echoing Nemet, Bolinger and Wiser conclude that energy analysts should develop a more nuanced understanding of technological change.

1.4 Recent Historical Data

Before proceeding to incorporate market forces into an IAM framework, it is informative to review the recent history of the global wind and solar PV industries in terms of several key indicators. This exercise serves to clarify the empirical motivation for the modeling effort and to suggest ranges for important parameters. Some empirical data is readily available, such as data on installed capacities (European Photovoltaic Industry Association, 2014; Global Wind Energy Council, 2014), wind turbine prices (Wiser and Bolinger, 2014), and solar PV module prices (Mints, 2012). To establish a history of market structure, Herfindahl-Hirschmann Index (HHI) time series are constructed from data on the market shares of major suppliers (Mints, 2014; REN21, 2014). The HHI is a widely applied measure of market concentration that is calculated by summing the squares of each firm's percentage market share. Higher HHI values reflect more concentrated markets, with an HHI of 10,000 corresponding to a pure monopoly. According to the U.S. Department of Justice, an industry is competitive if its HHI is below

1,500, moderately concentrated if its HHI is between 1,500 and 2,500, and highly concentrated if its HHI is above 2,500.

Figure 1 presents key indicators describing the wind and solar PV industries from 2000 through 2013. Both technologies diffused rapidly over this period. In 2013, cumulative installed capacity of wind was more than double that of solar PV, but the annual installed capacity growth rate of solar PV was more than double that of wind. The HHI and price trends of the two technologies exhibit notable similarities. The wind and solar PV industries became more concentrated after 2000, reaching HHI peaks in 2004 and 2003, respectively. Wind turbine prices rose each year from 2004 through 2009 while solar PV module prices rose each year from 2003 through 2008. It is interesting that the beginning of the period of price increases for each technology exactly coincided with the peak market concentration. Therefore, the data lend some credibility to the interpretation that rising prices were at least partially caused by higher markups resulting from more concentrated markets. Examining the most recent data, it seems that the higher prices encouraged entry of new producers, creating more competitive markets that ultimately caused prices to start falling again, with some lag. Even during the period of rising prices, installed wind and solar PV capacity grew rapidly and at generally accelerating rates. The relationship between price and demand for new capacity theoretically includes causal effects in both directions, but given that prices and capacity additions increased simultaneously, it appears that strong demand (to some extent the result of climate and renewable energy policies) enabled producers to charge higher prices.

Figure 1. Historical data describing the global wind and solar PV industries from 2000 through 2013.

The recent historical data presented here provide clear evidence that a standard learning curve formulation is an insufficient approach to modeling prices of renewable technologies. The standard learning curve could not produce alternating periods of price decreases and increases, as have been observed in the recent past. The data suggest that a more credible formulation could be developed by accounting for the influence of market structure and variations in demand.

1.5 Competitive Strategy Models

In the 1970s, consulting firms such as Boston Consulting Group often advocated aggressive expansion strategies based on anticipated cost reductions that would occur through learning by doing. The rationale was that the firm's costs would decline to a point at which it could seize market share from rivals, ensure a long-term cost advantage, and discourage entry of new firms (Day and Montgomery, 1983; Kiechel, 1981). In reality, this approach was rarely as successful as expected, and several landmark scholarly papers (Clarke et al., 1982; Lieberman, 1987) were written in the 1980s to analyze competitive strategy in markets where learning by doing is present. Applying the approach of this literature to renewable energy technology industries seems natural, but in practice it has not been incorporated into IAM analyses.

In the simplest case, a monopolist faces an optimal intertemporal pricing problem (Clarke et al., 1982). Due to learning by doing, setting a lower price and producing more output has the added advantage of lowering future production costs. As a result, the optimal pricing rule equates marginal revenue not with marginal cost, but with marginal cost plus an additional term that represents the present value of future cost reductions due to an increase in output. This sum is referred to as the *full long-run marginal cost* to distinguish it from the standard short-run marginal cost. Learning by doing makes it optimal to raise production levels, and the optimal price falls over time.

Lieberman (1987) generalized this framework to include multiple firms and learning spillovers. In this setup, some fraction of each firm's learning contributes to a common knowledge base that reduces costs for all firms in the market. As a result, the full long-run marginal cost includes an additional strategic term that represents the response of competitors to the firm's learning. If learning is more or less proprietary, this term induces the firm to increase output even more than in the monopolist case. But if learning spillovers are strong, this term provides an incentive to reduce output (because the firm's production lowers costs for competitors, who then increase output and lower prices).

1.6 Purpose and Organization

This article describes the development, implementation, and application of an IAM framework featuring technology markets with firms engaged in Cournot competition. This market-based framework has two important advantages compared to standard formulations of technological change such as exogenously assumed costs or learning curves. First, it captures market forces that affect prices (and therefore adoption and carbon emissions), such as market structure and learning spillovers across firms. Second, it expands the applicability of IAMs to cover questions of firm-level competitive strategy.

The remainder of this article is organized as follows. Section 2 describes the modeling framework and solution algorithm. Section 3 defines the scenarios designed to investigate how climate policy and learning spillovers interact with market structure to affect markups, renewable technology adoption, carbon emissions, and producer profits. Scenario results are presented and discussed in Section 4. The article concludes in Section 5 with a summary of valuable insights for modelers, policymakers, and energy strategists.

2 Methods

2.1 Overview

The approach of this study is to couple an IAM to a technology market model (TMM) similar in configuration to the market analyzed by Lieberman (1987). The following subsections first introduce each model individually, then describe the solution algorithm and iterative procedure used to achieve convergence in prices and quantities in each period. To generally orient the reader before commencing the detailed model description below, Figure 2 provides a broad visual overview of the information flows linking the IAM and TMM.

Figure 2. Overview of the iterative procedure that couples the IAM and TMM, making their prices and quantities converge in each period.

2.2 Integrated Assessment Model (MESSAGE)

The IAM employed in this study is a version of MESSAGE, a technology-detailed, least-cost optimization model of the global energy system (Riahi et al., 2007). It is developed and maintained by researchers at the International Institute for Applied Systems Analysis (IIASA) and is frequently included in prominent modeling exercises, such as those of the IPCC and EMF (Bruckner et al., 2014; Kriegler et al., 2014). Several versions of MESSAGE are available, each of which is tailored to research focusing on a different aspect of the linked energy, economic, and environmental systems. The version employed in this study is a reduced-form version of the model implemented in GAMS and originally designed for analyses examining the roles of uncertainty and foresight (Krey and Riahi, 2009). It is appropriate for this analysis because its GAMS framework enables structural modifications and coupling to the TMM. In addition, its limited sets of regions and technologies focus attention on the implications of incorporating renewable technology markets without unnecessary complexity. The model is deterministic and formulated as a linear program.

This version of MESSAGE has ten-year time steps and a 2100 time horizon. Model parameters are calibrated to historical data through the 2010 period, making 2020 the first decision period. It has four

regions and 11 electricity generation technologies(see Table 1).In addition, oil refining, liquid fuel production from coal, gas, and biomass, as well as hydrogen electrolysis are represented in the model to cover a wide range of primary to final energy supply routes. Energy end-use is modeled in a stylized fashion with three demand categories included: stationary electric demand, stationary thermal demand, and transport fuel demand. Energy savings are incorporated via so-called conservation cost curves that have been derived from the 11-region version of MESSAGE(Rogelj et al., 2013). Wind and solar PV are included in the model only as utility-scale generation options. Distributed generation modes are not explicitly represented, but they implicitly factor into the model since they have been included in the set of technologies used to establish the conservation cost curves that capture demand response.

Table 1.Regions and technologies featured in the reduced form version of MESSAGE.

Regions	Electricity Generation Technologies
<ul style="list-style-type: none"> • Organization for Economic Cooperation and Development • Eastern Europe and former Soviet Union • Asia • Latin America and Africa 	<ul style="list-style-type: none"> • Coal • Gas • Nuclear • Hydro • Biomass • Oil • Coal with CCS • Gas with CCS • Biomass with CCS • Wind • Solar PV

Technology choice in MESSAGE essentially works by deploying technologies in descending order of levelized cost until demands are met, subject to a variety of constraints. These constraints include resource availability, diffusion rate limits to prevent unreasonably rapid scale-up, a maximum share of intermittent renewables in the electricity mix, and potentially quantity-based climate policies. In this reduced-form version of MESSAGE, the intermittency constraint stipulates that generation from wind and solar PV cannot exceed 20% of end-use electricity demand plus 70% of conversion and primary energy sector electricity demands.This upper bound can be relaxed by investing in electricity storage.

2.3 Technology Market Model

The TMM represents a market similar in configuration to that analyzed byLieberman(1987). Let F denote the set of firms in the market and let n be the exogenously fixed number of firms. These firms

operate in a global market and no distinctions are made based on geographical location. The objective of each firm $f \in F$ is to maximize the net present value of profits over the next h periods including the current one. The parameter h thus defines the planning horizon, how far into the future the firm considers when analyzing its strategic decisions. Setting $h = 1$ establishes the myopic case in which firms only consider current profit; setting h to a high value establishes that firms are forward thinking, with a planning horizon in the distant future. Let T denote the set of periods that firms consider for planning purposes, so that $T = \{1, \dots, h\}$. All firms have a discount rate ρ that they use to compare present and future monetary values. Note that $\rho = \infty$ imposes the same myopic decision problem as $h = 1$.

Let $x_{f,t}$ denote the output of firm f in period t . These are the decision variables. A related quantity is $z_{f,t}$, the cumulative output of the firm over all periods prior to t . The cost function incorporates learning by doing, through which unit cost decreases as a function of cumulative output. Let λ denote the learning rate, the percentage reduction in unit cost with each doubling of cumulative output. The cumulative output argument in the cost function is a weighted sum of the firm's own cumulative output ($z_{f,t}$) and the cumulative output of all other firms ($z_{f-,t}$). The learning spillover parameter α controls the extent to which a firm's cumulative output reduces all other firms' costs. For example, setting $\alpha = 0.5$ specifies that two additional units of other-firm output reduce a firm's unit cost the same amount as one additional unit of its own output. The cost function is assumed to be linear with respect to output, reflecting constant unit cost. With these designations and assumptions, Equation 1 defines the cost function. The coefficient a is calibrated such that the function maps the observed 2010 cumulative industry output to the observed 2010 unit cost.

Equation 1

$$C(x_{f,t}, z_{f,t}, z_{f-,t}) = a(z_{f,t} + \alpha z_{f-,t})^{\log(1-\lambda)/\log(2)} x_{f,t} \quad \forall f \in F, t \in T$$

Equation 2 is the accounting mechanism for cumulative output, which is augmented by the output decision variables. The initial cumulative output $z_{f,1}$ is a parameter that represents the cumulative output of the firm prior to the current algorithm period. It includes historical cumulative output through 2010 as

well as the output levels determined by the algorithm in all periods prior to the current one. For example, if the algorithm is currently solving the 2040 period, $z_{f,t}$ will include the firm's historical output through 2010 as well as the determined values of its output decision variable in 2020 and 2030. It is assumed that all firms in the market produced an equal share of the historical cumulative output through 2010.

Equation 2

$$z_{f,t} = z_{f,1} + \sum_{\tau < t} x_{f,\tau} \quad \forall f \in F, t \in T$$

Firms face the inverse industry demand function of Equation 3, which determines the market price as a function of total industry output. It is characterized by constant price elasticity of demand ε and market size that expands exponentially at annual rate g . The period length Δ corresponds to that in MESSAGE (ten years). The coefficient b specifies the position of the demand curve. It is calibrated to anchor the demand curve to the point which represents the MESSAGE capital cost assumption (i.e. the last market price passed to it from the TMM) and resulting capacity addition in the MESSAGE optimal solution. The market growth rate g and elasticity ε are received directly from MESSAGE and are assumed to remain constant over the planning periods.

Equation 3

$$P(x_{f,t}, x_{f-,t}) = \left[\frac{x_{f,t} + x_{f-,t}}{b e^{g\Delta(t-1)}} \right]^{1/\varepsilon} \quad \forall t \in T$$

The profit maximization objective of each firm is expressed in Equation 4. The firm chooses its output in all periods to maximize the net present value of profits through the planning horizon.

Equation 4

$$\underset{x_{f,t} \forall t \in T}{\text{maximize}} \pi_f = \sum_{t \in T} (1 + \rho)^{-\Delta(t-1)} [P(x_{f,t}, x_{f-,t}) x_{f,t} - C(x_{f,t}, z_{f,t}, z_{f-,t})] \quad \forall f \in F$$

This market setup is a Cournot competition in which each firm solves for its optimal output schedule while treating the output schedules of all other firms as fixed. A Nash equilibrium of the game

exists wherever all firms are producing optimal quantities given the output decisions of all other firms. In other words, no firm could earn greater profit by unilaterally deviating from its output levels.

The conditions for Nash equilibrium are derived analytically by taking Karush-Kuhn-Tucker (KKT) conditions, the derivatives of every firm's profit function (Equation 4) with respect to the firm's own output levels in all periods. These KKT conditions make up a system of n by h equations for this same number of unknowns (each firm's output level in each period). Equation 5 provides the analytically derived Nash equilibrium conditions.

Equation 5

$$\begin{aligned}
 MR_{f,t} &= MC_{f,t}^{present} + MC_{f,t}^{future} \quad \forall f \in F, t \in T \\
 MR_{f,t} &= (1 + \rho)^{-\Delta(t-1)} \left[\left(\frac{x_{f,t} + x_{f-,t}}{b e^{g\Delta(t-1)}} \right)^{1/\epsilon} + \left(\frac{1}{\epsilon b e^{g\Delta(t-1)}} \right) \left(\frac{x_{f,t} + x_{f-,t}}{b e^{g\Delta(t-1)}} \right)^{\frac{1}{\epsilon}-1} x_{f,t} \right] \\
 MC_{f,t}^{present} &= (1 + \rho)^{-\Delta(t-1)} a (z_{f,t} + \alpha z_{f-,t})^{\log(1-\lambda)/\log(2)} \\
 MC_{f,t}^{future} &= \sum_{\tau > t} (1 + \rho)^{-\Delta(\tau-1)} \frac{\log(1-\lambda)}{\log(2)} a (z_{f,\tau} + \alpha z_{f-, \tau})^{\frac{\log(1-\lambda)}{\log(2)}-1} x_{f,\tau} x_{f,t}
 \end{aligned}$$

The marginal cost (MC) is decomposed into two parts. The present MC is simply the additional cost incurred in period t to raise output by one unit in that period. The future MC reflects the impact of output in period t on costs in future periods. Together, the two components of MC make up the full long-run MC, as it was referred to by Clarke et al.(1982).

The TMM is used to model markets for wind and solar PV capacity. All other technologies in MESSAGE retain their exogenously assumed capital cost time paths. The TMM is implemented in GAMS as a nonlinear program (NLP) with the equilibrium conditions defined in Equation 5 encoded as binding constraints. It is solved using the CONOPT solver. Any feasible solution that satisfies the constraints is a Nash equilibrium. Because the problem is nonlinear, it is possible that the KKT conditions permit multiple solutions, and therefore that the market has multiple equilibria. If multiple equilibria exist, the specification of the objective function constitutes a rule for selecting one of these equilibria as

the TMM solution. The approach taken here is to choose the equilibrium in which wind and solar PV producers earn the greatest combined total profits. The issue of multiple equilibria is discussed in more detail in Appendix A, which tests the robustness of results relative to the specification of the objection function and choice of NLP solver.

2.4 Model Coupling and Solution Algorithm

To describe the progression of the solution algorithm, it is useful to distinguish three periods: the algorithm period, the IAM decision period, and the TMM planning period (see Table 2). The algorithm period describes the overall progress of the algorithm from its start in 2020 through the 2100 time horizon. As the procedure advances through time, the algorithm period can be thought of as the present from a decision making standpoint. In a given algorithm period, the IAM decision periods include all periods from the algorithm period through 2100. Capacity additions and other decision variables for previous algorithm periods have already been determined. The number of TMM planning periods, beginning with the algorithm period, is determined by the planning horizon parameter h . Table 2 depicts an example in which $h = 3$.

Table 2. Summary of the solution algorithm. In each successive algorithm period, MESSAGE runs from the algorithm period through the 2100 time horizon, and firms in the TMM maximize profit over h periods beginning with the algorithm period.

Algorithm Period	Bold = IAM Decision Period						Red Background = TMM Planning Period				
2020	2020	2030	2040	2050	2060	2070	2080	2090	2100		
2030		2030	2040	2050	2060	2070	2080	2090	2100		
2040			2040	2050	2060	2070	2080	2090	2100		
2050				2050	2060	2070	2080	2090	2100		
2060					2060	2070	2080	2090	2100		
2070						2070	2080	2090	2100		
2080							2080	2090	2100		
2090								2090	2100	2110	
2100									2100	2110	2120

In each algorithm period, MESSAGE and the TMM exchange information, iterating until a convergence condition is satisfied (see Figure 2). The iteration begins with MESSAGE, which initially assumes wind and solar PV have the capital cost trajectories defined in the standard version of the model. The MESSAGE optimal solution includes quantities of wind and solar PV global capacity additions in the algorithm period. To estimate the price elasticity of demand for these quantities, additional MESSAGE runs are executed in which the capital cost parameters are perturbed and the resulting changes in capacity additions are observed. MESSAGE passes the TMM four pieces of information for each technology: (1) capital cost, (2) demand for new capacity, (3) price elasticity of demand for new capacity, and (4) annual growth rate of capacity demand. The TMM uses this information to initialize its demand curves, which take the constant price elasticity form described in the previous subsection. The TMM solution includes the equilibrium market price and global industry output for both technologies in the algorithm period. At this point, the routine tests whether the convergence condition is satisfied. The condition states that, in the algorithm period, TMM market prices are roughly equal to the capital costs assumed by MESSAGE, and TMM industry outputs are roughly equal to the optimal new capacity additions determined by MESSAGE³. In other words, at some price for capacity, the amount of new capacity the social planner would install equals the amount of capacity the market would produce with all firms acting strategically. If the convergence condition is satisfied, the procedure advances to the next algorithm period. If not, the TMM passes the equilibrium wind and solar PV market prices to MESSAGE, where they are interpreted as the capital costs of the two technologies in the algorithm period. MESSAGE establishes the profile of future capital costs by simply assuming a fixed percentage cost reduction in each future period. MESSAGE executes and the iterative loop continues until convergence is achieved.

3 Scenarios

³ Specifically, the algorithm declares convergence when TMM prices and MESSAGE capital costs differ by less than \$1/kW, and TMM outputs and MESSAGE global capacity additions differ by less than 1 GW. For some perspective, 2013 global capacity additions of wind and solar PV were 35 GW and 39 GW, respectively (REN21, 2014).

A goal of this study is to investigate how climate policy and learning spillovers interact with market structure to influence markups, renewable technology adoption, carbon emissions, and producer profits. Toward this end, two sets of scenarios are defined and evaluated: policy scenarios and spillover scenarios. Both sets include some scenarios featuring competitive wind and solar PV markets (each with 15 identical firms), and other scenarios featuring concentrated markets (each with three identical firms). These market structures correspond to HHI values of 3,333 and 667, respectively, bounds which roughly include the range of market concentrations observed in the wind and solar PV markets this century (Figure 1). A scenario summary is provided in Table 3.

The policy scenarios feature the same learning spillover assumption but different carbon tax profiles. These include two carbon tax ramps, where the tax starts low then gradually rises over time, and two carbon tax shocks, where a significant tax is introduced suddenly then remains constant through the time horizon. Similar ramps and shocks have been implemented in previous studies (Kriegler et al., 2015; Wilkerson et al., 2015) to account for the possibility that the shape of the tax profile – in addition to its level – can have an important effect on outcomes. The shock tax levels are calibrated to match the tax levels reached by the ramps in 2100.

The spillover scenarios feature the same carbon tax profile but different learning spillover assumptions. The four spillover assumptions span the full range from no spillovers ($\alpha = 0$) to perfect spillovers ($\alpha = 1$) of learning across firms.

Table 3. Scenario summary. Blue cells are policy scenarios, red cells are spillover scenarios, and purple cells are both policy and spillover scenarios.

	Competitive Markets (n = 15)				Concentrated Markets (n = 3)			
	$\alpha = 0$	$\alpha = 1/3$	$\alpha = 2/3$	$\alpha = 1$	$\alpha = 0$	$\alpha = 1/3$	$\alpha = 2/3$	$\alpha = 1$
Low Ramp								
High Ramp								
Low Shock								
High Shock								

Low Ramp	Introduced at \$10/tCO ₂ in 2020, rises 3% annually thereafter
High Ramp	Introduced at \$20/tCO ₂ in 2020, rises 3% annually thereafter
Low Shock	Introduced at \$106.41/tCO ₂ in 2050, constant thereafter
High Shock	Introduced at \$212.82/tCO ₂ in 2050, constant thereafter

Some basic parameter assumptions remain constant across all scenarios. The learning rate is assumed to be 7% for wind and 18% for solar PV. These estimates are based on central values from a range of empirical studies (e.g., Breyer and Gerlach, 2013; IEA, 2012; Kersten et al., 2011) and were adopted as best estimates in the IEA Technology Roadmaps (IEA, 2013, 2010). The discount rates in both MESSAGE and the TMM are set at 3%, an assumption that reflects a middle position in the ongoing discount rate debate (Nordhaus, 2007; Stern, 2007; Weitzman, 2007). Firms are assumed to maximize profit over a planning horizon h of three periods (30 years).

4 Results and Discussion

4.1 Policy Scenario Results

Figure 3 presents policy scenario results for wind and solar PV unit costs, prices, and markups. Wind prices are substantially higher in scenarios with concentrated markets than in those with competitive markets. Some of this difference can be attributed to slightly higher unit costs in the concentrated market scenarios (a result of weaker adoption), but most of it is explained by higher markups. Concentrated markets allow wind producers to exert market power, leading to markups in the 35–70% range. In contrast, a competitive market structure limits markups to less than 20%. Solar PV unit costs vary more across scenarios than wind unit costs. Solar PV is a less mature technology with a higher learning rate and greater potential for future cost reductions, but these are contingent on continued adoption. The wide range of future unit costs reflects varying adoption trajectories, determined endogenously in each scenario. Solar PV markups are generally similar to those of wind under both concentrated and competitive market structures. IAMs typically do not distinguish between cost and price, and do not represent markups. The results here suggest that this simplification is likely adequate if

markets are competitive but could be highly problematic if markets are concentrated. To account for the possibility of market power, standard IAM studies could use the markups derived here to parameterize scenarios or sensitivity analyses of future technology capital costs.

Figure 3. Policy scenario results: cost, price, and markup. In subfigures (a) and (b), solid lines represent prices and dashed lines represent unit production costs.

Notable exceptions to the high markups observed under concentrated market scenarios are the falling solar PV markups observed over the final periods in Figure 3d. The high and approximately steady markups up to this point correspond to a profit-maximizing solution in which solar PV producers sell insignificant quantities at very high prices. In this context, lowering prices in an attempt to seize market share from wind would be futile since solar PV is so much more costly; the firms earn higher profits by

satisfying negligible demand niches instead. Over the final periods, high carbon taxes and constraints on wind capacity growth provide a suitable opportunity for solar PV producers to increase profits. They reduce markups and solar PV begins to appreciably diffuse into the electricity supply mix.

For a given market structure, the results in Figure 3 offer only limited evidence to suggest a causal link from climate policy to markups. For example, the tax shocks seem to induce a spike in wind markups at mid-century under the competitive market structure, but similar results are not consistently observed for both technologies across all scenarios. However, if carbon taxes induce changes in market structure (not captured in the present framework), then markups would respond as they do in the competitive versus concentrated market scenarios.

Solar PV production cost declines to very low values toward the end of the century when markets are competitive. The plausibility of these values is difficult to assess, because perceived floors on solar PV production cost established by material and labor costs could theoretically be overcome by shifting to other inputs. Some IAMs impose a floor on solar PV capital cost, but approaches range from having no floor at all to imposing floors as high as \$2,000/kW (Baker et al., 2013). Regardless, it may be that the 18% learning rate assumed in these scenarios cannot be sustained indefinitely.

Global installed capacities of wind and solar PV are shown in Figure 4, along with global CO₂ emissions. Given that market structure has a significant influence on prices of wind and solar PV capacity, it is not surprising that different market structures result in very different technology adoption and emissions pathways. When market structure is competitive, wind is preferred to solar PV for the next several decades, but solar PV begins seizing market share at mid-century and ultimately dominates the electricity generation mix. This is evident in Figure 5, which depicts the capacity portfolios in 2040 and 2100. In these scenarios, solar PV capacity is available at very low prices (see Figure 3b), so the cost-minimizing solution is to flood the system with tremendous solar PV capacity. Even accounting for electricity storage requirements, the model finds this a more cost-effective strategy than investing in alternative clean energy technologies like nuclear or thermal plants equipped with CCS, or reducing electricity demand. Total generation is higher in the competitive market scenarios, and a large amount of

electricity is used in the production of hydrogen fuel. By stimulating pervasive diffusion of solar PV, competitive markets result in greater emissions reductions than concentrated markets. As seen in Figure 4b, for any given carbon tax, CO₂ emissions are lower under competitive markets. Market structure clearly plays an important role in determining the response of emissions to carbon prices.

Figure 4. Policy scenario results: installed capacity and CO₂ emissions.

When market structure is concentrated, solar PV prices cannot compete with wind. As a result, solar PV adoption is minimal until the very end of the century and substantial wind capacity continues to be added through the time horizon. In these scenarios, however, wind does not dominate the technology mix nearly as much as solar PV does in the competitive market cases (note the different vertical axis

scales in Figures 4a and 4b). While wind is deployed extensively, it is complemented by major contributions from nuclear, coal with CCS, and gas with CCS generation (see Figure 5). Reductions in wind cost and price are limited because the technology is further along its learning curve. A massive buildup of wind capacity to satisfy virtually all electricity demand (analogous to the massive buildup of solar PV capacity in the competitive market scenarios) is suboptimal because the lower wind learning rate means its price cannot decline enough to compensate for the storage investments this approach would require. The cost-minimizing solution features significant adoption of wind, but an overall more balanced portfolio with far less total capacity and generation as a result of demand response. Since the concentrated market structure impedes widespread diffusion of solar PV, CO₂ emissions are not reduced as much as under the competitive market structure. Of course, an important caveat to findings for both wind and solar PV is the highly simplified and aggregated treatment of variable renewables in the reduced form version of MESSAGE employed in this study. Regardless, market structure appears to be an important determinant of the optimal technology response to climate policy, with concentrated markets favoring more established clean technologies and competitive markets enabling adoption of less mature but potentially more promising alternatives.

Figure 5. Policy scenario results: installed capacity portfolios (percentage shares) in 2040 and 2100.

The path of global CO₂ emissions is sensitive to both the level and shape of the carbon tax. With a tax ramp, emissions continue to rise for several decades, reach a smooth peak, then decline for the rest of this century. With a tax shock, emissions are greater in the short run, but the system responds to the introduction of the shock with a sudden and drastic emissions reduction in 2050. Whether a carbon tax is implemented as a ramp or a shock has a noticeable influence on the optimal emissions abatement pathway even though MESSAGE is an inter-temporal optimization model with perfect foresight; with a more realistic foresight assumption, the difference between ramps and shocks could be larger.

4.2 *Spillover Scenario Results*

Figure 6 presents spillover scenario results for wind and solar PV costs, prices, and markups. The effects of market structure are similar to those observed in the policy scenario results. Concentrated markets lead to higher prices that are partially attributed to higher production costs (a consequence of weaker adoption) but are mainly a result of larger markups. As before, concentrated markets induce markups in the 35–70% range for both technologies, while competitive markets limit markups to less than 20%. The results in Figure 6 reveal important interactions between market structure and learning spillovers. Prices under the competitive market structure are much higher when learning spillovers are absent ($\alpha = 0$). This is particularly true for solar PV, as prices in the competitive market scenario without spillovers are closer to the much higher prices of the concentrated market scenarios than the lower prices of the competitive market scenarios with spillovers.

The tendency for concentrated markets to generate higher markups and prices appears to be mitigated by strong learning spillovers. For example, wind prices in a concentrated market are significantly lower with perfect spillovers ($\alpha = 1$), lying somewhere between prices in the competitive market scenarios and prices in the other concentrated market scenarios. With perfect spillovers the learning effect is more powerful since a given level of industry output results in lower production costs for all firms. Wind producers drop their markups in early periods (Figure 6c) to accumulate production experience faster (Figure 7a) and earn greater profits through lower future production costs. As the perfect

spillover assumption also applies to the solar PV market, there is an additional incentive for wind producers to reduce prices in this scenario in order to preserve market share against the threat of lower solar PV prices.

Figure 6. Spillover scenario results: cost, price, and markup. In subfigures (a) and (b), solid lines represent prices and dashed lines represent unit production costs.

The policy scenario results indicated that market competition is critical to the diffusion of solar PV. The spillover scenario installed capacity results in Figure 7b show that competitive markets are a necessary but not sufficient condition; even under competitive markets, widespread adoption of solar PV is contingent on the existence of learning spillovers across firms. In Figure 7b, solar PV capacity

proliferates in all competitive market scenarios except for the no spillover case ($\alpha = 0$), where it is barely deployed until the end of the century. Looking at the competitive market scenarios with spillovers, stronger spillovers lead to greater solar PV diffusion, but by far the most important distinction is whether spillovers are active (at any strength) or not. If a lack of spillovers precludes solar PV from penetrating the market, wind capacity continues to be installed in significant quantities throughout the entire century, which does not take place if spillovers are present and solar PV is deployed extensively. The capacity portfolio results in Figure 8 show that competitive markets without spillovers yield capacity portfolios similar to those derived in the concentrated market structure scenarios.

Figure 7. Spillover scenario results: installed capacity and CO₂ emissions.

The CO₂ emissions trajectories in Figure 7c reveal a very important point about the influence of market structure and spillovers on the emissions response to climate policy. Competitive markets result in lower CO₂ emissions than concentrated markets, but only if learning spillovers are active. Note that the competitive and concentrated market CO₂ pathways without spillovers ($\alpha = 0$) are almost identical, while the scenarios with spillovers yield much lower emissions under competitive markets. Solar PV appears to be a key technology for achieving large emissions reductions under a climate policy, but for solar PV to seize market share in the electricity system it requires competitive markets and learning spillovers that combine to reduce prices.

Figure 8. Spillover scenario results: capacity portfolios (percentage shares) in 2040 and 2100.

4.3 Learning Spillovers and Producer Profits

The scenario results presented up to this point indicate that stronger learning spillovers lead to a variety of desirable outcomes, particularly widespread diffusion of solar PV that results in significantly lower carbon emissions. Since firms exert some control over the magnitude of learning spillovers, it is important to assess whether wind and solar PV producers have a profit incentive to facilitate or obstruct these spillovers. This information is also highly relevant for strategists in these industries.

To explore the relationship between learning spillovers and profits, the scenario structure is expanded to allow for different spillover parameter (α) assumptions in the wind and solar PV markets. Denote these values α_{wind} and α_{pv} , respectively. The scenarios evaluated in this exercise all feature the high ramp carbon tax and the competitive market structure, but reflect variations in α_{wind} and α_{pv} . In all scenarios, one firm in each market, designated the leading firm, is parameterized with 20% lower initial production cost than its competitors. The move from identical firms to a market with a distinct leading firm means that market shares are determined endogenously, making the analysis of spillovers and profits more revealing.

Figure 9. The effect of spillovers in the wind and solar PV industries on the net present value (NPV) of leading firm profits. These scenarios assume the high ramp carbon tax and competitive market structure.

Figure 9a illustrates the effect of learning spillovers in both industries on the net present value of the leading wind firm's profits. It is immediately clear that profits are highest when learning does not spill over within the solar PV industry ($\alpha_{\text{pv}} = 0$). In this case, solar PV costs do not decline enough to make the technology a competitive substitute for wind, so demand for wind is high. A notable insight from Figure 9a is that the relationship between learning spillovers in the wind industry and leading wind firm profits is highly dependent on learning spillovers in the solar PV market. When $\alpha_{\text{pv}} = 0$, solar PV remains too costly to compete with wind and demand for wind capacity is unthreatened. In this case, leading wind firm profits are highest when $\alpha_{\text{wind}} = 0$; without spillovers, the leading firm sustains its substantial cost advantage relative to its competitors and profits from a large market share. When $\alpha_{\text{pv}} > 0$, solar PV

becomes a viable substitute for wind and threatens to displace wind from the energy system. In this case, the leading wind firm actually earns greater profits with stronger spillovers that reduce costs throughout the wind industry and help wind compete against solar PV. More generally, the results suggest that whether a firm has a profit incentive to facilitate or obstruct learning spillovers largely depends on the availability of cost-competitive substitute technologies.

Figure 9b is exactly analogous to Figure 9a, but for the leading solar PV firm. The results confirm that the firm's profits are highly dependent on learning spillovers within its industry. Across the rows (variations in α_{pv}), the profit outcomes suggest that there is an ideal middle ground in the tradeoff between weak spillovers that enable the leading firm to capture solar PV market share and strong spillovers that reduce costs in the industry as a whole and stimulate solar PV demand growth. This is manifest as profits which are greatest when $\alpha_{pv} = 1/3$. According to these results, the leading solar PV firm has a profit incentive to facilitate learning spillovers to help the industry compete with wind, but only to a point.

4.4 Price Learning Rates

The modeling framework of this study represents learning by doing at the individual firm level and allows for markups. This is different from the standard IAM approach, which models learning as an industry-level phenomenon and makes no distinction between cost and price. In the present framework, it is helpful to distinguish two learning rates. Let the *unit cost learning rate* (UCLR) describe the relationship between a firm's cumulative output and its unit production cost. Recall that the UCLR is exogenously assumed to be 7% for wind and 18% for solar PV in all scenarios. Let the *price learning rate* (PLR) describe the relationship between cumulative installed capacity and market price. The PLR is not an input assumption. It is an outcome that can be calculated from the scenario results and depends on a host of factors including climate policy, market structure, and learning spillovers.

The wind and solar PV PLRs for each scenario are calculated using a linear regression where the dependent variable is the logarithm of market price and the explanatory variable is the logarithm of cumulative installed capacity. In other words, a learning curve is fitted to the market price and cumulative

installed capacity time series, which are endogenously computed in each scenario. PLRs appear in Table 4, where blue cells correspond to wind and red cells correspond to solar PV.

Table 4. Price learning rates (%) calculated from the scenario results, with wind PLRs in blue cells and solar PV PLRs in red cells.

	Competitive Markets (n = 15)								Concentrated Markets (n = 3)							
	$\alpha = 0$		$\alpha = 1/3$		$\alpha = 2/3$		$\alpha = 1$		$\alpha = 0$		$\alpha = 1/3$		$\alpha = 2/3$		$\alpha = 1$	
Low Ramp			6.6	16.9							0.9	9.0				
High Ramp	4.6	10.2	6.4	17.6	7.2	18.6	7.9	19.1	2.0	-7.7	2.2	10.9	2.3	11.0	2.3	10.3
Low Shock			6.1	17.1							1.1	5.0				
High Shock			5.9	17.5							3.3	-4.2				

The PLRs in Table 4 show how climate policy, market structure, and learning spillovers can alter the relationship between experience and price. With competitive markets, PLRs are generally similar to the exogenously assumed UCLRs. This suggests that the standard IAM representation of learning is likely adequate in the absence of market power. With concentrated markets, PLRs are significantly lower. The wind PLR is less than half its UCLR in all concentrated market scenarios. In scenarios with appreciable solar PV adoption, its PLR is roughly half its UCLR. There are two scenarios where solar PV exhibits a negative PLR, although diffusion is minimal in these cases. It is not surprising that these scenarios are characterized by the absence of learning spillovers, high carbon taxes, or both. The absence of spillovers makes unit costs fall more slowly and high carbon taxes increase demand, encouraging larger markups.

These findings demonstrate that the modeling framework of this study endogenously captures the effects of climate policy, market structure, and learning spillovers on the relationship between experience and price. Given that most IAM analyses will likely continue to employ basic learning by doing formulations, the results contained in Table 4 could be used to inform learning rate parameterizations or sensitivity analyses to account for plausible ranges of these factors. In addition, given that most

empirically derived learning rates are computed using price data but IAMs typically apply these learning rates to costs, the results of this study offer some guidance as to how the empirically estimated learning rates could be properly adjusted for use in the models.

5 Conclusions

This article describes the development, implementation, and application of an IAM framework featuring technology markets with strategic firms engaged in Cournot competition. Empirical research has established that market dynamics can have a strong influence on prices, and therefore adoption, of renewable energy technologies (Bolinger and Wiser, 2011; Nemet, 2006). The presently proposed framework captures critical market forces, such as market structure and learning spillovers across firms, which traditional IAM formulations of technological change typically omit. In doing so, it adds an important dimension to the technology policy debate in a climate-constrained world and expands the applicability of IAMs to cover questions of firm-level competitive strategy.

Scenario results illustrate how carbon taxes and learning spillovers interact with market structure to determine markups for renewable technology capacity, adoption of these technologies, producer profits, and carbon emissions. Consistent with economic theory, prices are considerably higher in concentrated markets. These higher prices result in weaker adoption and higher carbon emissions. The results reveal a fairly consistent effect of market structure on markups. Competitive markets (parameterized with 15 identical firms) exhibit markups under 20% while concentrated markets (parameterized with three identical firms) exhibit markups in the 35–70% range. These findings suggest that the standard IAM formulation of endogenous technological change which does not account for markups is approximately valid if markets are competitive, but could be overly optimistic about the impact of renewable technologies if market power is significant in their industries. Diffusion of solar PV is particularly sensitive to market structure and learning spillovers because it is currently more expensive than wind and its price must decline significantly to make it competitive. The results indicate that widespread solar PV

adoption is a key component of ambitious emissions reductions, but that solar PV can only diffuse strongly if its industry is competitive with learning that spills over across firms.

Whether a leading producer has a profit incentive to facilitate or obstruct learning spillovers depends largely on the availability of cost-competitive substitute technologies. If solar PV prices remain too high for it to be a competitive substitute for wind, the leading wind producer can earn greater profits by obstructing spillovers, sustaining its cost advantage relative to rival wind firms, and controlling a large market share. But if solar PV prices decline to a point where solar PV threatens to displace wind from the energy system, the leading wind producer has an incentive to facilitate spillovers to reduce costs throughout the industry and help wind compete with solar PV.

Price learning rates (PLRs) were calculated by fitting learning curves to the endogenously computed market price and cumulative installed capacity time series in the scenario results. While the unit cost learning rate (UCLR) describing the relationship between an individual firm's cumulative output and unit production cost is an exogenous input assumption, the PLR is an outcome that depends on a host of other factors including climate policy, learning spillovers, and market structure. Results show that PLRs are similar to UCLRs under competitive market structure, but significantly lower – even negative – under concentrated market structure. Given that most IAM analyses will continue to employ simple learning by doing formulations of technological change, it is important that they consider how the exogenously assumed learning rates might be affected if market structure, climate policy, or learning spillovers evolve over time. The variation of PLRs across scenarios in this study can be used to inform learning rate parameterizations or sensitivity analyses to account for these factors.

The framework of this study captures important market forces that traditional formulations of technological change typically omit. But of course, it is not without limitations. The exogenously assumed unit cost learning rates are based on empirical data but it is unlikely that these constant learning rates could be sustained indefinitely. The learning curve formulation aggregates multiple sources of cost reductions and some of these (most prominently economies of scale effects at the unit and manufacturing levels) will be exhausted as scale frontiers are reached. The reduced form version of MESSAGE

employed in this study handles intermittency in a highly aggregated and simplified manner. Furthermore, market structure and learning spillover strength are not fixed in reality. Nevertheless, this study has demonstrated the incorporation of market structure into an IAM framework and applied this approach to evaluate how climate policy and learning spillovers interact with market structure to influence technological, economic, and emissions outcomes.

6 Acknowledgments

The author began this work at the International Institute for Applied Systems Analysis (IIASA), where he was supported by its Peccei Award. Continuation of this research was funded by the Department of Energy, Office of Science PIAMDDI grant (DE-SC005171) awarded to the Stanford University Energy Modeling Forum. Arnulf Grubler and Volker Krey of IIASA contributed significantly to the conceptual development of this project, and they provided valuable comments on drafts of the manuscript. James Sweeney and John Weyant of Stanford provided additional useful feedback. Two anonymous referees offered highly useful suggestions, and their considerable efforts are greatly appreciated.

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Appendix A. Multiple Equilibria and Robustness

As discussed in subsection 2.3, the nonlinearity of profit functions (a consequence of capturing learning by doing and spillovers) means that the TMM may have multiple Nash equilibria where no firm can increase its profit by altering its output levels unilaterally. The TMM is implemented as an NLP where the feasible solutions are the Nash equilibria which satisfy the KKT conditions (encoded as binding constraints). If multiple equilibria exist, the specification of the objective function constitutes a rule for selecting one of them as the TMM solution. The baseline approach taken in the main analysis is to choose the Nash equilibrium in which the wind and solar PV firms earn the greatest combined total profits. The purpose of this appendix is to test whether the principal findings of this study are robust to the specification of the objective function, and also to the choice of NLP solver. Six objective function specifications are considered: maximize wind and solar PV combined total profits (baseline specification), minimize wind and solar PV combined total profits, maximize wind total profits, minimize wind total profits, maximize solar PV total profits, and minimize solar PV total profits. In addition to the CONOPT solver used for the main analysis, the PATHNLP solver is employed as an alternative.

Figures A1, A2, and A3 show how results differ across the two solvers and six objective function specifications for a particular scenario, that with the competitive market structure, low ramp carbon tax, and spillovers described by $\alpha = 1/3$. Overall, the results are quite robust, certainly consistent enough to suggest that the possible existence of multiple equilibria does not compromise the main insights and conclusions drawn from this study. The CONOPT solutions exhibit no sensitivity to the objective function specification, while the PATHNLP solutions exhibit slight sensitivity limited to prices and markups. The two solvers produce very similar results. The only noticeable disparities, such as wind installed capacity from 2050 to 2070 and solar PV firm profits, are relatively insignificant.

Figure A1. Results for the competitive market structure, low ramp carbon tax, $\alpha = 1/3$ scenario: cost, price, and markup. Distinct identical lines indicate that different specifications of the objective function yield different solutions. Green lines correspond to the CONOPT solver and purple lines correspond to the PATHNLP solver. In subfigures (a) and (b), solid lines represent price and dashed lines represent cost.

Figure A2. Results for the competitive market structure, low ramp carbon tax, $\alpha = 1/3$ scenario: installed capacity, CO₂ emissions, and profit. Distinct identical lines indicate that different specifications of the objective function yield different solutions. Green lines correspond to the CONOPT solver and purple lines correspond to the PATHNLP solver. In subfigure (d), the first six pairs of bars correspond to CONOPT solutions and the last six pairs of bars correspond to PATHNLP solutions.

Figure A3. Results for the competitive market structure, low ramp carbon tax, $\alpha = 1/3$ scenario: installed capacity portfolios (percentage shares) in 2040 and 2100. In each subfigure, the first six bars correspond to CONOPT solutions and the last six bars correspond to PATHNLP solutions.