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

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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.

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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, respectively[1]. According to these figures, wind is already cost-competitive with conventional coal ($96/MWh) and conventional natural gas-fired combined cycle ($66/MWh) (EIA, 2014). Although wind is

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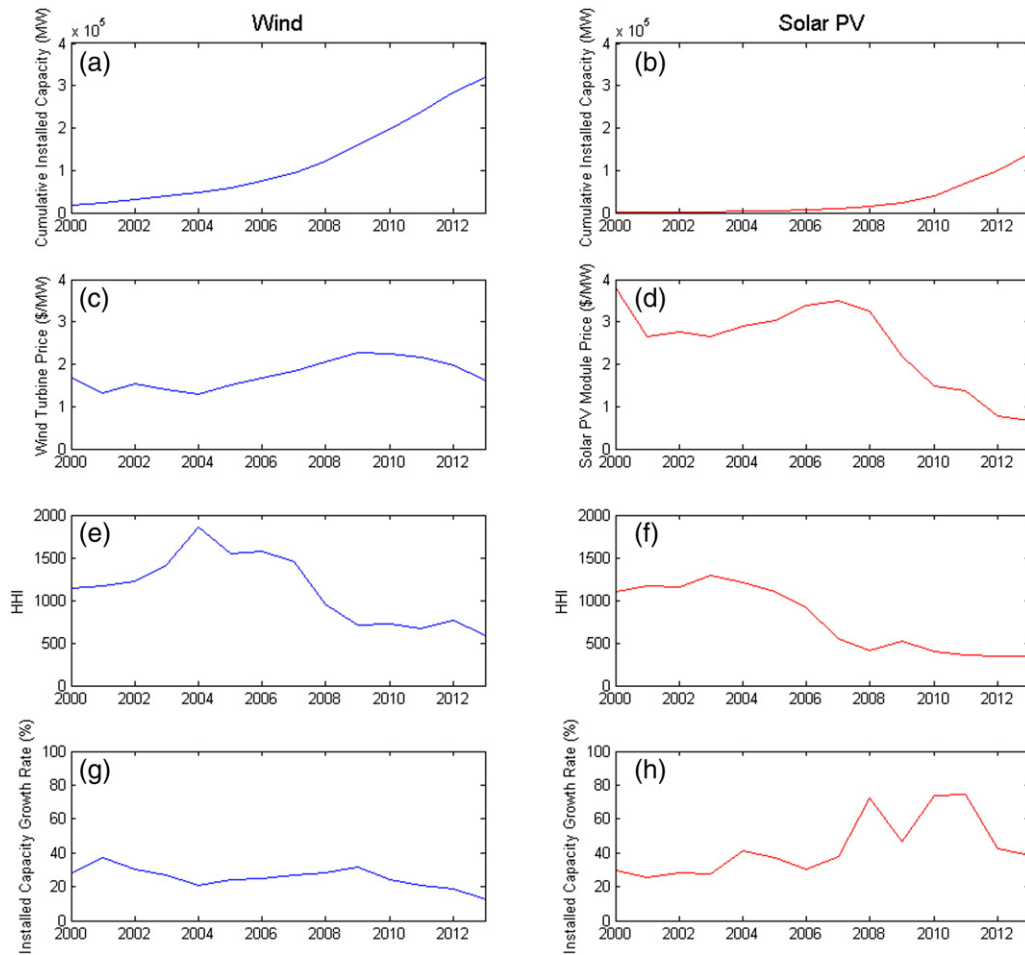
Fig. 1. Historical data describing the global wind and solar PV industries from 2000 through 2013.

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 and 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 Fig. 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 options[2], 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 CO_2e) 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:

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[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.