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The "Other" Benefits of Renewable Energy Promotion

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Abstract

Renewable energy policies address two market externalities at the same time as they (1) internalize the environmental cost of conventional energy production (GHG emissions and air pollution) and (2) appropriate earnings from learning-by-doing in the renewable energy sector.

Theoretical studies attempt to conceptualize the learning-by-doing gains, and others make some effort to measure the effect of various policy approaches to promoting renewable energy. This analysis is an attempt to determine the impact of learning-by-doing effects in the renewable electricity generation sector in Ontario on the optimal choice of policy instruments to promote renewable energy. A Computational General Equilibrium model is used to assess the social welfare changes associated with the introduction of a renewable portfolio standard, a subsidy on renewable electricity and a feed-in tariff. The results indicate that the Ontario feed-in tariff program represents the least cost policy option both with and without learning-by-doing.

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1 Introduction

The promotion of renewable energy and other 'green technologies' is a popular policy instrument mainly used to lower greenhouse gas (GHG) emissions and reduce other environmental stresses like air pollution. Yet policy interventions to increase output from these young industries generate a different kind of additional welfare benefits. They ensure that learning effects within the renewable energy sector are adequately compensated. As the experience of equipment manufacturers, project developers and site operators grows with rising output, their learning-by-doing triggers reductions in average or marginal production costs, which may spill over between firms and into other sectors of the economy or across borders. Such learning externalities can commonly not be appropriated by the actors investing in technological innovations, which means that economy-wide investment in renewable energy remains below the optimal level that would be achieved taking all environmental and learning externalities into account. Hence, both environmental and the"other" benefits of renewable energy policies need to be considered when assessing the cost effectiveness of renewable energy policies.

Over the last decade, a large number of studies debated scope and causes of learning externalities in innovative energy industries including offshore wind power (van der Zwaan, Rivera-Tinoco, Lensink, and van der Oosterkamp 2012), photovoltaics (Wand and Leuthold 2011), clean coal (Nakata, Sato, Wang, Kusunoki, and Furubayashi 2011), and CCS (Li, Zhang, Gao, and Jin 2012). These studies commonly explain the occurrence of cost reductions and quality improvements with increasing output by reference to learning or experience curve models, economies of scale, spill-over effects from research and development (R&D) or declining input factor prices. Most studies conclude that the benefits come from multiple possible sources.

This analysis employs a recursively dynamic computable general equilibrium (CGE) model of the Canadian economy to determine whether including the economic benefits related to learning-by-doing changes the order of economic preferability of three different renewable electricity policies: a subsidy, the Ontario feed-in-tariff, and renewable electricity performance standards. Two model runs are produced for each policy scenario, one including and one excluding learning-by doing effects on electricity generation costs. The same target share of electricity generation from renewable sources is assumed in all scenarios. The results indicate that the policy ranking is the same with and without learning-by-doing. The Ontario feed-in-tariff is the economically least costly policy, followed by the subsidy for renewable electricity production and lastly, the renewable portfolio standard.

The organization of the remainder of this paper is as follows. Section 2 discusses what will be called 'learning externalities' that are associated with increasing the level of output of some specific sector. Section 3 identifies a range of possible approaches to the modelling of such learning-by-doing effects. The focus will be the renewable energy sector, but the same general principles will apply to other industries as well. Section 4 presents a brief selective survey of the relevant literature on modelling learning-by-doing in CGE models. Section 5 then briefly describes the features of the model used to assess learning-by-doing impacts. Section 6 reviews illustrative findings with one CGE model formulation.

2 Learning Externalities

2.1 Learning vs. Scale Effects

Increasing output in a specific sector may generate benefits in the form of average or marginal cost reductions due to scale effects and learning effects as accumulating experience can cause endogenous improvements in factor productivity and/or quality. Neij, per Dannemand Anderson, Durstewitz, Helby, Hoppe-Kilpper, and Morthorst (2003) distinguish between three different sources of experience-based learning:

- Learning through R&D. Knowledge from growing experience may feed back into the technology design process.
- Learning through manufacturing. Accumulated experience in equipment manufacturing may lead to process improvements in purchasing, production, distribution etc., which may cause manufacturing costs to drop.
- Learning from utilization. This type of learning occurs, for example, when workers become more skilled in handling specific equipment, which reduces maintenance cost and down times.

Scale-based cost reductions can also have different sources as outlined by Junginger, Faaij, and Turkenburg (2005):

- Mass production. Standardization of the product allows for expansion of production facilities, which may reduce the cost of each unit. In the renewable energy sector, one can think of two scale effects at different points in the value chain. For example, the mass production of wind turbines decreases the per unit production costs. Additionally, the cost of wind electricity generation declines as the size of wind farms increases.
- Product redesign. For example, increasing the size of the individual wind turbine also leads to lower specific costs per turbine.

In this analysis, the term learning-by-doing is understood in a wide sense, encompassing endogenous improvements in production factor efficiency driven by increased output.

2.2 Learning Externalities

As alluded to above, gains from learning and scaling can occur at multiple points in the renewable energy value chain, including the equipment manufacturing stage, the installation stage and the electricity production stage. At all stages, benefits may be restricted to the specific firm, sector and country experiencing the growth in production output or they may spill over to other firms, sectors and countries. Such spill-over effects constitute a market failure as inappropriable knowledge externalities incentivize firms to free ride and delay investment in novel technologies in order to benefit from others' experiences. Hence, renewable energy policies such as subsidies and feed-in tariffs aiming at creating a sizable market for renewable energies may be welfare-enhancingeven independent of avoided environmental externalities. Peters, Schneider, Griesshaber, and Hoffmann (2012) find evidence of significant cross-border spill-over effects of so-called demand-pull policies in the case of solar photovoltaic technology. In particular, their findings indicate that observed market growth is the same for domestic and foreign demand-pull policies, suggesting a need for supranational renewable energy policy coordination. However, Peters, Schneider, Griesshaber, and Hoffmann (2012) use patents as an indicator of innovation, which does not necessarily reflect the full cross-border impact of endogenous technological change due to learning and scale effects. In terms of choice of policy instruments, Gans (2012) shows that carbon pricing as stand-alone policy is insufficient to achieve learning benefits in renewable energy industries. Similarly, Chen and Khanna (2012) study cost developments in the US corn ethanol industry since 1983 and the results indicate that policies aiming at increasing the output in infant industries can be effective in generating cost reductions and overcoming the market failure related to learning externalities. In contrast, policies aiming at increasing input prices, e.g. a carbon tax, as a means to foster innovation are found to be less effective. Complementary targeted policies are required. While not specifically looking at the renewable energy industry, the analysis by Melitz (2005) is still relevant when discussing the learning effects of policy market interventions. Melitz (2005) develops a model of infant industry protection to assess the welfare impacts of domestic production subsidies, tariffs and import quotas. He finds that the choice of adequate instruments is partly dependent on the industry's learning potential. Contrasting these studies are the conclusions drawn by Wand and Leuthold (2011) who find that learning benefits in the solar PV industry are largely occurring at the global scale with domestic policies for renewable energy promotion playing only a minor role.

2.3 Methodological Issues

There exists controversy in the literature concerning the factors contributing to learning externalities in renewable energy sectors and the methodologies used for disaggregating empirical cost data (Neij 2008). Many analyses attribute only part of the observed cost reductions to endogenous factors such as learning and scaling driven by volume growth (Nemet 2006). Other, exogenous factors deemed important in driving changes are public R&D investment, factor price changes and exogenous technological change (Söderholm and Sundqvist 2007). These factors can reinforce or offset gains from growing experience levels van der Zwaan, Rivera-Tinoco, Lensink, and van der Oosterkamp (2012). The relative contributions of different factors are likely to change over the life time of a technology. In particular, the potential for learning is higher at early development stages and decreases as the technology matures. At this point, scale effects due to mass production are more likely to become the key driver of cost reductions (Junginger, Faaij, and Turkenburg 2005). High marginal returns on increases in production in a technology's early development stages play an important role in achieving competitiveness with incumbent technologies. Hence, policies aiming at internalizing these large learning externalities can leverage significant welfare improvements.

3 Modelling Learning Externalities

3.1 Experience curves

Endogenous improvements in productivity and factor quality are typically formalized through experience curve models, which are specified as logarithmic relations linking the percentage increase in output and the resultant percentage fall in average or marginal cost. Depending on whether learning occurs at the equipment manufacturing, installation or electricity generation, experience levels are commonly either approximated by produced capacity, installed capacity or by cumulative electricity produced respectively. Costs are commonly measured in $/ kW produced or $/ kWh generated. However, definition of experience and cost measures is not trivial. Neij, per Dannemand Anderson, Durstewitz, Helby, Hoppe-Kilpper, and Morthorst (2003) emphasize that the different experience and cost measures relate to different types of learning outlined above. For example, they claim that learning by using will not be reflected in the experience curve when equipment cost are chosen as the dependent variable. In order to account for learning-by-using effects the correct measure would be the actual production cost of electricity generated from wind. Consequently, as also pointed out by Junginger, Faaij, and Turkenburg (2005), experience curves based on varying measures of experience and costs are not comparable.

Traditional learning curves are one-factor models. They subsume all factors contributing to cost reductions over time in one parameter, the learning rate as a function of cumulative experience. However, given the uncertainties around the sources of industrial benefits, this approach is likely to lead to biased interpretations. Hence, some recent studies develop two- or multi-factor models to address to provide a more disaggregate and accurate picture of the causes of declining costs. Two-factor models commonly include public R&D investment as additional independent variable (Yeh and Rubin 2012). Söderholm and Sundqvist (2007) develop a four-factor model to explain investment cost developments in wind sector of four European countries by additionally considering scale effects and feed-in tariff prices. The latter is expected to counter cost reductions as it makes less efficient sites more attractive and generally lowers competition and thus the incentive to innovate. Some studies include a time trend to account for cost reductions due to exogenous technological progress that is independent of cumulative output (Ferioli and van der Zwaan 2009). With every added variable, the omitted variable bias becomes less distorting. However, multi-factor models require detailed data which may not be available in many cases. This is why McDonald and Schrattenholzer (2001) questions the added value of separating the two endogenous factors, learning and scaling, in long-term energy models.

This discussion already indicates that estimated learning rates tend to vary significantly across studies, depending on the used data set and model specifications (Söderholm and Sundqvist 2007). Table 1 provides an overview of recent studies on cost reductions in the wind energy sector. Learning rate range between 1.77% and 19%. The wide range can be explained by differences in time periods and geographies, the degree of disaggregation of cost drivers and the ways in which cost and experience are measured.

3.2 Using Experience Curves in General Equilibrium Models

The discussion so far has been centred on the empirical construction of experience curves and determination of the learning rate. Focus will now shift on the use of experience curves in larger economic equilibrium models as a way to incorporate the effects of endogenous technological change. Such equilibrium models are commonly used to assess the welfare impacts of renewable energy policies. In particular, decisions on how to include learning-by-doing into the wider model will determine the choice of adequate learning rates. Key choices on how to model learning benefits can be broadly divided into two groups. One set of choices relates to the source of learning benefits while the other one relates to their assumed scope.

Source of benefits The decision is whether to disaggregate of endogenous cost reductions into those due to learning effects and those due to scaling effects. The used learning rate needs to be chosen accordingly, i.e. it needs to reflect the same level of aggregation.

Nature of benefits Mechanisms to be considered include those where the benefits take the form of efficiency improvements (more output from a given quantity and quality of inputs) and those that involve improved factor quality. Both kinds of benefits could alternatively be thought of as increasing returns to scale in historical sectoral output. This interpretation is consistent with one of the efficiency or quality mechanism.

Table 1: Reported Learning Rates

Study	Scope	LR	Cost/Experience	Factors included
Ek and Söderholm (2010)	Wind, Europe, 1986-2002	17%	investment cost/global installed capacity	public R&D with lbs rate of 20%
Qiu and Anadon (2012)	Wind, China, 2003-2007	4.1-4.3%	electricity cost/national installed capacity	lbd and lbs of manufacturers and developers; excluding scale effects
van der Zwaan, Rivera-Tinoco, Lensink, and van der Oosterkamp (2012)	Offshore Wind, Europe, 2005-2011	3% [1]	investment cost/European installed capacity	scale and learning effects
Söderholm and Sundqvist (2007)	Wind, Europe	1.77-8.25%	investement cost/European installed capacity	scale and R&D and policy effects
Junginger, Faaij, and Turkenburg (2005)	Wind, global, 1990-2001	18-19%	investment cost/national installed capacity	scale and learning effects
Neij, per Dannemand Anderson, Durstewitz, Helby, Hoppe-Kilpper, and Morthorst (2003)	Wind, Denmark, 1981-2000	17%	generation cost/national production	scale and learning effects

Electricity vs. equipment Learning-by-doing can occur at different levels in the renewable energy value chain. The literature distinguishes between learning-by-doing in equipment production, installation, and electricity generation. Empirical learning rates will differ across stages.

Reference levels It is important to determine the relevant reference point for these curves: Is it the global level of output, is it national levels of output or here in the case of a Canadian regional model, is it, for example the level of output in the province. Needless to say if the latter definition of the reference level of output is used, the gains from moving down the learning or experience curve are likely to be dramatically higher than if the relevant reference level is global or even national output.

Another set of modelling choices relates to assumptions on the scope or reach learning externalities. To what extent are learning benefits assumed to be restricted to the country, sector, and firm where the increase in output occurred? Is learning assumed to be linked to individual machines and workers?

Embodied versus non-embodied Productivity gains could be embodied or non-embodied. This distinction was first introduced by Rosenberg (1982). If, for example, newer equipment is becoming more efficient due to design modifications based on learning-by-using, the new equipment can be said to embody the technological improvement. Likewise, if specific workers are more productive as a result of producing large outputs, their learning would be considered embodied in that factor (labour). Disembodied benefits, by contrast, are related to improved general, shared knowledge about how to use the technology most productively. This knowledge may, for example, be documented in manuals or best practice guidelines but it is not physically embodied in either capital factors (technology hardware) or labour factors (skilled workers). In modelling terms, embodied learning changes the efficiency of input factors, while disembodied learning causes alterations in the production function itself. In their study on cost reductions in the Chinese wind power sector, Qiu and Anadon (2012) find evidence that most learning took place at the inter-firm rather than the intra-firm level, which implicitly assumes either high degrees of capital and labour mobility between firms or a relatively large share of disembodied rather than embodied industrial benefits.

Factor specificity Productivity gains from accumulated experience could be associated with one factor or another, most importantly capital or labour, or they could be neutral across all factors.

Sector-specificity If output increases cause factors to be more productive, they may be more productive only in the sector where the learning has accrued, or the benefits could spill-over into other industries. In the case of labour, the (embodied) skills learned by specific workers could apply to just the sector where the worker learned them, or they might be more generally applicable, in which case the worker would take them her when moving between sectors. None of the studies reviewed here, explicitly discusses inter-sectoral spillover effects.

Geographic specificity Similarly to learning externalities across sectors, the extent of industrial benefits can be local, regional, national or global in scope. Of the studies included in the selected survey in table 1, only Ek and Söderholm (2010) measure experience levels in terms of installed capacity worldwide as opposed to nationally. While not formally modelling cross-border spillover effects in their analysis, Qiu and Anadon (2012) recognize that the learning rate they identified for the Chinese wind industry may be lower than those reported in previous studies for the U.S. and Europe as the Chinese wind industry already benefited from previous learning gains achieved in these regions.

4 Selective Survey

Having introduced key modelling issues that arise when incorporating endogenous industrial benefits into economic equilibrium models, in this section three recent Computable General Equilibrium (CGE) studies containing experience curves will be discussed. The inclusion of experience curves into climate policy models is generally more common in bottom-up energy system models than in general equilibrium models, which makes these studies particularly relevant to this discussion. The three studies vary in their choices of modelling options identified above. Reichenbach and Requate (2011) assess policy options in renewable energy markets with learning by doing spill overs and imperfect competition. Rasmussen (2001) investigates the impact of endogenous technological change on the cost of CO2 abatement in Denmark. Schumacher and Kohlhaas (2007) analyse alternative approaches to modelling learning by doing in the German renewable energy sector and EU-wide spill over effects.

Comparing the studies' varying approaches, the following observations are particularly interesting:

- (Rasmussen 2001) focuses on industry benefits in the production sector for renewable energy equipment, whereas Schumacher and Kohlhaas (2007) alternatively also examine learning by doing effects in the renewable energy generation sector. Reichenbach and Requate (2011) consider both upstream and downstream learning by doing.

- All three studies define efficiency increases due to technology change as the source of cost reductions. The potential for additional scale effects occurring at the same time is not explored - at least not explicitly.

- None of the three selected studies considers economy wide spill over effects, however, Schumacher and Kohlhaas (2007) examine cross-border benefits within the renewable energy industries in the European Union.

- Only Schumacher and Kohlhaas (2007) explicitly assume learning by doing to improve the efficiency of labour and capital at the same time. Reichenbach and Requate (2011) define learning by doing as occurring at the firm level without further specification. Rasmussen (2001) assumes the cost of a unit of renewable energy capital to decline over time due to intertemporal learning by doing spillovers.

- Rasmussen (2001) explicitly mentions that efficiency improvements due to endogenous technological change only apply to new vintages of capital, emphasizing that learning by doing benefits are embodied. Schumacher and Kohlhaas (2007) also assume productivity improvements embodied in capital but consider them non-embodied for all other input factors. Reichenbach and Requate (2011) model learning spill-overs between firms occurring from one period to the next, independent of new capital investment, which indicates that non-embodied productivity gains.

Finally, none of the discussed studies considered models spillover benefits in the simplest way which is to assume that they are factor-neutral, non-embodied, and sector specific.

5 The Model

FiT-rd is a recursive dynamic multi-region CGE model of the Canadian economy. It is designed to simulate immediate and transitional economic impacts of different climate policy scenarios including renewable energy quotas and feed-in tariffs. In particular, the recursive dynamic character of FiT-rd means that in each period, the representative consumer makes an investment decision based on rates of return in the current period. One period's purchases of investment goods causes the capital stock to increase the next period. The capital is subsequently allocated among sectors to equalize rates of return. The model's agents can be considered myopic, since there is no mechanism whereby anticipation of future expected events can affect current behaviour.

The following subsection describes the model and the data sources used.

5.1 Production

Nested constant-elasticity-of-substitution (CES) production functions are used to model firms' input choices regarding the key production factors capital, labour and a nested aggregate of all other inputs such as energy and material. For renewable energy firms an additional fixed factor is considered, which represents the finite availability of renewable energy sites in each period. Because the supply of this factor is fixed, the supply curve of the renewable electricity sector is upward sloping in each period.

Firms produce a composite of goods for domestic consumption (that is consumption within the province as well as export within Canada) as well as goods for export.

5.1.1 Electricity

The electricity sector is composed of two sectors, the renewable generating sector and the conventional generating sector. The sectors are technologically similar with key differences. First the renewable sector has dramatically lower input shares of fossil fuels. The conventional generators generate conventional electricity, whereas the renewable sector generates renewable electricity.

In the case of the conventional sector, the output includes some for domestic markets and some for export. By contrast, the renewable electricity sector produces only electricity for Canadian markets.

The renewable and conventional electricity produced in a given region are combined in a CES aggregate to produce the electricity used in final and intermediate demands in the home region and other regions of Canada. As mentioned above, the elasticity of substitution is denoted σ^{cr}. The default value used for this elasticity is 0.5 and it is assumed to be constant over the entire horizon considered.

5.2 Factor Markets

Three primary factors of production are distinguished: capital, labour, and specific resources. Capital is assumed to be both region and sector specific. This allows the capital stock of a specific sector in a specific region to accumulate (or fall) over time. Labour is considered mobile between sectors within a province, but immobile between provinces.[2] To determine total labour supply, each household is assumed to trade off between leisure and consumption. Although the model allows for the determination of equilibrium unemployment by either a wage curve formulation or a rigid real wage formulation, all scenarios presented in this paper assume full employment in all periods.

5.3 Government and Taxation

Government spending by all levels of government is fixed at baseline levels in all experiments considered. All revenues (federal and provincial) accrue to the province's representative agent, and that agent purchases the fixed bundle of government services. These services do not enter into the representative agent's preferences.

The net deficit or surplus of the public sector in each province will only change to the extent that factor and input taxes change in response to the policy under consideration. Any policy-induced public expenditures, as in

[2] Although the model structure allows for some labour mobility between provinces, this aspect of the model was not active in any of these scenarios.

the case of subsidies to renewable energy, are financed by a corresponding increase in labour taxes. In the case of the feed-in tariff, a tax on all electricity consumption is set in such a way as to finance the feed-in-tariff paid on renewable production. In the case of the renewable portfolio standard, the policy costs are born entirely by the private sector.

5.4 Investment Demand

In FiT-rd the overall level of investment in a given period responds to average rates of return with a constant elasticity formulation. Higher average rates of return in a given period lead to higher levels of investment in the subsequent period. The default value of the parameter is ϵ^i is $\frac{1}{2}$.

Total investment in a region is allocated among those sectors with the highest rates of return.

5.5 Consumer demand

Household consumption is modeled in a rather aggregate fashion as distributional impacts are not the focus of this analysis. One representative agent in each province receives all factor income as well as government transfers. The net transfer to the representative agent equals the difference between total federal and provincial taxes collected and the level of purchases of government services which is fixed in each period. Given their budget constraints, the representative agents maximize utility given their preferences over a CES bundle of consumption goods and leisure.

5.6 International and inter-provincial trade

FiT-rd allows for bilateral trade among the provinces and with the rest of world following the Armington (1969) approach. According to this approach, domestic goods and imports from the rest of the world are nested in a CES function.

A given region consumes a composite of goods produced in Canada and goods from the rest of world. Domestic goods are a CES aggregate of goods produced in the home province and goods imported from other provinces. This domestic goods composite is substitutable for goods from the rest of world. The elasticity of substitution among domestic sourced goods is 3, whereas the elasticity of substitution between the domestic composite and rest of world goods is 6.

Canada is assumed to be a price taker on the global market for both exports and imports, whereas relative prices between provinces are determined endogenously. An elasticity of transformation function is used to specify the ease with which Canadian goods can be transformed into exportable goods versus those for the domestic (Canadian) market. The assumed elasticity of transformation is 1. Each region's balance of trade is fixed in real terms in each period. This ensures that the trade surplus or deficit in each province, and therefore total net foreign saving in Canada, remains fixed at a benchmark level.

5.7 Data

The model is calibrated to the economic transactions (quantities and prices) in a benchmark year as compiled in Statistic Canada's symmetric provincial input-output tables for the year 2005. The benchmark set includes data from the IO tables on production, intermediate use, final demands, sectoral capital earnings and sectoral expenditures on wages and salaries as well as information on inter-provincial and international trade flows.

Since renewable energy technologies are not differentiated from conventional technologies in the Statistics Canada provincial IO data, Natural Resources Canada data on electricity generating, consumption and trade was used to disaggregate the utilities sector as far as production and trade. Once electricity generating was split from utilities, the split between renewable and conventional electricity for the benchmark year was done using extraneous data from NRCan and other sources[3] The factor intensity of the renewable electricity sector was calibrated using information provided in Wing (2008)[4].

6 Simulation assumptions

6.1 Baseline

The model was solved for the years 2010–2050 in five year increments.

[3]Further detail available on request.

[4]The estimates provided are based on cost and technology information on 18 different electricity generation technologies is provided by the US Environmental Protection Agency.

The model is first calibrated to an artificially generated baseline with exogenous consensus provincial growth rates. In the baseline, assumptions on the penetration of total renewable electricity in Ontario are based on projections to 2030 by the National Energy Board (National Energy Board 2011).

Renewable electricity is assumed to remain a constant share of the market after the end of the NEB forecast. There is some uncertainty about what is included in the baseline, since the baseline is national in scope. For Ontario, it would seem to exclude impacts of the Green Energy and Economy Act. We are interpreting the baseline as excluding this policy measure.

The baseline forecasts are interpreted as including not just the impact of bau policies, but, when learning by doing is present in the model, also the learning effects related to the bau level of output associated with these policies. Hence, the policy simulations only measure additional learning effects generated by the additionally introduced policies.

6.2 Key Modelling Parameters

The analysis is focused on learning-by-doing effects in electricity generation from renewable sources. Renewable energy technologies include relatively young and still innovative technologies such as wind, solar, geothermal and small hydro.

Our central case learning rate is 5%. The relevant cumulative output is the renewable electricity generated in Ontario. The representation used assumes that the learning by doing results in a factor-neutral technological improvement that is not embodied in any factor.

$$c_t = c_{t-1} \left(\frac{Y_t}{Y_{t-1}} \right)^{-\gamma}$$

The other key parameter is the elasticity of substitution between conventional and renewable electricity sources. A value of 1 indicates that a change in the relative prices of renewable and conventional electricity will cause proportional changes in the relative production volumes. This implies that there is no cost to switching back and forth between the two. Values below 1 assume that electricity from renewable sources is an imperfect substitute and the lower the elasticity value the greater the cost of switching. Likely barriers to substitution include, for example, technological problems as grids and storage capacities are not compatible with the lower reliability and greater fluctuation in electricity supply from renewable sources. The elasticity of substitution is set to 0.5.

7 Results

7.1 Simulations

The environmental target assumed in all three policy scenarios is to double the share of electricity from renewable sources relative to the baseline in each period. Three policy scenarios are considered.

Renewable Portfolio Standards (rps) In this scenario electricity generators are required to produce the target share of electricity from renewable sources without financial support from the government.

Subsidy (sub) The government guarantees electricity producers subsidies that cover the cost of renewable electricity generation to meet the target share. The subsidy is financed through a labour tax increase.

Ontario Feed-in-Tariff (ofit) In this scenario, the subsidy is financed through a general tax on all domestic consumption of electricity within Ontario.

All scenarios are run twice, one time with learning-by-doing, and one time without it. This allows for comparing the economic impacts of including endogenous learning effects on renewable electricity generation volumes, social welfare, etc.

In all of our tables, we use the percentage change in consumption as a welfare measure. Since government spending is fixed at the baseline level in all the experiments. The change in consumption reflects the change in income resulting from changed returns on investment over the period.

7.2 Central Case (Overview)

Table 2 shows our central case welfare results, showing the welfare summary for both the central case (with learning) and without learning. The target of doubling the market share of renew ables is a strict target in 2050, as the penetration of renewables rises to 28% of total generation.

One regular feature of the consumption effects in all of our runs (including all sensitivity runs) is the ranking of the three policy instruments. The ofit policy has the lowest social cost among the three considered, followed (often closely) by the subsidy and trailed by the rps approach, often by a considerable amount. In our central case results, the consumption losses under ofit are modest (less than .5% of GRP[5]) the subsidy approach is only slightly more costly, with 2050 consumption losses just over .5%. The rps losses are significantly higher at almost 2%. The other finding is that, with the otherwise identical parameter settings, the presence or absence of learning by doing has a relatively modest impact on consumption relative to the choice of instrument used to promote renewable energy.

The policy instruments differ in two key respects: 1. their coverage (or base) and 2. the way that they are implicitly financed.The subsidy is provided only to renewable generators, with no direct impact on conventional electricity producers. The subsidy is paid for through a tax on labour income. The feed-in tariff involves a subsidy paid to renewable generators, plus a consumption tax on all electricity (renewable and conventional). This tax is set high enough to finance the subsidy, so the ofit policy is essentially financed by a tax on electricity consumption. The renewable portfolio standard is self-financed by the electricity sector. That is, the conventional generators profits have to cross subsidize the losses associated with their share of the renewable sector. This differs from the previous two cases because the policy is based on production rather than consumption.

7.2.1 Factor Markets

An overview of the factor market results is presented in Table 3. The subsidy to renewable electricity causes real wages[6] to fall and the rental rate to rise. This is in part because electricity generation is capital intensive in both the renewable and conventional generating sectors. The subsidy is financed through a tax on labour, further depressing real wages.

There is an aspect of both the rps and ofit instruments which works against the conventional sector and in favour of renewables. The rps has a more profound negative effect on both real wages and the real rental rate[7]

[5] Gross Regional Product

[6] Real wages are reported as the percentage change in the net of income tax purchasing power of wages.

[7] The rental rate is measured in real terms (what could be bought with the rental rate.

because it has a broader base than the ofit.

In the case of the ofit and rps the change in investment has the same sign as the change in rental rate. Reductions in the rental rate reduce investment. With the subsidy, the rental rate goes up a small amount (under .25%), but this isn't enough to increase investment. The impact of the reduction in funds available to invest offsets the rather small increase in rental rates.

7.2.2 Electricity Market

Although all the policy instruments used achieve the same target rate of renewable to total generation, the target is achieved dramatically differently using the different instruments. With the subsidy, the total production of all electricity rises by 20% relative to baseline by 2050. Renewable generation rises by over 140%.

Under the ofit, total electricity production rises by about 2%, but in this case, conventional generation falls by over 14%, with renewable generation rising by just over 100%.

With the rps, the total production of electricity falls by 50%. In this case, the increased share of renewable electricity is being brought about by a large reduction in the production of conventional electricity. Even the renewable production *falls* relative to baseline. This result emphasizes the importance of trade under the rps. The rps raises the production cost of electricity in Ontario, but the export market is quite elastic, leading to a dramatic response in exports.

Percentage changes are reported relative to the baseline value.

Table 2: Welfare (%) Central Case

	Learning								
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	-0.07	-0.11	-0.16	-0.20	-0.25	-0.31	-0.38	-0.38	-0.38
rps	-0.25	-0.46	-0.67	-0.91	-1.19	-1.52	-1.95	-1.97	-1.98
sub	-0.10	-0.16	-0.23	-0.31	-0.39	-0.49	-0.62	-0.62	-0.61
	No Learning								
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	-0.07	-0.12	-0.18	-0.24	-0.30	-0.36	-0.45	-0.45	-0.45
rps	-0.25	-0.47	-0.71	-0.97	-1.26	-1.60	-2.02	-2.02	-2.02
sub	-0.10	-0.18	-0.26	-0.35	-0.45	-0.57	-0.72	-0.72	-0.72

Table 3: Factor Market Summary (%) Central Case

	Wages (%)								
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	-0.06	-0.10	-0.14	-0.18	-0.23	-0.28	-0.35	-0.34	-0.34
rps	-0.49	-0.84	-1.13	-1.44	-1.76	-2.09	-2.49	-2.50	-2.51
sub	-0.10	-0.17	-0.24	-0.32	-0.41	-0.51	-0.65	-0.64	-0.64
	Rental Rate (%)								
ofit	-0.11	-0.19	-0.25	-0.32	-0.40	-0.48	-0.58	-0.57	-0.57
rps	-0.77	-1.25	-1.62	-1.95	-2.08	-2.19	-2.28	-2.28	-2.28
sub	0.06	0.08	0.12	0.15	0.18	0.21	0.24	0.24	0.25
	Investment (%)								
ofit	-0.04	-0.06	-0.08	-0.10	-0.13	-0.15	-0.18	-0.18	-0.18
rps	-0.24	-0.38	-0.49	-0.59	-0.59	-0.59	-0.57	-0.57	-0.56
sub	0.00	-0.01	-0.01	-0.01	-0.02	-0.02	-0.03	-0.03	-0.03

Table 4: Electricity Market Summary (%) Central Case

Renewable Production (%)									
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	100.4	100.9	101.5	102.2	102.9	103.5	104.3	104.3	104.3
rps	81.4	67.8	54.9	40.3	28.0	14.4	-2.5	-3.4	-4.0
sub	106.8	111.2	116.0	121.2	127.0	133.4	141.3	141.3	141.3
Conventional Production (%)									
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	-2.9	-4.6	-6.3	-8.1	-10.1	-12.1	-14.4	-14.4	-14.4
rps	-12.1	-20.3	-28.0	-36.3	-43.2	-50.6	-59.2	-59.5	-59.8
sub	0.2	0.3	0.4	0.5	0.6	0.8	1.0	1.0	1.0

7.3 High Case

We also considered a case with high potential for learning by doing gains in the renewable electricity sector. In this case, renewable electricity is more easily substitutable for conventional electricity and the learning rate is higher. The results are summarized as before in Table 5 (Welfare) and 6.

The qualitative findings are similar. The Ontario feed-in tariff is the lowest cost way of achieving the stated target, with the subsidy close behind. The factor market impacts have the same pattern, but in almost all cases the reductions are somewhat lower than in the central case. The exception is the effect on the rental rate with the subsidy which is the same in the two formulations.

Table 5: Welfare (%) 'High' Case

	Learning								
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	-0.05	-0.07	-0.09	-0.11	-0.14	-0.17	-0.20	-0.20	-0.20
rps	-0.12	-0.19	-0.26	-0.33	-0.42	-0.52	-0.65	-0.65	-0.65
sub	-0.08	-0.11	-0.14	-0.18	-0.23	-0.28	-0.35	-0.35	-0.34
	No Learning								
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	-0.05	-0.09	-0.13	-0.18	-0.22	-0.27	-0.33	-0.33	-0.33
rps	-0.12	-0.22	-0.32	-0.42	-0.54	-0.67	-0.82	-0.82	-0.82
sub	-0.08	-0.14	-0.20	-0.27	-0.35	-0.43	-0.55	-0.55	-0.55

7.4 Relative Impact of Learning

The question of the relative impact of learning by doing under different policy instruments was also considered. Table 7 presents the reduction in welfare cost associated with learning under various parameter settings and policies. In all cases we considered (including some others not reported here) except one, the biggest percentage reduction in welfare cost comparing the learning by doing to the non learning by doing case occurred almost always under ofit. One would expect that the policy with the highest increase in production of renewable energy should have the biggest reduction in welfare cost

Table 6: Factor Market Summary (%) 'High' Case

	Real Wages (%)								
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	-0.05	-0.07	-0.08	-0.10	-0.12	-0.15	-0.18	-0.18	-0.18
rps	-0.23	-0.37	-0.48	-0.61	-0.74	-0.88	-1.05	-1.06	-1.06
lbd	-0.08	-0.12	-0.15	-0.20	-0.25	-0.30	-0.38	-0.37	-0.37
	Rental Rate (%)								
ofit	-0.10	-0.14	-0.18	-0.22	-0.27	-0.32	-0.39	-0.38	-0.38
rps	-0.39	-0.60	-0.78	-0.96	-1.15	-1.34	-1.55	-1.55	-1.55
sub	0.04	0.07	0.10	0.14	0.17	0.21	0.24	0.24	0.25
	Investment (%)								
	2010	2015	2020	2025	2030	2035	2040	2045	2050
ofit	-0.03	-0.05	-0.06	-0.08	-0.09	-0.11	-0.13	-0.13	-0.13
rps	-0.12	-0.19	-0.24	-0.30	-0.36	-0.41	-0.48	-0.48	-0.48
sub	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01

attributable to the learning. There would seem to be more to the story, since the increase in renewable electricity production under ofit is not quite as high as the increase under the subsidy.

Table 7: Relative Reduction in Welfare

	Case		
	Central	High	Low
ofit	16%	39%	11%
rps	2%	21%	1%
sub	15%	35%	12%

The exception to the general observation that the welfare costs from ofit are reduced most by learning is in the case with low potential for learning by doing gains in renewable electricity. In that case the elasticity of substitution between conventional and renewable electricity is 0.25 and the learning rate is 5%.

7.5 Conclusion

The public discussion around the effectiveness and efficiency of the Ontario Green Energy Act continues, fuelled by critical press coverage and the recent introduction of Bill 39, which had it not been defeated by the Provincial government in late April, would have abandoned the feed-in tariff program. The results of this model simulation indicate that in at least one respect, the Ontario feed-in tariff program is the preferred choice out of the options considered. A limited scenario analysis indicates that this top position in the policy ranking is robust to changes in two key modelling parameters, the learning rate and the elasticity of substitution between conventional and renewable electricity. Including learning-by-doing into the model estimations does not change the order of preference either, but in fact, reinforces it.

Two other conclusions are suggested. First, learning by doing reduces the cost of expanding renewable energy, but only to the extent that renewable energy expands *relative* to baseline as a result of the policy. Second, the gains associated with the learning by doing mechanism seem to be high (often highest) with the ofit instrument. As mentioned, this could be because the increase in output with ofit tends to be relatively high.

A key qualification to our findings is that we do not take account of the welfare effects associated with reduced emissions. This is often not an issue with 'cost-effectiveness' type of analyses, because they tend to hit a given environmental target. In our scenarios, although we have a common target, the pollution damages associated with different policies is likely ot be quite different.

7.6 Extensions

There are multiple ways in which we plan to extend our analysis.

1. We intend to port the model to the EC-PRO provincial data. This data includes

    - linked greenhouse gas and other air emissions
    - replication of a detailed Energy 2020 forecast of the provincial economies, energy demand and emissions
    - better energy supply and pricing detail
    - inclusion of margins

We currently use a common target of the share of renewable electricity generated. Using the EC-PRO data would permit us to target total greenhouse gases emitted in the production of electricity.

2. The model identifies all regions of Canada, but our analysis has been restricted so far to Ontario.

3. A more systematic sensitivity analysis is called for to determine the relative influence of various model parameters on modeling results including the learning rate, the output reference level, elasticities of transformation and funding models.

4. We are looking for better evidence to guide our choice of the learning parameter. In particular, we have typified the externalities as being felt within Ontario's renewable sector, but nowhere else. One of the specifics issues we are pursuing is the extent to which there are 'local' activities where the learning by doing gains can arise. This could help us understand the appropriateness of alternative learning rates.

5. We also intend to provide more reporting of the trade impacts of this measure between Ontario and both the other provinces, as well as Ontario and the rest of world.

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