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The Renewable Power Generation Module (RPGM) – An extension to the GWS model family to endogenize technological change in the renewable power generation sector

Kirsten S. Wiebe
Christian Lutz

Gesellschaft für Wirtschaftliche Strukturforschung mbH
Heinrichstr. 30
D - 49080 Osnabrück

Kirsten S. Wiebe (wiebe @gws-os.com)
Tel.: +49 (541) 40933-230
Fax: +49 (541) 40933-110
Internet: www.gws-os.com

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Anschriften der Autoren

Kirsten S. Wiebe

Gesellschaft für Wirtschaftliche Strukturforschung (GWS) mbH, Heinrichstr. 30, 49080 Osnabrück, wiebe @gws-os.com

Christian Lutz

Gesellschaft für Wirtschaftliche Strukturforschung (GWS) mbH, Heinrichstr. 30, 49080 Osnabrück, lutz @gws-os.com

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1 THE PROJECT: GRETCHEN

The BMBF project ``The impact of the German policy mix on technological and structural change in renewable power generation technologies" analyzes the impact of a renewable energy policy mix on technological change, welfare (economic development, employment), trade and structural change using a global macro-economic input-output model. The analysis requires several steps:

1. Identifying the effect of the policy mix on innovation and technological change.
2. Quantifying the effect of technological change on the model parameters and variables.
3. Analyzing the resulting effect on the economy.

In this paper a renewable power generation (RPG) module for the INFORUM type econometric input-output models (see Eurostat, 2008) such as GINFORS (Lutz & Wiebe, 2012) or PANTA RHEI (Lehr et al., 2012) is developed. The RPG technologies that we have selected for further analysis are wind (on- and off-shore) and solar PV.

Globally, increasing deployment of renewable power generation technologies is accelerated by strongly decreasing costs of these technologies. Deployment, in turn leads to cost decreases via scale effects and this interdependence can be captured in learning curves, which is a concept to model technological change. Using this concept it is possible to – at least partly – endogenize technological change more precisely regarding renewable energy technologies in economic models. So far, technological change is either set exogenously (autonomous energy improving technological change) or price-induced in economic models. Introducing endogenous technological change is necessary to adequately analyze not only the direct effects of technological change, but also the indirect effects on important macro-economic indicators such as growth, employment, welfare and trade as well as their feedback to the electricity sector.

The paper is organized as follows: The next section introduces the concept of learning curves with a focus of applications to renewable power generation (RPG) technologies. Section 3 gives a short overview of the macro-economic modelling framework, in which the RPG module (RPGM) will be implemented. Section 4 describes the RPGM in detail, followed by the presentation of first results in Section 5. Section 6 concludes.

2 THE CONCEPT OF LEARNING CURVES FOR RPG TECHNOLOGIES

In macro models the treatment of technological change is still a major source of cost differences of climate change mitigation (IIASA 2009), despite various research efforts in the last years. Most models compared in an OECD/IEA (2009) study set technological progress exogenously by assumption. Johnstone and Hasic (2009, p. 161) examined the

effects of public policies on innovation in the area of renewable energies in a cross-section of OECD countries over the period 1978-2003, finding that the empirical results indicate a strong influence of policies on innovation in renewable energy technologies. Schwark (2010) compares two CGE models with regard to the modeling of technical change (endogenous/exogenous) and the resulting effects on the impacts of carbon taxes on different industries. The main finding is that endogenizing technical change using ‘gains from specialization’ reveals dynamic growth patterns that cannot be reproduced in a model with exogenous technical change. Overviews on modeling technical change in growth theoretic models as well as large-scale econometric models can be found in Löschel (2002) and for models developed more recently in Kahouli-Brahmi (2008).

Most recent efforts to endogenize technological change in economic models of climate change mitigation often abstract from specific technologies. Acemoglu et al. (2012) look at environmentally directed technological change in a simple one-good-two-sector growth model with environmental constraints. According to their analysis substitutability of clean and dirty inputs is very important to avoid growth losses. Optimal environmental policy includes carbon taxes and research subsidies. One major conclusion is that (p.28) “it would be useful to develop a multi-country model with endogenous technology and environmental constraints,” to discuss global policy coordination and to deploy the link between environmental and trade policy.

Popp et al. (2010) differentiate between price-induced, R&D-induced and learning-induced technological change to be included in aggregate energy-environment models. He identifies a need for future research in the areas of modeling of policy instruments that are closer to the real world policy mix, progress on learning curve and directed R&D modeling. Löschel and Schymura (2013) additionally consider directed technological change, e.g. the support of clean technologies. They further give a comprehensive overview on technological change in CGE models. Kahouli-Brahmi (2008) distinguishes between four different types of learning (learning-by-doing, learning-by-researching, learning-by-using, learning-by-interacting) and economies of scale.

Both, learning-by-doing and learning-by-searching can be modeled using learning curves. Learning curves model the economic development of technologies; this is for example the costs of a certain technology depending on the cumulative production volume of the technology. The general idea is that through the learning-by-doing effect, i.e. when producing more and more of the technology, costs decrease. The one-factor learning curve is represented by

$$C_t = mQ_t^{-\beta} \tag{1}$$

with C_t being the costs of the technology at time t, Q_t being the cumulative production of the technology at time t, β the elasticity of learning-by-doing with the corresponding progress rate $2^{-\beta}$ or learning rate $1-2^{-\beta}$, and m a normalization parameter with respect to the initial conditions, e.g. $C(Q_0)$. The learning rate corresponds to the cost decrease which can be realized with every doubling of the cumulative production.

According to Wiesenthal et al. (2012b) early investment, policy intervention and the initial market conditions for the technology are important for cost reduction. Hence, not only cumulative production volumes, but also other factors influence the economic development of the technology. This can for example be captured in two factor learning curves, which combine learning-by-doing and learning-by-searching:

$$C_t = mR_t^{-\gamma} Q_t^{-\beta}, \tag{2}$$

with R_t being the cumulative R&D spending on the technology at time t (as a proxy for the knowledge stock) and γ the elasticity of learning-by-searching. Wiesenthal et al. (2012b) further propose an improvement to the one-factor learning curve by disaggregating the costs into two parts, one part (α) corresponding to the "learning" components and the other part $(1-\alpha)$ where no cost improvements take place. This results in the following learning curve:

$$C(Q) = \alpha C(Q_0)\left(\frac{Q}{Q_0}\right)^{-\beta} + (1-\alpha)C(Q_0). \tag{3}$$

This case may be for example useful when looking at the total costs of installing a PV module on a roof, where not only the module but also labor needs to be paid. Wang et al. (2011) estimate that in a conventional PV system the costs for the module are only about half of total specific investment costs. The non-module costs are usually summarized as balance of system (BOS) costs. Kahouli-Brahmi (2008) analyzes 77 learning-by-doing and 17 learning-by-(re)searching rates that were estimated in different energy-environment-economy models between 1974 and 2007. Among these were 33 learning rate estimates for wind, nine for solar PV and one for CSP. The learning-by-doing rates for wind vary between -3% and +20%, with a median of 12% and half of the estimates being between 6% and 15% (Fig. 5 on p. 143); For solar PV the variation in the rates is lower: the median is at about 20% and half of the rates are between 18% and 22%. The variation in the learning rates is not only due to the use of different data sets, different geographical coverage (some look at the global development, while others only consider the development in individual countries or country groups) or different time spans, but also due to the use of different

proxies for cost and cumulative production volume development. Investment costs, capital costs and prices (all in EUR/USD per kW) or energy production costs (in EUR/USD per kWh) were used as proxies for the cost development and cumulative installed capacity or cumulative sales (in MW) or cumulative electricity production (in TWh) were used as proxies for experience (cumulative production volume). The reviewed learning-by-researching rates for wind differ even more, with values between 5% and 28%, while those for solar PV are between 5% and 14%.

In Wiesenthal et al (2012a), the authors estimate both one-factor (1FLC) and two-factor learning curves (2FLC). They find learning rates of 7%, 7.5% and 20% for Wind onshore, Wind offshore and PV, respectively for the 1FLC with respect to capacity, and 9.5%, 10.5%, and 25% for the 1FLC with respect to R&D. For the 2FLC the learning rates with respect to capacity installed are 3%, 2% and 18% and with respect to R&D 10%, 10% and 9.5%, for wind onshore, wind offshore and PV respectively (Table 4, p. 110).

Technological change in renewable power generation technologies occurs at different stages of the production chain and affects all three stages invention, innovation and diffusion. The learning concepts presented above and used in the subsequent analysis, deal with the diffusion of the final RGP technologies at the macro-economic level.

3 The Global Interindustry Forecasting System (GINFORS)

The global INFORUM type model GINFORS (Global INterindustry FORecasting System) describes the economic development, energy demand, CO2 emissions and resource inputs for 50 countries, 2 regions, 41 product groups, 12 energy carriers and 9 resources. The regions are “OPEC” and “Rest of the World”. The explicitly modeled region “OPEC” and the 50 countries cover about 95% of world GDP and 95% of global CO2 emissions. The aggregated region “Rest of the World” is needed for the closure of the system. The model is documented in Lutz et al. (2010). Current applications of the model can be found in Barker et al. (2011), Giljum et al. (2008), Lutz and Meyer (2009a, 2009b, 2010), Lutz and Wiebe (2012) and Lutz (2010). The related German model PANTA RHEI has been applied to endogenize technological change in a few industry sectors as iron and steel and paper (Lutz et al. 2005 and 2007) and to evaluate the German energy concept (Lindenberger et al. 2010).

GINFORS is in many respects close to neoclassical CGE models, but shows some major differences. One is the representation of prices, which are determined due to the mark-up hypothesis by unit costs and not specified as long run competitive prices. But this does not mean that the model is demand side driven, as the use of input-output models might suggest. Even though demand determines production, all demand variables depend

on relative prices that are given by unit costs of the firms using the mark-up hypothesis, which is typical for oligopolistic markets. Firms are setting the prices depending on their costs and on the prices of competing imports. Demand is reacting to price signals and thus determining production. Hence, the modeling in GINFORS includes both demand and supply elements.

Allowance prices and carbon tax rates are endogenous to the model. To avoid long solving procedures, the prices are changed in an iterative process manually until the GHG reduction target is reached. Allowance prices increase the shadow prices of energy carriers and reduce energy demand according to the specific price elasticities. Different allocation methods therefore have no direct influence on energy demand and the emission levels in the model. But increasing profits of private companies in the case of grandfathering deliver macroeconomic impacts other than government spending financed by auctioning revenues.

All behavioral parameters of the model are estimated econometrically, and different specifications of the functions are tested against each other, which gives the model an empirical validation. An additional confirmation of the model structure as a whole is given by the convergence property of the solution which has to be fulfilled on a yearly basis. The econometric estimations build on times series from OECD, IMF and IEA from 1980 to 2006. However, for a number of variables the data were only available for a shorter time period. The modeling philosophy of GINFORS is close to that of INFORUM type modeling (Almon, 1991) and to that of the model E3ME from Cambridge Econometrics. Common properties and minor differences between E3ME and GINFORS are discussed in Barker et al (2011b).

4 The renewable power generation module (RPGM)

The renewable power generation module (RPGM) is an extension to the usual energy-environment-economy of the GWS model family, as e.g. GINFORS or PANTA RHEI. These models consist of a combination of a model for the economic development and a first extension (the energy module), which models the energy balance. The interaction of the RPGM with the economic core model and the energy module is multilateral: the RPGM takes information from the other two, but also provides information. The RPGM provides information about the costs of renewable power generation as well as capacity installed to the energy module. In turn it gets information on electricity demand, which is jointly generated by the economic core and the energy module. Further, the change of the composition of electricity generation technologies also affects the input structure of the production of electricity generation technologies. Wind mills and PV systems need other components than a coal or gas fired plant to produce electricity. This has implications for

the production structure of the overall economy and, therefore, needs to be implemented in the economic core model as well. These interlinkages are shown in Figure 1 and described in more detail in Section 4.2.

4.1 Modeling capacity installed and costs of RPG technologies

Figure 1 also shows the basic concept of the RPGM. This basic concept holds for both technologies Solar PV and wind, that are modeled separately in the RPGM. The RPGM distinguishes between global and national variables. Those quantities modeled at the country level are highlighted in blue (and green and red for the energy module and the macro-economy); those modeled at the global level are not highlighted. Global capacity installed at time *t*, C_{Gt}, is the sum of all countries', *c*, capacity installed at time *t*, C_{ct} (top right box in Figure 1):

$$C_{Gt} = \sum_c C_{ct} \ . \tag{4}$$

Global capacity is the only (in case of a one-factor learning curve) or one of two (in case of a two-factor learning curve) determinants of the costs of technology. For the model, we assume that the initial conditions are given by capacity installed and costs (here PV module prices and wind turbine prices[1]) in the year 2010, so that the one-factor learning curve is

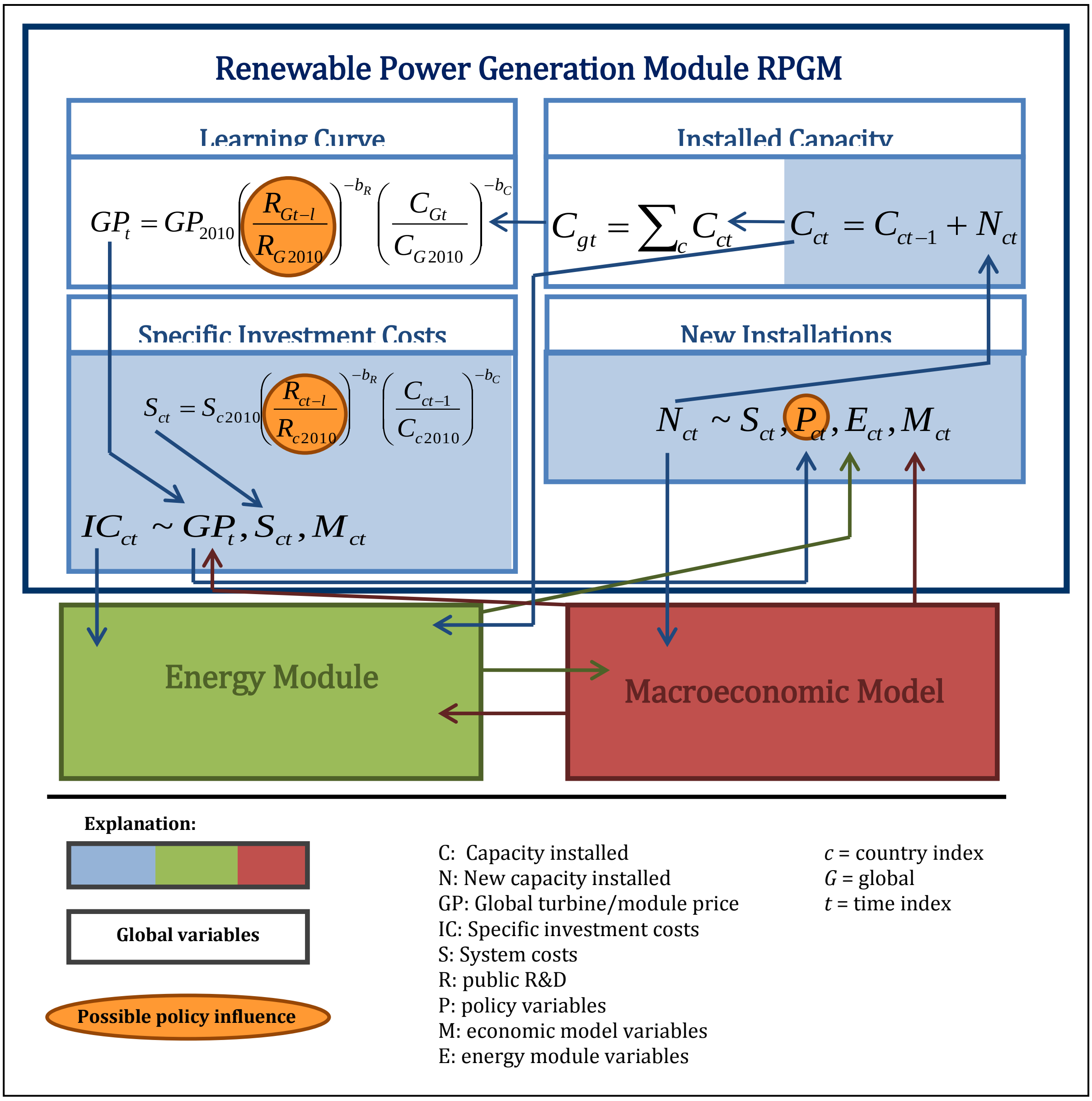
$$GP_t = GP_{2010}\left(\frac{C_{Gt}}{C_{G2010}}\right)^{-b_C} , \tag{5}$$

with GP_t being the global average module and turbine prices per Watt at time *t* and b_C the learning parameter with respect to global capacity installed. The learning parameter b_C is estimated in the model, see Section 4.2. The two factor learning curve additionally includes government spending on R&D for each RPG technology (R_{Gt-l}), with l being the time lag between first R&D spending and the installation year (see e.g. Wiesenthal et al. 2012a, p. 106), and the corresponding learning parameter b_R is also estimated within the model:

$$GP_t = GP_{2010}\left(\frac{R_{Gt-l}}{R_{G2010}}\right)^{-b_R}\left(\frac{C_{Gt}}{C_{G2010}}\right)^{-b_C} . \tag{6}$$

[1] Modules and, to a lesser extent, turbines can easily be shipped and are thus traded on a global market, for more details, see Section 5.1.

Figure 1: Model structure



Specific investment costs IC_{ct} differ between countries. National costs not only depend on average global module and turbine prices G_t, but also on national cost components such as system costs S_{ct}, local costs for connection to grid, wages or other macro-economic factors, all represented below by M_{ct}:

$$IC_{ct} \sim GP_t, S_{ct}, R_{ct-l} M_{ct} \tag{7}$$

The development of national system costs can also be modeled using the learning curve approach with both one factor (national capacity installed) and two factors (national capacity installed and national public R&D spending[2]). Since learning may only occur with a small lag and to avoid an endogeneity problem in the model, capacity installed enters the learning curve with a lag of one year:

$$S_{ct} = S_{c2010}\left(\frac{C_{ct-1}}{C_{c2010}}\right)^{-b_C} \tag{8}$$

$$S_{ct} = S_{c2010}\left(\frac{R_{ct-l}}{R_{c2010}}\right)^{-b_R}\left(\frac{C_{ct-1}}{C_{c2010}}\right)^{-b_C} \tag{9}$$

These costs in turn influence the amount of new installation of PV modules, CSP plants and wind mills. New capacity installed may also be influenced by policy measures, i.e. investment support, feed-in-tariffs, quotas, etc., all represented in P_{ct} below. Further, it may depend on electricity demand and other energy module variables E_{ct}, e.g. levelized costs of electricity[3] or energy prices, as well as macroeconomic factors M_{ct}:

$$N_{ct} \sim S_{ct}, P_{ct}, E_{ct}, M_{ct} \tag{10}$$

Investment in each technology IT_{ct} can then be calculated as

$$IT_{ct} = N_{ct} S_{ct}\,. \tag{11}$$

Total capacity installed in every country is determined by capacity installed in the previous year plus new installations[4]:

$$C_{ct} = C_{ct-1} + N_{ct}\,. \tag{12}$$

[2] For fully capturing the learning effect, it would also be useful to include private R&D spending; however, publically available data series are too short to include in an econometric analysis. In addition, private R&D spending on the individual technologies may be hard to capture as it may not be completely reported or may only capture spending directly related to the technology, but not indirectly.

[3] LCOE is widely used as a measure to evaluate RPG technologies for policy development (IRENA, 2013).

[4] New capacity installed is calculated for the past as the difference between capacity installed in year t minus capacity installed in year t-1, so that “new capacity installed” is in fact only the increase of capacity installed. Hence, no depreciation is necessary. This assumption is possible because the model only covers 40 years (1990 to 2030), which is less than twice the life span (about 25 years) of the RPG technologies.

Total electricity generated by each RPG technology is capacity installed multiplied by (constant) load hours Lh_c, which are about 750h for solar PV and about 1700h for Wind in Germany (calculations based on OECD & IEA, 2013):

$$EG_{ct} = C_{ct} Lh_c \tag{13}$$

According to IRENA (2013, p.82), levelized costs of energy (LCOE), which enters the equation for new capacity installed above, can be calculated as:

$$LCOE_{ct} = \frac{\sum_{\tau=1}^{n} \left(IT_{ct} + OM_{ct} + FC_{ct}\right) / (1+r)^{\tau}}{\sum_{\tau=1}^{n} EG_{ct} / (1+r)^{\tau}} \tag{14}$$

with OM_{ct} being operation and maintenance costs, FC_{ct} being fuel costs (which do not occur in case of wind and solar power), r being the discount rate and n the life time of the system. OM costs are mainly technology specific. As OM is often provided by technology producers and specified in long-term service contracts, assumptions about their development – yearly costs as per cent of the IT - can be deduced.

4.2 Links between RPGM, energy module and economic model

The economic core model, based on input-output tables and the corresponding energy module for the individual countries (those parts highlighted in red and green in Figure 1) are linked using bilateral trade on the industry level. The basic idea of the economic models is shortly described in Section 3 above. The energy module is used for a projection of the energy balance. An energy balance presents generation and use of all energy carriers within a country. A more detailed description of the economic core model and the energy module is beyond the scope of this paper; relevant for RPGM are its links with the energy module, i.e. the information RPGM gives to the energy module and gets from the energy module, as well as the links of both modules with the macro-economic core model.

RPGM → Energy module

RPGM provides capacity installed and electricity generated by wind and solar power to the energy module. In the energy module, electricity generation depends on electricity demand (and transformation losses). In Europe, regulations (e.g. German renewable energies act – EEG) give priority to feed-in renewable electricity into the grid. Thus, all electricity generated by RPG technologies, is sold and fed into the grid. Further, the amount of electricity generated by nuclear power is set for the next few years. Variable costs of nuclear power plants are below marginal costs of generation with only a few exceptions

over the year. The remaining electricity needed to satisfy electricity demand is then calculated within the energy module and allocated to be produced by gas and coal fired plants. Within the energy module, the demand for the different energy carriers, i.e. also the demand for electricity, depends on relative energy prices. Overall energy demand is also driven by economic activity of the demanding sector. The price for electricity is currently determined by the price equation in the input-output model. These, however, are not actual Cent/kWh prices, but rather a price development at the sectoral level. In reality, electricity prices are influenced by the costs of producing electricity, i.e. by LCOE. In contrast to economy-energy models such as the models described here, power systems models, such as PLEXOS[5] or the European Power Generation Model[6], include a detailed representation of the different power plants, their size and their costs structure, as well as of changing energy demand depending on the time of day and time of year. This information of the differences in energy demand can be used to determine the use of power plants for electricity generation using the merit order principle. The marginal power plant, i.e. the one with highest generation costs of the plants producing electricity at a given time, sets the electricity price.

Energy module → RPGM

The energy module provides information about electricity demand and energy prices, both of which may have an influence on new capacity installed of the RPG technologies, represented by E_{ct} above. Additional information provided by the energy module are GHG emissions, which are calculated for each energy carrier and each industry using constant emission factors (estimated from IEA 2012a & b). (Higher) prices for GHG emissions will increase the price competitiveness of RPGM.

RPGM → macro-economic core

More RPG capacity installed changes the structure of the electricity production sector, e.g. lower demand for fossil fuels, as well as the structure of the electricity generation facility production sector. PV module / wind turbine production and on-site installation require different inputs from other sectors than those required by fossil fuel power plants. Hence, in an input-output model, the input coefficients for both production of electricity and manufacture of power plants (which usually is not modeled individually, but included in the machinery and equipment sector) need to change accordingly (see Lehr et al., 2012, for more details). Not only the economic input structure changes, but also investment flows.

[5] http://www.energyexemplar.com/

[6] by PROGNOS http://www.prognos.de/

Investment in RPG technologies is calculated within RPGM, but the money spend needs to be generated somewhere else in the economy. Investment in conventional power plants will be reduced. RPGM therefore partly provides the amount of investment needed in the electricity sector to the economic model.[7]

Macro-economic core → RPGM

The general economic development determines the demand for investment goods such as RPG technologies, but also constraints the overall investment budget. Different macro-economic factors, e.g. economic growth, investment in infrastructure, wages, employment, production prices etc. influence the demand for PV systems (at the household level as well as in the public and private sector) and wind parks (from both public and private investors). So far, only the total amount of new capacity installed is modeled. The model may get more precise when differentiating between small and large scale RPG systems, but this requires a more detailed representation of the energy system. The macro-economic development also determines the development of public and private R&D spending, which enters the RPGM in Equations (6) and (9).

Energy module ←→ macro-economic core

The main purpose of the energy module is a better and more detailed representation of the energy sector in the macro-economic input-output model, where the energy sector is just one of many. The energy models receive the vector of gross production by industry and final demand by branches as well as industry prices, energy import volumes from the input-output models. The trade model delivers energy import prices and energy export volumes to the energy models. The energy models calculate primary and secondary energy demand for all energy carriers included in the IEA energy balance (2012b) in detail, the conversion of energy and CO_2 emissions of the different fossil energy carriers. Based on energy import prices the energy models further determine wholesale and retail prices for the energy carriers, which are delivered to the input-output models.

4.3 Data for RPGM

An overview of the data needed for the Renewable Power Generation Module is given in Figure 1. The data are PV and wind capacity installed at the national and global level, global average (and preferably also national) module and turbine prices, national system

[7] This is the case, when modeling new capacity installed and then calculating investment using Equation (11), the approach followed here. It is also possible to endogenously determine investment into the individual RPG technologies and then calculate capacity installed using the inverse of Equation (11). Then, the investment equation may directly depend on macro-economic factors.

costs as well as specific investment costs, i.e. the costs of installing one MW of PV (in MW peak) or wind capacity. Further, some data provided by the energy module and the macro-economic model as well as policy variables are needed.

Data for global capacity installed and average global PV module and wind turbine prices are taken from the Bloomberg NEF (2012). Historical data is available for the years 1990 to 2011 and projections are provided until 2030. Here, prices are used as a proxy for the costs in the learning curve. The price data is provided in million Euros per megawatt for wind turbines and in USD per watt for PV modules, both in 2011 prices.

Figure 2 shows the development of global average PV module and wind turbine prices in Euros per MW[8] (dashed lines) and the development of specific investment costs in Germany (solid lines). The prices serve as proxy indicators for the development of specific investment costs for installation of wind turbines and PV modules on the global level. The price decrease is especially visible for the PV module prices that decreased from about 6 Euro/Watt in the nineties to less than 1 Euro in 2012. The prices for wind turbines, which are a more mature technology, decreased very slowly compared to PV module prices, from about 1.80 Euro/watt to about 1.00 Euro/watt.

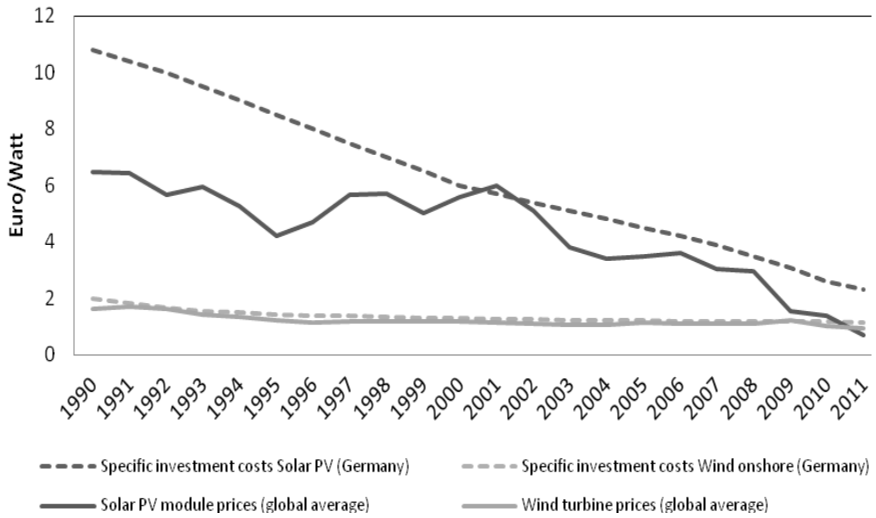
German specific investment costs, that not only include the costs for PV modules, but also for the remaining components for a PV system such as inverters, which are usually summarized as the balance of system (BoS) components, decreased at a similar rate as global average module prices. Figure Y1 shows that the costs of the module accounts for about half the specific investment costs, which confirms the finding of Wang et al. (2011). Still, global average prices for the years around 2000 are significantly higher than half of German specific investment costs. However, this is due to the large share of new PV installations in Asia (see Figure 3), where PV module prices were higher than in Europe. During those years where new installations were dominated by installation in Europe, i.e. in the beginning of the 1990s and around 2010, the relationship between module prices and investment costs suggested by Wang et al. (2011) holds.

Global capacity installed increased significantly in the last two decades for both wind and solar PV. Germany dominated wind capacity installed until about the year 2000, when it started to loose shares to other countries, especially Spain and the US. Deployment in Spain doubled between 2006 and 2011, while deployment in the U.S. even quadrupled during those years. Solar PV installations still are highest in Germany, quintupling between 2008 and 2011, and, thus, driving the global development of solar PV capacity installed.

[8] The USD values were converted into Euro using the Official exchange rate (LCU per US$, period average), Indicator PA.NUS.FCRF from WDI (2013).

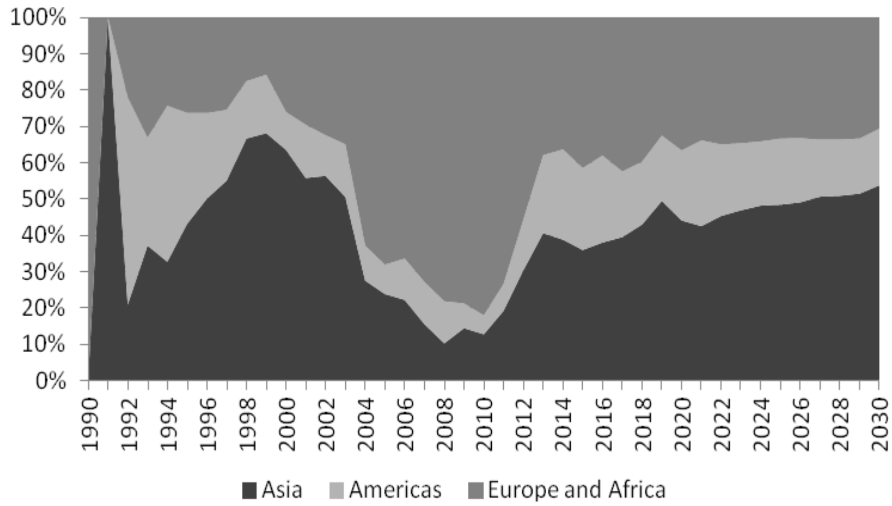
The data for global government R&D spending on Wind, solar PV and CSP technologies is calculated as the sum over all countries included in OECD & IEA (2013), since no global, IEA or OECD aggregate is available. The underlying assumption is – of course – that no other countries' governments spend a significant amount on R&D for these technologies. Since government R&D mainly finances basic research, the effect of government spending on R&D on actual capacity installation may only have a lagged effect, as has also been suggested by Wiesenthal et al. (2012a). Hence, Figure 5 displays global annual public R&D spending on wind, solar PV and CSP since the mid-seventies, when it was first recorded. Global R&D spending reached its first maximum for the three technologies in the years around 1980, when the second oil crises hit the global economy.

Figure 2: Prices and costs for wind and solar PV



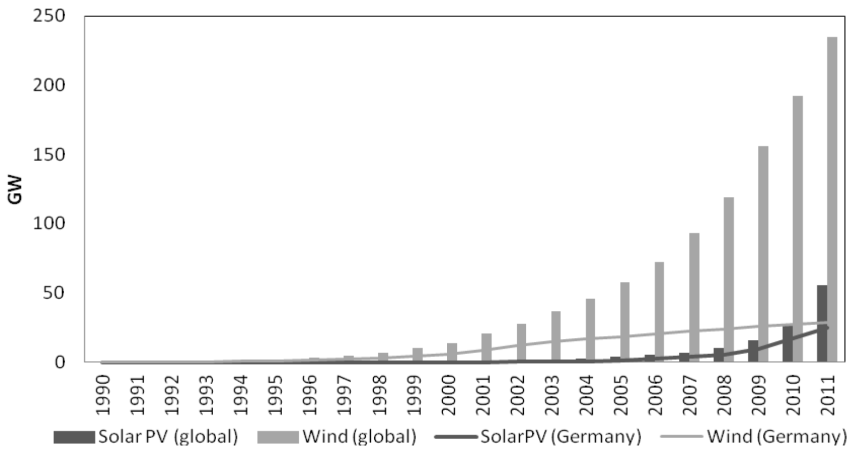
Source: Bloomberg NEF (2012) for global data, BMU (2011) for German data.

Figure 3: Regional shares of new solar PV module installations



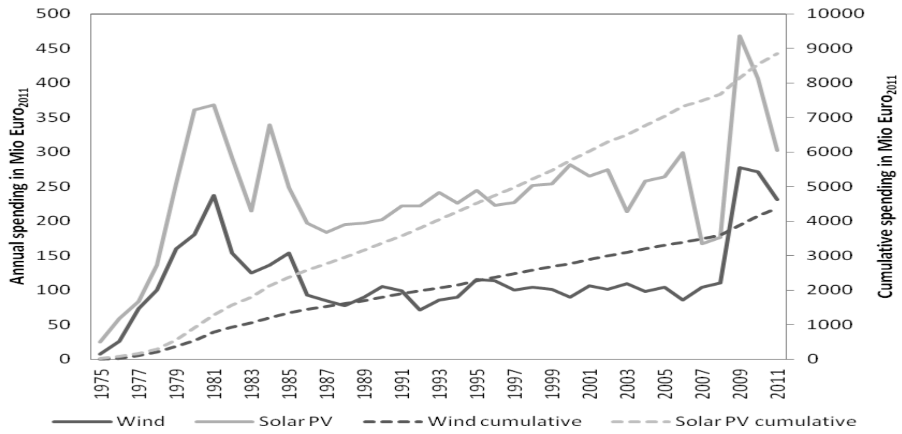
Source: Bloomberg NEF (2012), historical data until 2011, projections for 2012 – 2030

Figure 4: Global capacity installed (wind and solar PV)



Source: Bloomberg NEF (2012) for global data, BMU (2012)/IEA (2012) for German data.

Figure 5: Global government R&D spending on wind and solar technologies



Source: own calculations based on OECD & IEA (2013)

5 First Results

Currently, two of the four technologies are modeled, that are solar PV and wind onshore. Further, country specific results are displayed for Germany, for which the data presented above is readily available.

5.1 Global learning curves

The learning curves for module and turbine prices are assumed to be the same across the globe, i.e. they are estimated using data on global capacity installed and global average

prices by Bloomberg NEF (2012). Modules and, to a lesser extent, turbines can easily be shipped and are thus traded on a global market. The remaining cost components for installing the PV system on a roof or setting up a wind park also depend on local cost components. The global learning curve is therefore estimated for module and turbine prices. This may be further detailed in relation to the different parts of the value chains later. Figures 6 and 7 show the relation between capacity installed of solar PV / wind and the corresponding module / wind turbine prices. The negative relation between capacity installed and prices is clearly visible. The global learning parameters are estimated using the one-factor learning-by-doing specification of the learning curve as well as the two-factor learning-by-doing and learning-by-searching learning curve, corresponding to Equations (5) and (6) above:

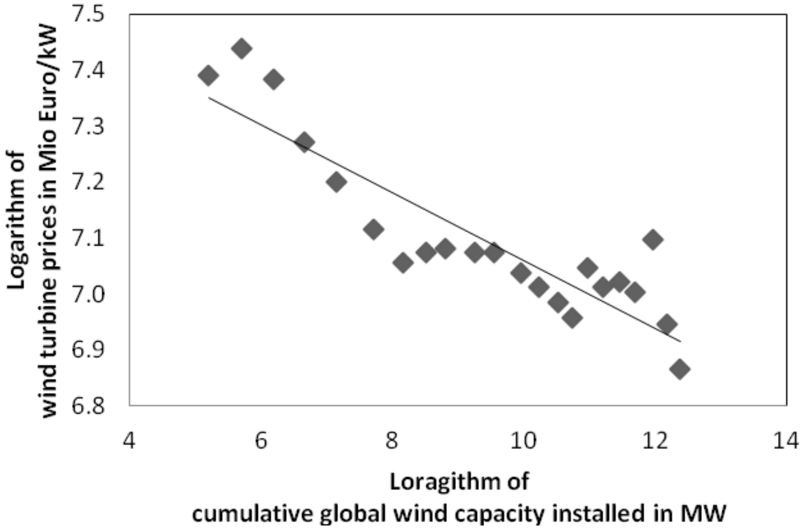
$$\ln\left(\frac{GP_t}{GP_{2010}}\right) = -b_C \ln\left(\frac{C_{Gt}}{C_{G2010}}\right) + \varepsilon_t \tag{15}$$

$$\ln\left(\frac{GP_{Gt}}{GP_{G2010}}\right) = -b_R \ln\left(\frac{R_{Gt-l}}{R_{G2010}}\right) - b_C \ln\left(\frac{C_{Gt}}{C_{G2010}}\right) + \varepsilon_t . \tag{16}$$

The estimation results are displayed in Table 1. The learning-by-doing parameters are highly significant for the one- and two-factor learning curves for both technologies.The learning rates though are rather low compared to the majority of rates reviewed in Kahouli-Brahmi (2008), compare Section 2. The learning-by-doing rates of 3.8% for Wind and about 17% for solar PV would belong to the lower quarter of the total set of rates. However, they are still higher than the minimum rates found in the literature. In Kahouli-Brahmi (2008), the learning rates estimated using turbine and module prices as a proxy for costs seem to be lower than the rates estimated using specific investment costs. As there is a large drop in PV module prices over the last years, the overall fit of the estimation, was rather low. As the drop was not captured by the two-factor learning curve as well, see below, there was something else that influenced the price development. The obvious reason was the production overcapacity for PV modules. Following economics 101, large supply of a good is associated with a low price of that good. As data for global production capacities are not yet available in a form that could be included in the model[9], this fact was approximated by a dummy variable for the years 2011 and 2012, which was highly significant in the one-factor learning curve for PV modules, see second column of Table 1.

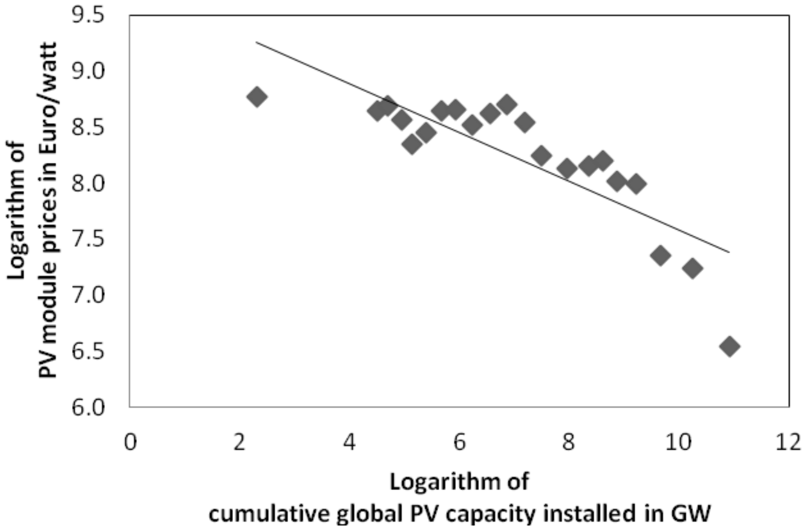
[9] The data are available from the German magazine Sonne, Wind & Wärme

Figure 6: Learning curve data - Wind



Source: see Figures 2 and 4

Figure 7: Learning curve data – Solar PV



Source: see Figures 2 and 4

When additionally including the learning-by-searching factor represented by global publich R&D spending, neither of the learning parameters for solar PV is significant. The learning-by-searching rates for PV are not significant in this estimation for any lag length tested, but higher than those found in the literature reviewed by Kahouli-Brahmi (2008). The learning-by-researching parameters in Table 1 are only significant for wind with a lag

of 15 years. Including a significant learning-by-researching rate reduces the learning-by-doing rate. Given the long lag length for which R&D spending eventually becomes significant, however, casts some doubt on the existence of this relation for the data at hand.

Table 1: Global learning curve estimations

Global prices	**Solar**	**Solar**	**Solar L4**	**Wind**	**Wind L11**	**Wind L15**
Learning-by-doing parameter *bC*	0.273	0.270	0.158	0.056	0.056	0.026
(t-value)	*(15.81)*	*(17.41)*	*(0.89)*	*(13.32)*	*(3.11)*	*(2.10)*
Lagged Learning-by-searching parameter *bR*			0.655		0.003	0.050
(t-value)			*(0.64)*		*(0.05)*	*(2.56)*
Overcapacity PV module production 2011-2012		-0.425	-0.602			
(t-value)		*(-2.43)*	*(-1.83)*			
Adj. R^2	0.784	0.826	0.821	0.799	0.789	0.839
DoF	20	19	18	22	21	21
Time limits	1992-2012	1992-2012	1992-2012	1990-2012	1990-2012	1990-2012
Learning-by-doing rate	17.2%	17.1%	10.4%	3.8%	3.8%	1.8%
Learning-by-searching rate			36.5%		0.2%	3.4%

5.2 SYSTEM COSTS

The system costs, i.e. in case of Solar PV those costs related to the installation of a PV system excluding the module differ across nations. This is due to differences in costs in the balance of system costs, inverters, remaining hardware components, on-site installation and profits, see e.g. Seel et al. (2012) for a comparison of costs for residential PV systems in the US and Germany. For wind, the prices from BNEF (2012) not only include turbines but also the balance of plants components (foundation, electrical components etc.). The modelling of the two technologies therefore differs at this point. While the development of the PV system costs can also be modeled using the one- and two-factor learning curve approach, corresponding to Equation (8) and (9) above, this step is left out for wind. The equations are:

One-factor specification for each technology

$$\ln\left(\frac{S_{ct}}{S_{c2010}}\right) = -b_C \ln\left(\frac{C_{ct-1}}{C_{c2010}}\right) + \varepsilon_t \tag{17}$$

Two-factor specification for each technology

$$\ln\left(\frac{S_{ct}}{S_{c2010}}\right) = -b_R \ln\left(\frac{R_{ct-l}}{R_{c2010}}\right) - b_C \ln\left(\frac{C_{ct-1}}{C_{c2010}}\right) + \varepsilon_t . \tag{18}$$

Results for PV system costs in Germany are displayed in Table 2. Note that capacity installed is included with one lag in the estimation, based on the assumption that learning does not occur immediately, but rather with one year lag, and to avoid endogeneity problems. The corresponding learning-by-doing rate is 10%. Again, the learning-by-searching-rate is not significant for any lag length, but reduces the learning-by-doing rate. The estimated learning-by-researching rate, though not significant, is quite high with 39%, when included with a one year lag. For longer lag lengths the learning rate and its significance are reduced substantially.

Table 2: Learning curve system costs Germany

System cost	Solar	Solar L1	Solar L4
Learning-by-doing parameter *bC*	0.1491	0.0916	0.1222
(t-value)	*(21.03)*	*(1.82)*	*(2.95)*
Learning-by-searching parameter *bR*		0.7083	0.2419
(t-value)		*(1.15)*	*(0.66)*
Adj. R^2	0.8518	0.8540	0.8477
DoF	21	20	20
Time limits	1991-2012	1991-2012	1991-2012
Learning-by-doing rate	10%	6%	8%
Learning-by-searching rate		39%	15%

5.3 Specific investment costs

Specific investment costs (Equation 7) may depend on module prices, system costs, R&D spending and possibly other macro-economic factors. Note that when implementing all equations into the RPGM, R&D spending should not occur in both the system costs equation and then also in the specific investment costs equation in addition to system costs. But, R&D spending is, again, not significant. Table 3 shows that the specification of the specific investment cost regression is not very robust. Since 1990 and 1991 seemed to be outliers, a reduction of the time horizon was tested. This, however, resulted in large changes in the other coefficients: for global price a drop from about 0.37 to 0.04 and 0.05, leaving the coefficient insignificant; and an increase of the coefficient for system costs from 0.68 to about 0.95. The inclusion of R&D spending did not bring about large changes in the other coefficients.

The global price for wind turbines is highly significant for explaining specific investment costs for wind power in Germany (data from BMU, 2012). Still, the overall fit of the regression is lower compared to Solar PV. At this point a more detailed specification of the equation is left for future research, when the RPGM module is implemented into the macro-economic model with the energy extension. A first approximation of including the

macroeconomic development was attempted by using GDP as a proxy variable. GDP and its growth rate have an insignificant effect on the development of specific investment costs for both technologies solar PV and wind in Germany. (The results are not displayed in the table.) This may be different, when including factors that are more specific to the industries relevant for solar PV production or wind turbine production and installation, such as wage development in the electrical machinery sector or the construction sector or capital costs.

Table 3: Specific investment costs Germany

Specific investment cost	Solar	Solar	Solar	Solar	Wind
Global price	0.3780	0.36578	0.03889	0.05191	1.1181
(t-value)	*(2.59)*	*(2.29)*	*(0.27)*	*(0.36)*	*(82.632)*
System cost	0.6756	0.6778	0.93488	0.95692	
(t-value)	*(7.43)*	*(7.24)*	*(9.58)*	*(9.71)*	
Public R&D L4		0.072		-0.30557	
(t-value)		*(0.22)*		*(-1.16)*	
Adj. R^2	0.925	0.921	0.942	0.943	0.874
DoF	21	21	19	19	22
Time limits	1990-2012	1990-2012	1992-2012	1992-2012	1990-2012

5.4 Additional capacity installed

The last equation to estimate for RPGM to close the circle of dependencies is additional capacity installed. Possible determinants of additional capacity installations are specific investment costs, or its components (i.e. module prices and system costs), and energy market and macro-economic factors. As the links to the energy model and the macro-economic model are still missing in the empirical implementation, we have only tested including the electricity price and GDP as an exogenous variable in this estimation. GDP – again – turned out to be insignificant. The diffusion of renewable energy technologies in Germany was and still is largely supported by policy measures, especially demand pull policy measures. The most well-known and very effective policy measure is the feed-in tariff as part of the EEG (Erneuerbare Energien Gesetz). For PV in particular, the decision of installing small scale PV systems on their roofs was driven by the expected return on investment by private households. A possible representation of this expected return is the difference between the feed-in tariff and the levelized costs of electricity production (FiT – LCOE).

Specific investment costs are significant, while including global prices and national system costs individually are not significant (compare specification S8). The elasticity of new installations with respect to specific investment costs is very high, when including specific investment costs as the only explanatory variable (specification S1). When implementing this equation in a projection model, PV installations in Germany grow exponentially over

the next decade, which is actually what has been witnessed over the past two to four years. Hence, it is necessary to decelerate that development. This has been the reasoning behind the degression in FiT. Including the margin between feed-in-tariff and levelized costs of electricity as a determinant turns out to have a positive and significant effect. Thus, lowering FiT should lessen additional installations. However, the elasticity of new installations with respect to specific investment costs remains high (compare specifications S2 and S3).

Table 4: Additional capacity installed in Germany

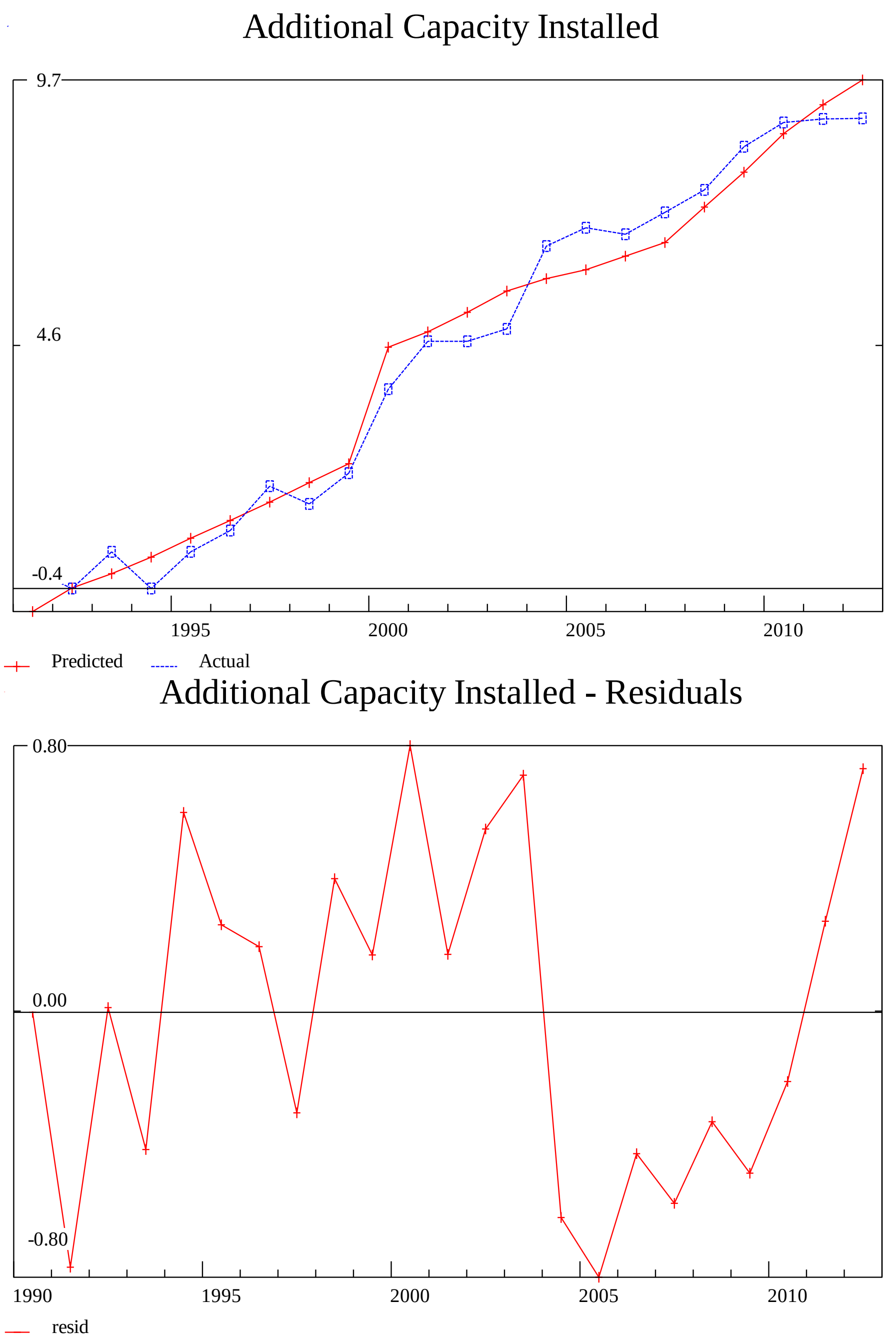
Additional capacity (all in ln)	**S1 Solar**	**S2 Solar**	**S3 Solar***	**S4 Solar**	**S5 Solar***	**S6 Solar**	**S7 Solar**	**S8 Solar***	**W1 Wind**
intercept	60.592	38.643	37.298	10.511	35.626	34.610	32.433	20.493	70.701
(t-value)	*(18.69)*	*(8.41)*	*(8.02)*	*(0.69)*	*(1.88)*	*(2.84)*	*(11.47)*	*(3.62)*	*(13.36)*
Specific investment costs	-6.551	-3.872	-3.690	-1.540	-3.083	-2.741	-2.607		-8.893
(t-value)	*(-17.4)*	*(-6.97)*	*(-6.53)*	*(1.41)*	*(-2.26)*	*(-3.33)*	*(-6.98)*		*(-12.1)*
Global price								-0.696	
(t-value)								*(-1.03)*	
System cost								-0.977	
(t-value)								*(-0.85)*	
FiT – LCOE		1.039	1.074	1.467	1.237	1.077	1.102	1.698	
(t-value)		*(5.37)*	*(5.58)*	*(6.60)*	*(4.32)*	*(5.92)*	*(9.57)*	*(7.89)*	
Electricity price HH				3.007	0.472	-0.231			
(t-value)				*(2.12)*	*(0.26)*	*(-0.18)*			
EEG Dummy 2004FF						1.355	1.321		
(t-value)						*(4.32)*	*(5.40)*		
Adj. R^2	0.935	0.973	0.974	0.982	0.974	0.991	0.991	0.948	0.873
DoF	20	19	19	18	18	17	18	18	20
Time limits	1991-2012	1991-2012	1991-2012	1991-2012	1991-2012	1991-2012	1991-2012	1991-2012	1991-2012

*lagged FiT-LCOE and lagged Electricity Price HH, bot hone year lags

Figure 8 shows the actual development of additional capacity installations (blue) and development of predicted additional capacity installations for specification S2 and also plots the residuals. It is clearly visible that there is a systematic underestimation of the development of PV installations between 2004 and 2010. Including the electricity price of households as an additional determinant (specifications S4 and S5) increases the fit of the regression, but does not entirely explain the underestimation mentioned before. As PV installations are highly policy driven and the only policy measure included in the model so far is the feed-in-tariff, the underestimation may be due to missing policy effects so far. When looking at the development of PV installations it becomes apparent that the strongest increases were in the years in which the EEG or an amendment to the EEG were announced and put into force. The increases in 2000 and 2009 are already covered by the EEG-related variable FiT-LCOE. The 2004 increase, however, was not. Modelling the

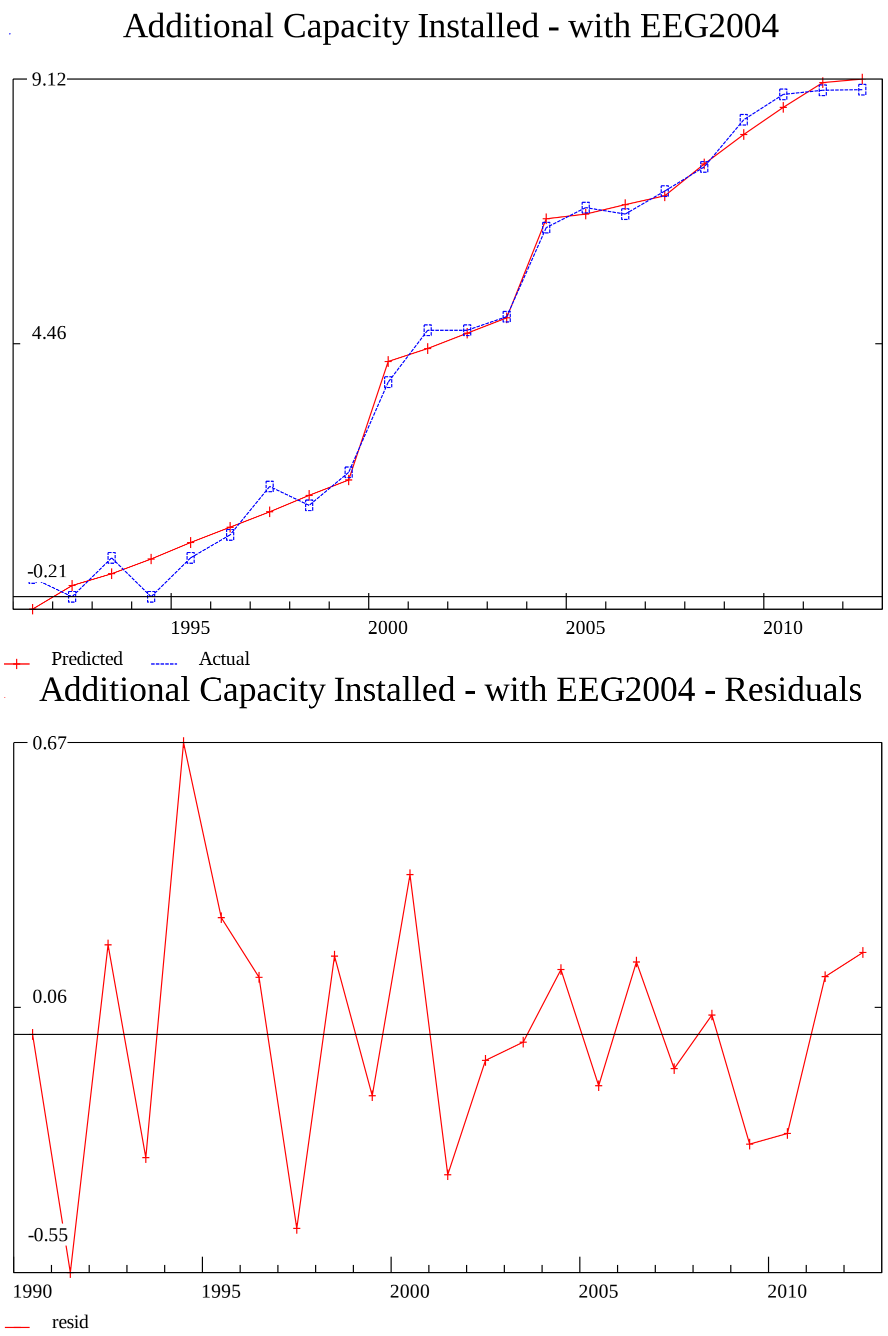
announcement effect using dummy variables for the year of the announcement and the following years shows exactly this: the dummy variable for 2004 and the following years (D2004FF) is positive and highly significant (specifications S6 and S7), the corresponding dummies for 2000 and 2009 are not significant (not shown in the table). Figure 9 clearly shows the better fit of the regression including the D2004FF; this becomes especially apparent when looking at the plotted residuals for the years between 2004 and 2010. When including D2004FF, the electricity price is insignificant in determining additional capacity installed.

Figure 8: Estimation of additional PV capacity installations



Source: own calculations with Interdyme/G7

Figure 9: Estimation of additional PV capacity installations with EEG 2004 dummy

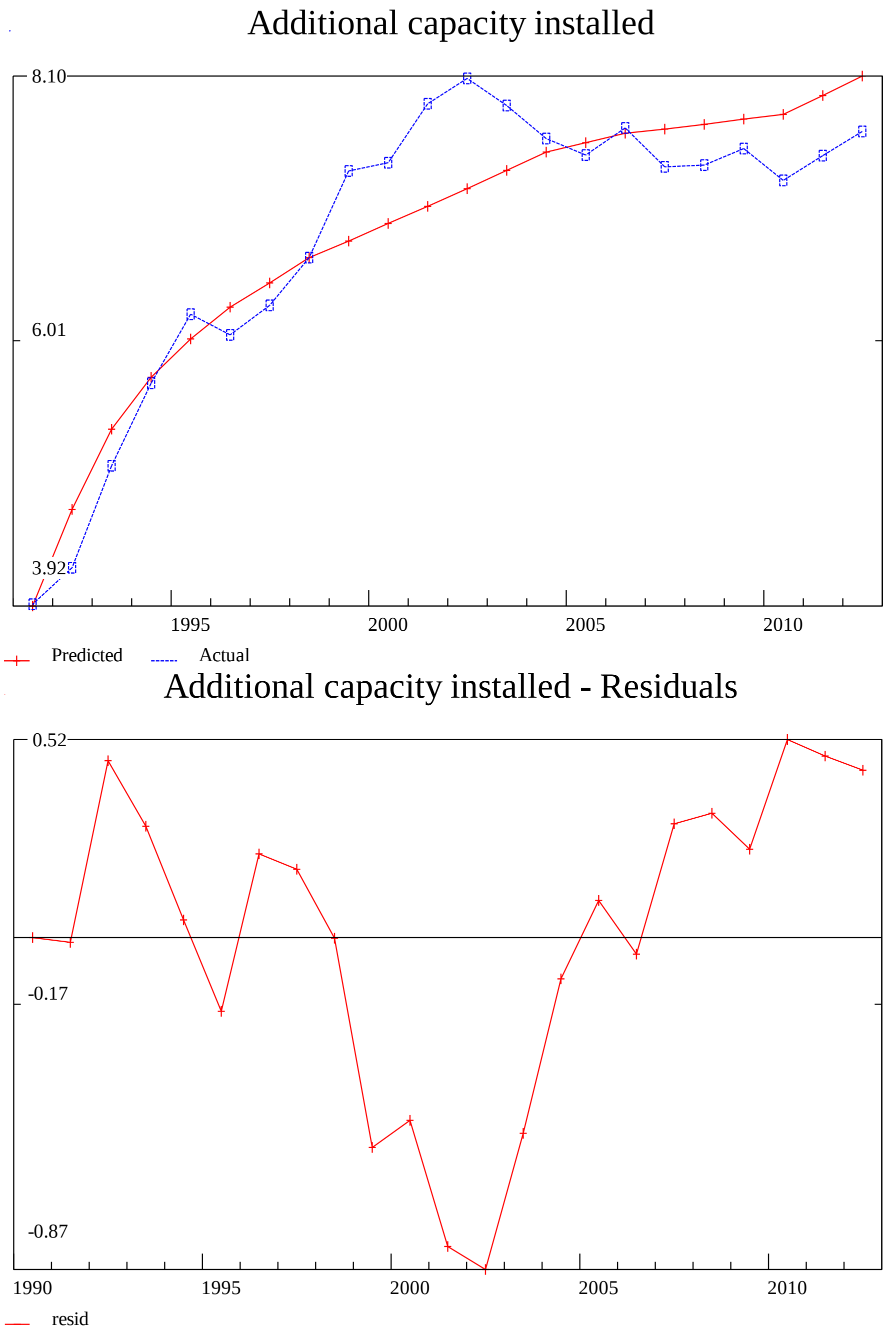


Source: own calculations with Interdyme/G7

Figure 10 shows the regression for additional wind capacity installations. Even though the general trend is estimated quite good, the years following 2000 are substantially underestimated. This may be due to policy effects that are not yet considered in the specification. A first step was simply counting the number of policy measures relevant for wind, which were in force in every year between 1990 and 2012. The count is based on the policies that are part of the IEA/IRENA Policies & Measures Database (http://www.iea.org/policiesandmeasures/). This simple approximation of a possible policy

influence was insignificant in the regression. Further research regarding the effects of policy measures on wind, but also in PV installations is necessary. However, a more structured appraoch, as for example the policy mix concept developed by Rogge and Reichardt (2013) is necessary.

Figure 10: Estimation of additional wind capacity installations



Source: own calculations with Interdyme/G7

6 CONCLUSION AND NEXT STEPS

The approach described here is a first step to endogenously determine national investments in RPG technologies, electricity generation costs and global feedback loops of national policy measures (incl. export of policy measures) on RE investment and electricity production costs. This paper explains the theoretical construction of the renewable power generation module RPGM and its links to the energy module and the macro-economic core model. The empirical results presented here only concern the RPGM and still need to be implemented in the energy-environment-economy model. The main result of the macro-level analysis of the BMBF research project will be the endogenization of technological change in an empirical macro-economic model. The link to the other work packages (micro and meso level) is given through operationalizing the policy mix concept developed by Rogge and Reichardt (2013) during the course of the Gretchen Project. Here, this mainly concerns the demand pull instruments of the policy mix elements. However, other elements may be important as well. The quantification of the existing policy mix elements for inclusion in the model is a non-trivial step in this analysis. One approach, as suggested by Breitschopf (2013), developed in WP 2 of the project, is to count the number of policies for each policy mix element and then use the different counts as proxy variables for the impact of the renewable power policy mix. A quick analysis using the total count of policies relevant for either technology showed that this simple proxy variable was not significant in determining additional capacity installations. Hence, a more detailed approach possibly distinguishing between the different policy element types and better quantification than a binary approach may be necessary.

Technological change in renewable power generation technologies occurs at different stages of the production chain and affects all three stages invention, innovation and diffusion. The learning concepts used in the analysis deal with the diffusion of the final RGP technologies at the macro-economic level. The representation of the relationship between renewable deployment and the development of costs of these in the model is based on global learning curves. These are estimated using data on specific costs, capacity installed and R&D. We test both one factor and two factor learning curves and compare our results to those of existing studies, see e.g. (Wiesenthal et al., 2012) for an overview. The learning curves reflect both learning-by-doing, indicated by capacity installed, and learning-by-searching, indicated by R&D spending.

In a next step, the RPG module will be implemented in a projection model that determines the development of the macro-economy of selected countries. The outcomes of the projection model include, next to the usual macro-economic indicators, sectoral demand for electricity. Electricity supply from RPG technologies is calculated from capacity installed (using the respective load hours of the year 2010, partly adapted if more information is available). Capacity installed is endogenous to the model, depending on

electricity demand and on relative prices of the different energy carriers. The costs for the different RPG technologies are determined by the learning curves, thus depending on capacity installed, R&D spending and the learning rate. In addition, both costs and capacity installed may also be influenced by the RPG technology policy mix. The switch from fossil fuel power generation technologies to RPG technologies implies a changing structure of intermediate demand and, hence, a change in the composition of sectoral production. Thus, the transformation of the electricity sector feeds back into the economy.

This RPG extension of the macro-economic model, an econometric input-output model, will contribute to a better understanding of the interaction between the deployment of renewable energy technologies and macro-economic indicators such as employment, GDP and sectoral production. The implementation of endogenous technological change in the model considers the different approaches to modeling technological change (TC) as outlined by Löschel and Schymura (2013): Learning-by-doing, R&D (learning-by-searching), price induced TC and directed TC. The learning curves capture both learning-by-doing and learning-by-searching. By including R&D spending in the learning curves, R&D support policies can be explicitly considered in the model. The demand for electricity from different energy carriers depends on relative prices, thus indicating price-induced TC, where ‘dirty’ power generation competes against ‘clean’ power generation. Prices for electricity from RPG technologies depend on costs, but are also often directly influenced by policy measures, e.g. through feed-in-tariffs. The model will be used to analyze the impacts of the policy mix on technological change, welfare (economic development and employment), trade and structural change.

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