Empirical evidence on renewable electricity, greenhouse gas emissions and feed-in tariffs in Czech Republic and Germany

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Empirical evidence on renewable electricity, greenhouse gas emissions and feed-in tariffs in Czech Republic and Germany *

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Abstract

In this paper we estimated relation between greenhouse gas abatement and share of renewable energy resources in Germany and Czech Republic. We also analysed the dependence between annual installed capacities of RES and respective feed-in tariffs. We took the empirical data of annual installed capacities and regressed it on respective feed-in tariffs (FIT) and/or their polynomials. The analysis resulted in optimum intervals for some types of RES, which are summarised in our paper. We could not collect most of the data for the Czech Republic, since the Energy Regulatory Office of the Czech Republic does not publish the time series for RES, unlike Germany, which publishes a comprehensive database regarding RES. Optimum intervals in our paper indicate at which values of FIT the biggest amount of installed capacities is anticipated. Thus, if FIT scheme to be continued after 2017, FITs should be set inside these intervals. These intervals assume that there are not any caps and restrictions.

Keywords: Renewable energy, feed-in tariff, Czech renewables, German Renewables

JEL Codes: G32, L94, L51, O44, Q28.

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1 Introduction

This paper provides a simple econometric analysis of renewable energy resources (RES) and their connection with greenhouse gas (GHG) emission and feed-in tariffs. We run the regressions of GHG abatement by the means of RES-E, RES-H/C and RES-T on RES-E, RES-H/C and RES-T share in final gross consumption respectively. In addition, we estimate GHG abatement for 2020. We also analyse how FITs and installed capacities of RES are correlated. Therefore, we will try to find the optimum intervals of FITs for each type of RES by analysis of empirical data. We are not analysing actual generation of energy by RES, since it is dependent on weather conditions and etc. i.e. factors which are hardly can be controlled. Likewise, we are not analysing the results of auctions already held in Germany, since there is no enough data in order to draw some conclusions, nonetheless some summary about this scheme is provided. Thereby, the optimum intervals we found can be used until 2017, unless European Commission will not postpone the removal of FIT support mechanisms. Moreover, FITs inside the optimal intervals do not minimise overall costs of supporting RES, they are indicating FITs values at which installed capacities of RES can be maximised.

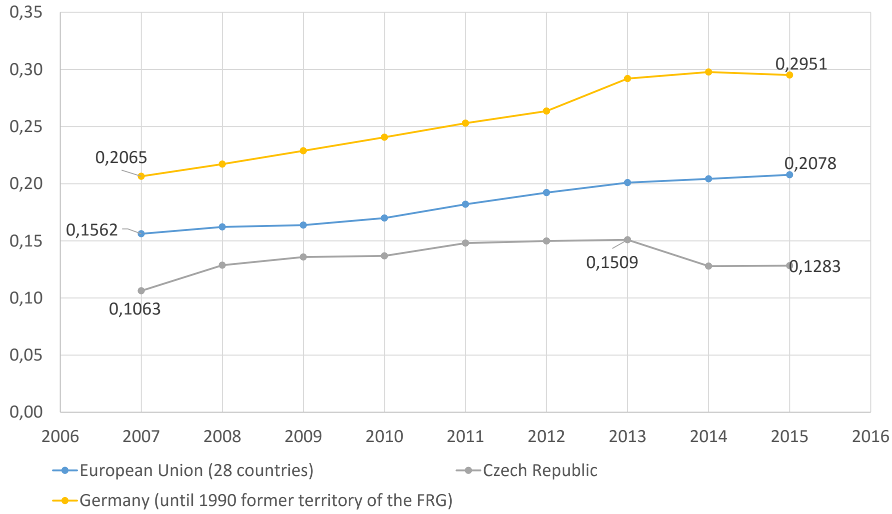
2 Renewables and greenhouse gas emissions

2.1 Renewables supporting policies

German Renewable Energy Sources Act (EEG) is widely considered as a very successful tool for increasing share of RES in electricity consumption. Nonetheless, this has come with excessive costs for end customers. German household electricity prices went up from 14 EURcent/kWh in 2000 to 29 EURcent/kWh in 2013, see Figure 1 for more details about the development of prices for households.

Among RES technologies, only large hydropower stations are not dependent on support, which is provided by EEG (Frondel et al., 2009), since hydropower is a very mature

Figure 1: Prices for households



Eurostat

technology. End customers through so-called EEG levy pay all additional costs associated with subsidies. In 2000, EEG levy was 0.19 EURcent/kWh and increased to the level of 6.24 EURcent/kWh in 2014. See Figure 2 for more details about the price structure of German households. The overall cost of EEG subsidies increased drastically during 2009 – 2014, from about EUR 5 billion in 2009 to some EUR 25 billion in 2014. (Poser et al., 2014).

Price structure for Czech households is different. As it can be seen from Figure 3, taxes and levies account for moreless same portion since 2008. In fact, it slightly increased from 2.21 EURcent/kWh in 2009 to 2.36 EURcent/kWh in 2015, growth of only 6.8%. Whereas in Germany for the period from 2009 to 2014[1] growth was 64%. However, the surcharge for support of RES went up from 6.7 EUR/MWh in 2010 to 19.8 EUR/MWh in 2014[2]. The development of price structure of Czech households is depicted in Figure 3.

From 2001 until 2008, amount of feed-in tariffs in Germany went up from some EUR 1.6 billion to EUR 9 billion. With such large amounts of subsidies, only 211.1 million euros

[1]no data for 2015
[2]ERO

Figure 2: German price structure

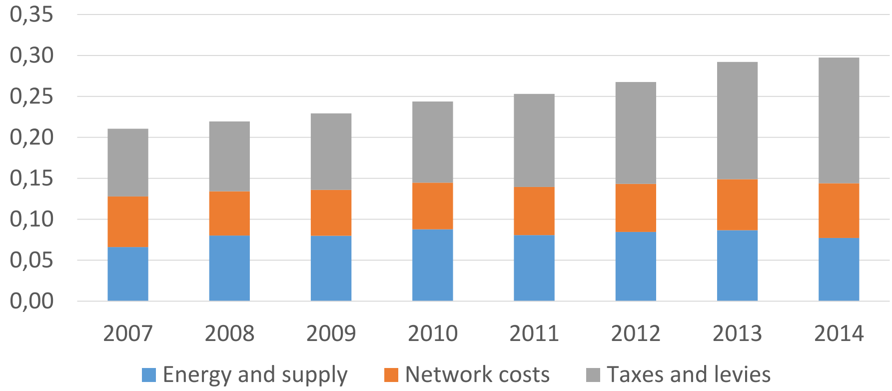


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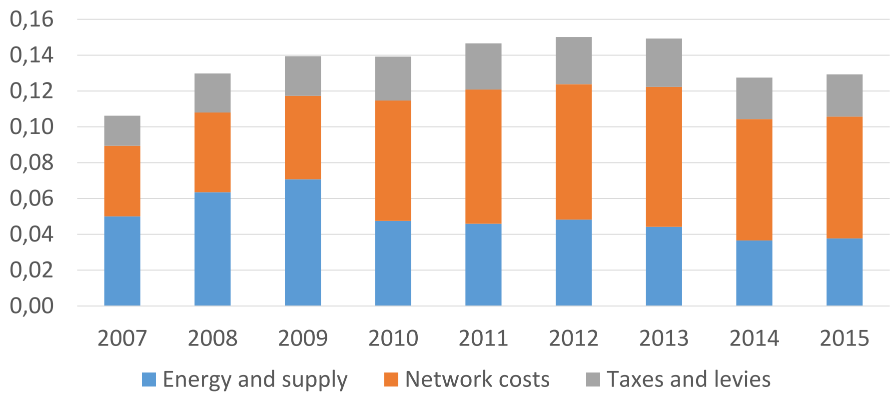
Figure 3: Czech price structure



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were allocated to R&D in renewable energies by government, this accounts for 3% of the total expenses related to FITs (Frondel et al., 2009). Nonetheless, these support schemes have been very successful in aspect of increasing installed capacities of RES. In Germany, photovoltaics, the recipient of highest FITs, increased its capacity from 100 MW in 2000 to 5311 MW in 2008. In the Czech Republic, installed capacity of PV between 2008 and 2010 soared from 39.5 MW to 1959.1 MW. In addition, Prusa et al. (2013) calculated that in 2011 average usage of Czech PV plants was only 1099 hours (12.54% of the total number of hours in the year) and the total cost of PV subsidies was about EUR 972 million and EUR 216 million out of this amount is "the pure dead weight loss". Prusa et al. (2013) define the pure DWL as follows: The pure DWL component is a net loss to the economy, because it captures the extent of inefficient electricity production. p_{02} . The pure DWL is equivalent to an artificial cost which would not exist were it not for the subsidies. This cost appears because money is invested in PV production capacity that is more expensive than other feasible sources.

Feed-in tariffs are usually granted for 20 years, this is a good feature for investors, since they can be assured in long-term support. So even if they would be abolished this year, additional costs will still be paid for 19 years by end customers, if no retrospective legislation will be put in force. While, putting retrospective laws in force is a very bad signal for investors, since they cannot be confident with safety of their investments. In 2010, Czech Republic introduced retroactive legislation in the form of a withholding tax of 26% for photovoltaics with installed capacity of over 30 kW valid for 2011 – 2013. Furthermore, Czech government cancelled previously guaranteed tax-free period of first five years of a project life. The impact was instantaneous, annual installed capacities of PV plummeted from 1494.5 MW in 2010 to 11.9 MW in 2011, 99.2% decrease in just one year. Average annual installed capacities for the period 2011 – 2014 is 27.075 MW, furthermore, in 2014 there was even negative installed capacity, i.e. dismantling of some[3] PV stations. Moreover, such legislative action of the Czech government also indirectly impacted wind sector, in 2011 only 1.1 MW of wind capacity were installed, whereas in 2010 24.6 MW of wind capacity were installed, 95.5% decrease in just one year.

[3]65 MW

Hydropower also was affected, in 2011 1.5 MW of hydropower capacity were dismantled, while in 2010 19.6 MW of hydropower capacity were installed, i.e. more than 100% decrease. Of course we cannot claim, that PV, wind and hydropower sectors declines were caused solely by the Czech legislative action. For instance, additional reason for PV sector decline is a stoppage of connections into the grid for new PV plants in 2010, this problem is more explained in section 3.1.1. Nevertheless, we see that a large drop in installed capacities occurred next year after Czech government introduced such an unpopular legislation.

In Germany, FITs for wind farms put in operation in 2003 are expected to be lower than prices for electricity in 2022 (Frondel et al., 2009). Therefore, it will take 19 years for wind farms to be competitive without subsidies. It should be mentioned that onshore wind is considered as moreless mature technology.

Furthermore, technology specific feed-in tariffs reduce competition within RES. If FITs would have been same for all types of RES, we would not be able to claim that PV installations would had resulted in same capacities as now. Though in Germany, installations of PV plant capacities exceed that ones of biomass, biomass has generated much more energy than solar PV plants. So if subsidies would be the same, it probably would be more economically reasonable to invest into biomass sector rather than into PV sector. Prusa et al. (2013) found out that in the Czech Republic, for PV plants to be non-loss making either prices have to go up seven times or costs have to be reduced seven times.

Whilst prices for end customers increased, wholesale prices have decreased. In Germany, base load prices plummeted from 90-95 EUR/MWh in 2008 to 37 EUR/MWh in 2013. This created financial problems for utilities that operated thermal power plants. German utilities companies stocks went down by almost 45 percent from 2010 to 2014 and credit ratings are lowered for them from A to A- or in case of RWE even to BBB+ (Poser et al., 2014).

Frondel et al. (2010) suggest instead of excessive subsidies for RES to invest more in

R&D. Now producers of RES-E are induced to be more cost efficient via degressive rates of FITs.

Likewise, Menanteau et al. (2003) suggest introduction of "optimum environmental tax". So consumers would be induced to choose between efficient use of energy from conventional resources or use energy from RES without such tax. So if the cost of pollution and other environmental damage from conventional production of energy can be properly estimated such Pigovian tax can be introduced. This would correct the market imperfections (Menanteau et al., 2003). We know similar tax as tax on CO2 emissions.

2.2 Problems of integrating renewable energy into the grid

One more problem of renewables is grid connection. Producers of RES-E are entitled to have a priority access into the grid. But locations of some plants are far away from the grid, for instance offshore wind farms in Germany. So expansion of transmission grids needs large investments. Investment costs for Germany are estimated to be approximately EUR 40 billion (Poser et al., 2014) over the decade. There is the "Grid Development Plan" in Germany, which encompasses development of infrastructure and connection of north offshore wind plants with southern regions. In 2012, energy transition induced four German TSOs to spend EUR 1.15 billion[4] on network infrastructure.

In the Czech Republic, the most favourable locations for wind farms are along the German and Polish borders, as well as Slovakian border and also in the Moravian highlands. Accordingly, they are remote from the biggest consumption centers such as Prague, Ostrava and Brno. Until 2023, Czech TSO is going to invest into expansion of the grid CZK 60-70 billion[5] (EUR 2.2 - 2.59 billion; exchange rate is 27) this is the biggest investment in the history[6] of the country. However, this expansion is planned not only due to increasing installed capacities of RES but mainly because of increasing capacity

[4]https://ec.europa.eu/energy/en/content/2014countryreportsgermany
[5]Jirous et al., 2011
[6]as of 2011.

of nuclear power. In contrast with Germany, Czech Republic is not planning to abandon nuclear power.

In the Czech Republic, in February 2010 due to technical reasons Czech TSO requested stoppage of connections into the grid for new PV plants. Czech TSO stated that excessive amount of new PV plants can threaten security of the grid.

For grid operators there are also so-called grid balancing costs. Such costs arise due to intermittent character of some types of RES. Wind and solar technologies are dependent on weather, so when there is no wind wind farms do not generate electricity and when there is a cloudy sky PV plants do not generate electricity. Thus, grid operators must balance out electricity capacities in the grid in order to prevent stoppages of electricity supply and security of the grid. Next section discusses intermittency problem more detailed.

2.3 Intermittent character of renewable energy

Many proponents of RES say that RES will decrease dependency from depleting fossil fuels. However, RES tend to have intermittent character. For example, onshore wind farm with installed capacity of 100 MW will produce only 20-35%[7] of electricity that it would have produced if suitable weather conditions were holding all the year round – this is known as the capacity factor. For solar PV plants, the capacity factor is between 10-20%[8].In order to save customers from blackouts backup energy systems must be in place. In Germany, on January 5, 2012 solar and wind combined production was 500 GWh, maximum for that year; and minimum was on December 19, 2012 with combined production of only 30 GWh. Therefore, large backup capacities of thermal power plants must be in place (Poser et al., 2014).

There are different ways to tackle the problem of intermittency, the major ones are:

- Use of fossil fuels, so at times when RES-E producers are unable to meet the de-

[7] FS-UNEP, 2016
[8] See prev. note

mand, conventional plants start to produce electricity. Maintenance of such systems is costly. For Germany, amount of EUR 590 million in 2006 was calculated by Erdmann (2008). The use of fossil fuels is relatively easy and cheap only in case of long-term balancing (i.e. days or week notice).

- Transmission of surplus from one location to another, this requires good interconnection between locations. This goes back to the development of the grid and also may require good collaboration between the states. In addition, it will increase the grid balancing costs.

- Demand response, so when RES expected to produce low volume of electricity, large industrial and commercial customers are paid by the grid operator to lower their consumption of electricity by switching off machines and/or air conditioning etc. The amount of payment must be properly calculated, nevertheless this method is costly and difficult to implement. This method is relatively easy to implement in medium-term notice (i.e. hours).

- Energy storage, surplus of produced RES-E is stored and when RES-E producer cannot meet the demand stored electricity is fed into the grid. Probably the best option in short notice (i.e. seconds to minutes).

The latter option is promising because prices for batteries have been falling. For example, prices of electric vehicle batteries are steadily decreasing. The average cost per kWh fell from some 1000 $ in 2010 (EUR 757.57, exchange rate is 1.32, which is average monthly rate for 2010) to some 390 $[9] in 2015 (EUR 354.55, exchange rate is 1.10, which is average monthly rate for 2010). The decrease is caused by technological improvements as well as economies of scale. This is also driven by increasing demand for electric vehicles. There are two types of storage: so-called "behind the meter" and the grid-scale storage.

[9]See prev. note

Behind the meter storages are located inside the buildings and reserved for self use. Germany has a subsidy programme for small-scale PV installations with storage effective from 2013. By the end of September 2015, 27 000 storage systems were sold with capacity of 136 MWh[10].

Grid-scale battery storages are of much larger capacities and located close to wind farms or solar plants. For instance, in Germany 5 MWh storage system was put in operation for utility which operates a large share of wind energy. In 2015, worldwide 1220 MW[11] of grid-scale projects were announced.

Nonetheless, the storage systems increase the costs of RES-E. In 2015, German levelised cost of electricity for onshore wind farm with storage of 50% of total installed capacity is 120 $/MWh[12] (EUR 109.09, exchange rate is 1.10), which is 48% higher than without storage capacity. For PV plants such cost is 198 $/MWh[13] (EUR 180, exchange rate is 1.10), which is 85% higher than without storage. Consequently, we see that storage systems increase the costs substantially, yet these costs tend to decrease, since prices for batteries decrease and overall development of storage technology is promising.

In addition, wholesale prices have become dependent on weather conditions. Wholesale prices go down when the sun shines and the wind is strong and go up when no wind and no sun but high demand for power remains. Therefore, price forecasts for futures have become more subtle and complicated.

2.4 Reduced CO2 emissions

Prices of CO2 emission certificates, which are traded on European Emissions Trading System (ETS), have never been above 30 EUR/tonne of CO2. In 2008, calculated cost of abatement one tonne of CO2 emission by PV in Germany was 716 euros and by wind energy was 54 euros (Frondel et al., 2009). Therefore, from economic point of view it is

[10] See prev. note
[11] See prev. note
[12] See prev. note
[13] See prev. note

much more beneficial to buy certificates than subsidize renewable energies.

Nevertheless, in 2009, about 340 million metric tonnes of CO2 emissions were saved by the use of RES in EU. Taking the price of 15 EUR/tonne of CO2 in 2009, savings will result in EUR 51 billion for 2009 year alone (Poser et al., 2014).

In order to see correlation between change in RES share in gross final energy consumption and greenhouse gas (hereinafter GHG) abatement for Germany we will run the following regressions[14]

$$
\begin{aligned}
GHGE &= \beta_0 + \beta_1 RESE \\
GHGHC &= \beta_0 + \beta_1 RESHC \\
GHGT &= \beta_0 + \beta_1 REST
\end{aligned}
$$

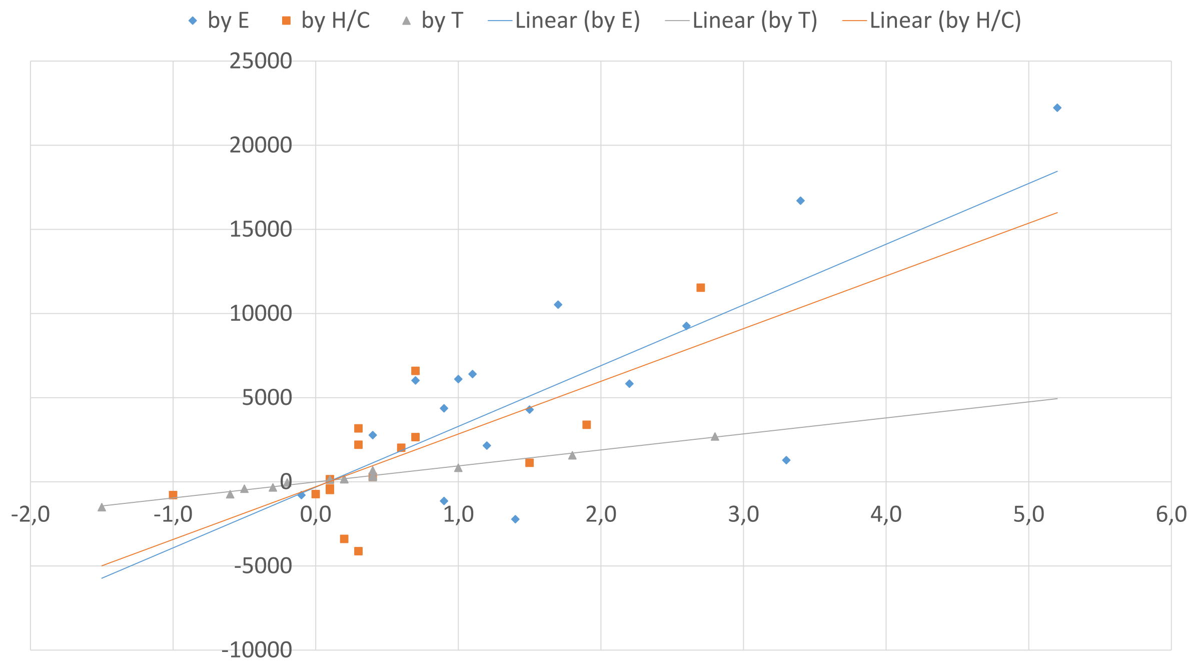
where, $GHGE = GHGE_t - GHGE_{t-1}$, i.e. yearly change in amount of GHG abatement induced by change in RES-E share in gross final electricity consumption; and $RESE = RESE_t - RESE_{t-1}$, i.e. yearly change of RES-E share in gross final electricity consumption. Analogously, other two regressions should be read. Likewise, all three regressions were tested for heteroskedasticity (hettest), normality (swilk) and specification test for omitted variables (ovtest) results can be found in Appendix A in notes under the relevant table.

No regressions were run for the Czech Republic due to lack of data.

Figure 4 is a scatter plot for all three regressions. Y-axis is measured in tonnes of CO2 equivalent and X-axis is measured in percentage points. Regression of GHG abatement by RES-E resulted in R-squared of 0.5653, i.e. 56.53% of variability in dependent variable is explained by the independent one. Likewise, equation of the regression – a blue line –

[14] Stata outputs for all regressions can be found in Appendix A.

Figure 4: GHG abatement by different types of RES



is:

$$\widehat{GHGE} = \underset{(1820.415)}{-317.18} + \underset{(845.79)}{3609.046} RESE$$

Coefficient is statistically significant even at 1% significance level. Thus, one percent increase of RES-E share in gross final electricity consumption results in abatement of 3609.046 tonnes of CO2 equivalent. Constant in this regression is statistically insignificant.

Regression of GHG abatement by RES-H/C has R-squared of 0.5113. Equation of the regression line – an orange line – is:

$$\widehat{GHGHC} = \underset{(818.14)}{-290.5662} + \underset{(818.3969)}{3132.254} RESHC$$

Constant is statistically insignificant, whereas coefficient is statistically significant even at 1% significance level. Therefore, when RES-H/C share in final energy consumption in heating and cooling is increased by 1%, GHG abatement increases by 3132.254 tonnes of

CO2 equivalent.

Regression of GHG abatement by RES-T has R-squared of 0.9851, which is almost perfect correlation. Equation of the regression line – a grey line – is:

$$\widehat{GHGT} = \underset{(31.26)}{-6.637} + \underset{(31.3)}{951.2398} REST$$

Here constant is also statistically insignificant and coefficient is statistically significant even 1% significance level. Thus, 1% increase in RES-T share energy consumption in transport increases GHG abatement by 951.239 tonnes of CO2 equivalent.

Having these results and estimations of RES shares from Table 2.2 we can estimate the amount of GHG abatement in 2020 by multiplication of relevant coefficients with estimated shares of relevant RES. Thereby, we have the following estimations:

$$RES - E_{2020}\text{x}coef.RESE = 139309.2$$
$$RES - H/C_{2020}\text{x}coef.RESHC = 48549.94$$
$$RES - T_{2020}\text{x}coef.REST = 12556.37$$

All estimations are measured in tonnes of CO2 equivalent. Thus, we have that in 2020 year alone total estimated GHG abatement is 200 415.5 thousand tonnes of CO2 equivalent, according to German NREAP 215 million tonnes of CO2 equivalent will be prevented by 2020, thus there is less than 7% discrepancy between my estimations and German NREAP estimations. Taking into account that prices of certificates on ETS should increase, savings in money equivalent will be significant. If we take current price[15] of EU Emission Allowance – 6.05 EUR per tonne of CO2 equivalent, we can estimate that savings in 2020 year alone will be 1.213 billion EUR. However, these estimation is assuming that prices will remain at its current level, whereas they must go up, since the

[15] 6/5/2016 13:14

number of the certificates will gradually go down. This estimation is conducted in order to show you the size effect of GHG abatement.

3 Installed renewable capacity and feed-in tariffs

3.1 Model

We are going to analyse dependence between feed-in tariffs and installed capacity of each type of RES-E in Germany and the Czech Republic via linear regression. Firstly, we will use simple linear regression, our dependent variable will be installed capacity in year t, MW_t, and independent variable will be FIT in year t, FIT_t. Thus, the equation will be:

$$MW_t = \beta_0 + \beta_1 FIT_t$$

Then for some types of RES we will add polynomial of second order and in two cases polynomial of third order, in case of Czech solar RES we will add a polynomial of fourth order and a dummy, reasoning will be explained later. Therefore the equations will be:

$$MW_t = \beta_0 + \beta_1 FIT_t^2 + \beta_2 FIT_t$$

$$MW_t = \beta_0 + \beta_1 FIT_t^3 + \beta_2 FIT_t^2 + \beta_3 FIT_t$$

$$MW_t = \beta_0 + \beta_1 FIT_t^4 + \beta_2 FIT_t^3 + \beta_3 FIT_t^2 + \beta_4 FIT_t + \beta_5 D$$

All successful regressions (i.e. p-value of F-test is lower than 0.05 or in some cases lower than 0.1) were tested for heteroskedasticity (hettest), normality (swilk) and specification test for omitted variables (ovtest) results can be found in Appendix A in notes under the relevant table.

For Germany data will be taken between years 2000 and 2015. However, if value of FIT_t for some t is zero, then this year is omitted. There are such cases in landfill, sewage and mine gas RES, where FITs were introduced in 2004, in geothermal RES, where FITs were introduced also in 2004, and in offshore wind RES, where FITs were introduced in 2009. The data for Germany is taken from Federal Ministry for Economic Affairs and Energy. It should be mentioned that each technology-specific average FIT for a given year will be used as FIT_t.

For the Czech Republic data will be taken for 2002 – 2015 period. No restrictions on value of FIT_t are imposed. Nevertheless, for the Czech Republic we managed to collect much less data than for Germany. We could not find data about installations of biomass and biogas[16] RES. The data for the Czech Republic is taken from the Energy Regulatory Office.

3.2 Results of the model

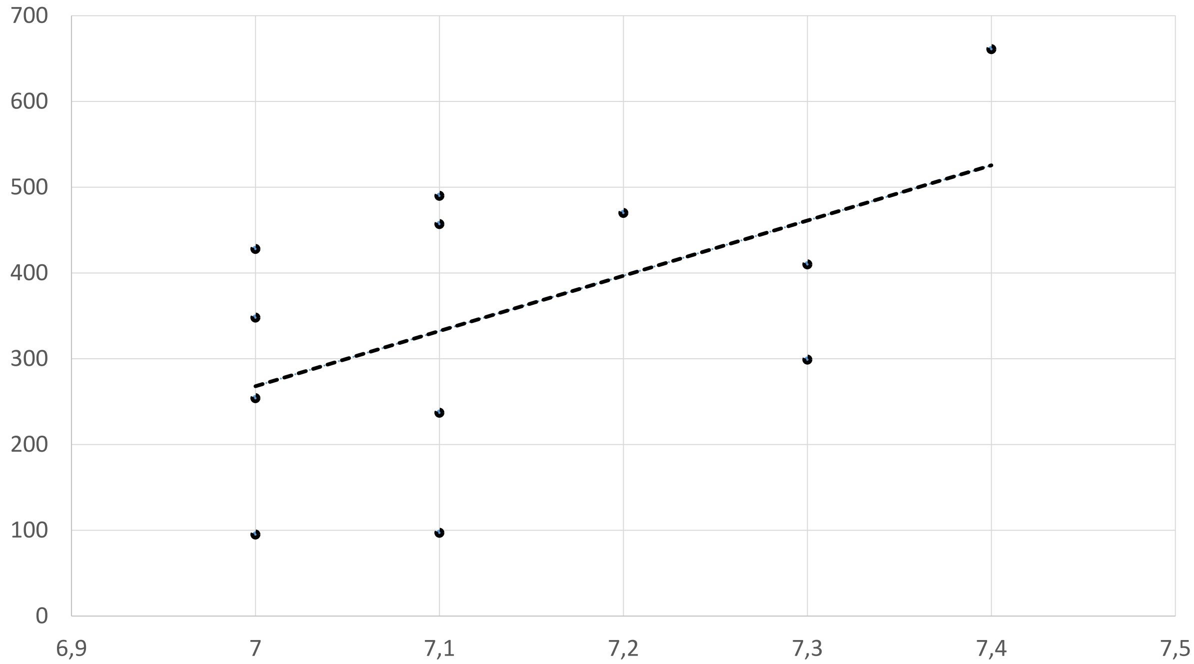
Regression for German hydropower resulted in statistically insignificant coefficient of FIT, p-value of the coefficient is 0.543. In addition, R-squared is only 0.0271, which means that only 2.71% of variability in dependent variable is explained by the independent one. Finally, regression itself is insignificant, since p-value of the F-test is 0.5426. This is caused by the fact that sites for such RES technology are scarce, since can be located only on rivers. Therefore, there is no relation between the size of FIT and installation amounts. Average annual growth rate of installed capacity for the period of 2001 – 2015 is 0.99%. It should be noted, that hydropower is the most mature type of RES among all, since it has been developing for decades.

Regression for Czech hydropower also resulted in statistically insignificant coefficient of FIT, p-value of the coefficient is 0.585. R-squared of the regression is only 0.0527. This is caused by the same reasons as in German case.

Figure 5 is a scatter plot for German landfill, sewage and mine gas RES. Y-axis is the amount of annual installed capacity of this RES in MW. X-axis is a feed-in tariff in

[16]For biogas we managed to find such data for 2006 and 2007, but then in ERO reports such data is missing.

Figure 5: German landfill, sewage and mine gas



BMWi and own computations

EURcent/kWh. Equation of the line is:

$$\widehat{MW} = \underset{(2325.79)}{-4239} + \underset{(325.99)}{643.87}FIT$$

Thus, one cent of FIT corresponds to 643.87 MW of installed capacity. For instance, if in year t+1 FIT will be increased by one cent, then installed capacity will be increased by 643.87 MW in comparison to year t. p-value of the coefficient is 0.076[17], i.e. coefficient is statistically significant at 10% significance level. Likewise, overall significance of the regression is achieved only at 10% significance level, since p-value of the F-test is 0.0765. In addition, so far maximum change of FIT was 0.2 cent, increase in 2011 from 7.2 to 7.4 and decrease in 2013 from 7.3 to 7.1. R-squared of this equation is 0.2806, i.e. independent variable explains 28.06% of variability of dependent variable. Though, average growth rate of FIT between 2005 and 2015 is only 0.14%, average annual growth rate of installed capacity is 20.97%.

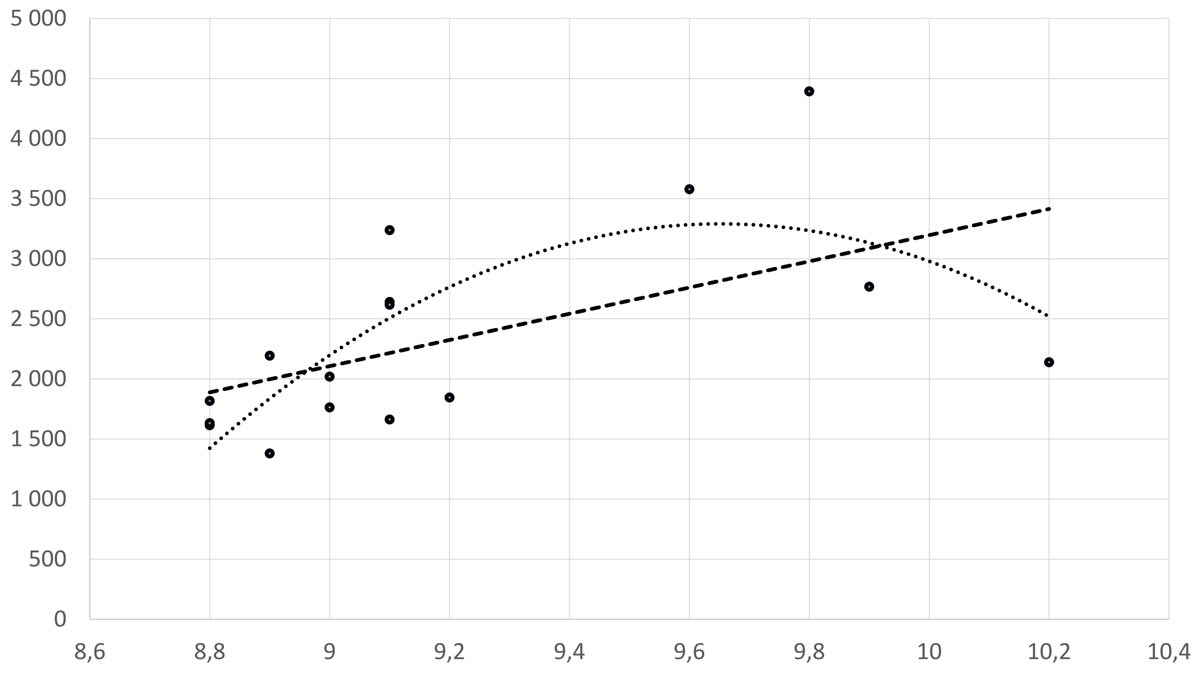
[17]For full Stata output of all regressions see Appendix A.

No regression was run for the Czech Republic due to lack of data.

Geothermal type of RES started to develop in Germany in 2007, when the first 2 MW of this type of RES were installed. Average growth rate of installed capacity is 55%, nonetheless there were years with no increase at all and years such as 2012, when 13 MW were added, resulting in 260% increase in comparison to 2011. Regression resulted in statistically insignificant coefficient and constant, with p-values 0.34 and 0.55 respectively. Moreover, overall regression is insignificant, p-value of the F-test is 0.3396. This is caused by scarcity of this type of RES, i.e. special site needed to be found in order to generate geothermal energy. Therefore, feed-in tariffs do not impact amount of installed capacity of this type of RES.

No regression was run for the Czech Republic due to lack of data.

Figure 6: German onshore wind



BMWi and own computations

Figure 6 is a scatter plot for German onshore wind RES. Y-axis and X-axis are same as in Figure 5. Equation of the dashed line is

$$\widehat{MW} = \underset{(3906.02)}{-7703.76} + \underset{(423.84)}{1090}\, FIT$$

Therefore, one cent of FIT corresponds to 1090 MW of installed capacity. For instance, if in year t+1 FIT will be increased by one cent, then installed capacity in year t+1 will be increased by 1090 MW in comparison to year t. R-squared of this equation is 0.3208, i.e. independent variable explains 32.08% of variability of dependent variable. p-value of independent variable is 0.022, i.e. it is statistically significant at 5% significance level, whereas, p-value of constant is 0.069, i.e. it is not statistically significant at 5% significance level, however at 10% significance level it is statistically significant. But, Breusch-Pagan test for heteroskedasticity yields that there is a constant variance[18]. Nevertheless, when we add in the model a polynomial of the second order, Breusch-Pagan test for heteroskedasticity rejects null hypothesis, which is constant variance of dependent variable fitted values. Likewise, R-squared increases to the level of 0.5525, all coefficients and constant are statistically significant at 5% significance level. The equation of this model – dotted line – is:

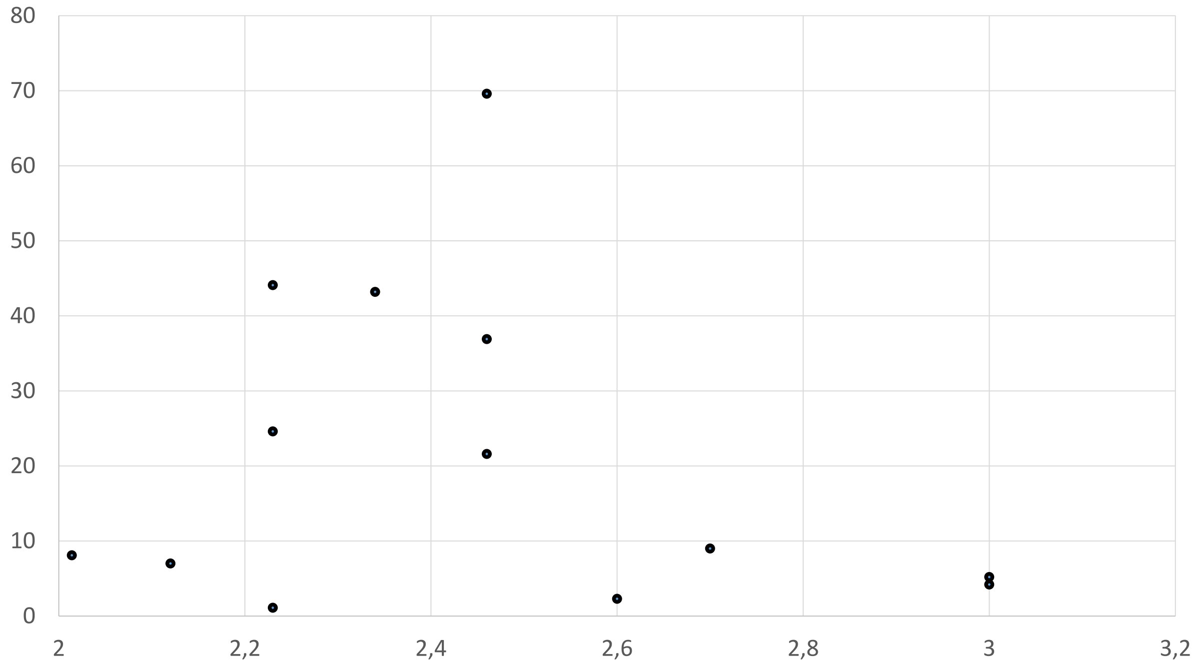
$$\widehat{MW} = \underset{(991.01)}{-2570.459}FIT^2 + \underset{(18714.03)}{49620.89}FIT - \underset{(88148.72)}{236183.6}$$

By calculating the maximum of this parabola we find the optimum FIT for onshore wind RES, i.e. under this FIT the maximum annual installed capacity is anticipated. The optimum FIT is 9.65 EURcent/kWh. Therefore, higher FITs are inefficient, since they result in lower installed capacities at higher expenses. Likewise, FITs below 8.52 will result in negative installed capacities. Therefore, FITs should be set inside (8.52;9.65] interval. In addition, average growth rate of FIT is only 0.40% for the period of 2001 – 2015, average installed capacity growth rate is 14.16%.

Figure 7 is a scatterplot for Czech wind RES. Y-axis is in MW of installed capacity and X-axis is a feed-in tariff in CZK/kWh. I have run various regressions: simple ones, with polynomials of the second, third and even fourth orders. No regression was successful. It is seen from Figure 7 that data is very dispersed, thus very difficult to draw a line which

[18]See Appendix A for p-value of other tests.

Figure 7: Czech wind



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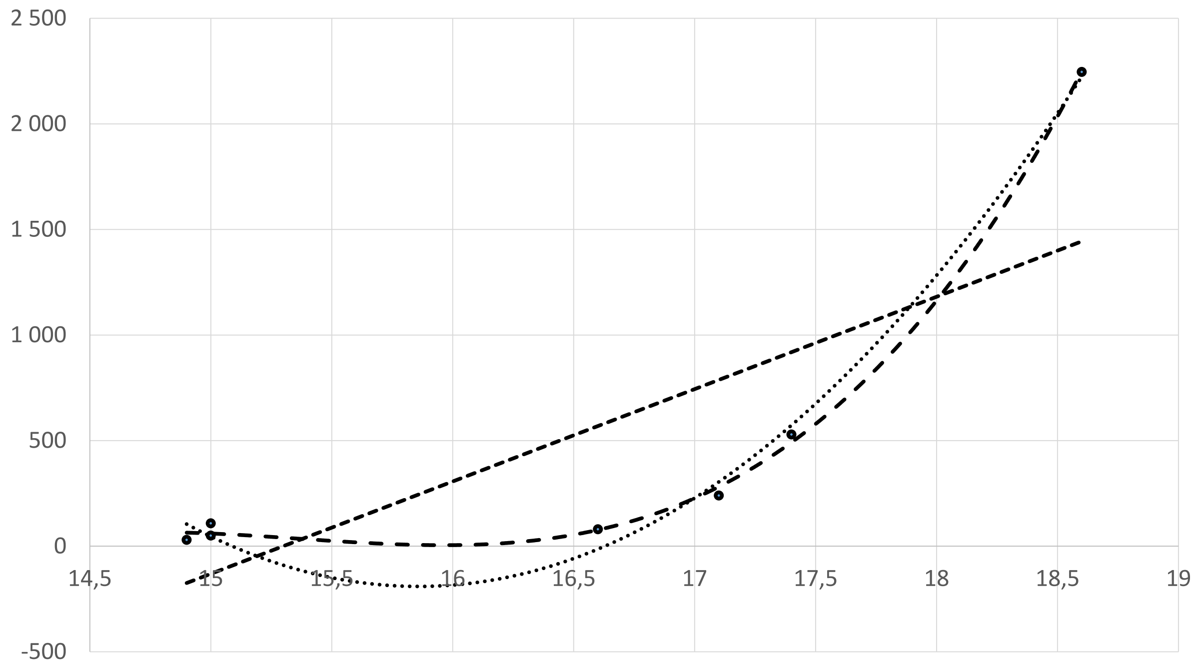
would approximately match the pattern. In all regressions, overall p-values were greater than 0.1706. Thus, we can conclude that wind installations are independent from FITs.

Figure 8: German offshore wind



BMWi and own computations

Figure 8 is a scatter plot for offshore wind RES in Germany. Y-axis and X-axis are same as in Figure 5. Equation of the dashed line is

$$\widehat{MW} = \underset{(2616.775)}{-6702.93} + \underset{(159.46)}{438.46}FIT_t$$

Hence, one cent of FIT corresponds to 438.46 MW of installed capacity. For instance, if in year t+1 FIT will be increased by one cent, then installed capacity will be increased by 438.46 MW in comparison to year t. R-squared of this equation is 0.6019, i.e. independent variable explains 60.19% of variability of dependent variable. Independent variable is statistically significant at 5% significance level, p-value of constant is 0.051, i.e. constant is almost statistically significant at 5% significance level. Yet, Ramsey RESET test concludes that we have omitted variables[19]. Accordingly, when we add in the model a polynomial of second order, R-squared of the model increases to the level of 0.9910, i.e. model explains 99.1% of variability in the dependent variable. In addition, all coefficients and constant are statistically significant even at 1% significance level. The equation of the model – dotted line – is:

$$\widehat{MW} = \underset{(26.86775)}{353.0522}FIT^2 - \underset{(886.7051)}{11207.84}FIT + \underset{(7275.592)}{88725.89}$$

The minimum corresponds to the point where derivative changes its sign, i.e. negative marginal returns change to increasing marginal returns. The minimum here is 15.8727, parabola at this point is below zero, i.e. when FIT is set at 15.8727 annual installed capacity will be negative. So producers of RES will dismantle their wind farms. Actually, parabola is negative when values of FIT are inside [15.0764;16.6691] interval. Therefore, FITs should not be set inside this interval. However, such model implies that FIT set at 0 will result in 88725.89 MW of installed capacity, which is barely can make sense. In order to exclude this shortcoming of the model, we add a polynomial of third order, and

[19]See Appendix A for p-values of tests.

now the model – wide dashed line – is:

$$\widehat{MW} = \underset{(24.15052)}{9}\,9.41284FIT^3 - \underset{(1216.998)}{4656.334}FIT^2 + \underset{(20371.35)}{72632.58}FIT - \underset{(113251.5)}{377268}$$

All coefficients and constant are statistically significant at 5% significance level. R-squared increased a little bit to the level of 0.9986. There are two points where derivative is zero: 15.1436 and 16.082. Inside the interval of these two values marginal returns are negative. Therefore it is inefficient to set FITs inside this interval. In addition, FITs set below 14.5612 result in negative installed capacities. Accordingly, FITs should be set inside the intervals (14.5612;15.1436] and $(16.5519; +\infty)$. We excluded interval (16.082;16.5519) because FITs set inside [14.6736;15.1436] interval result in same installed capacities but with lower FITs.

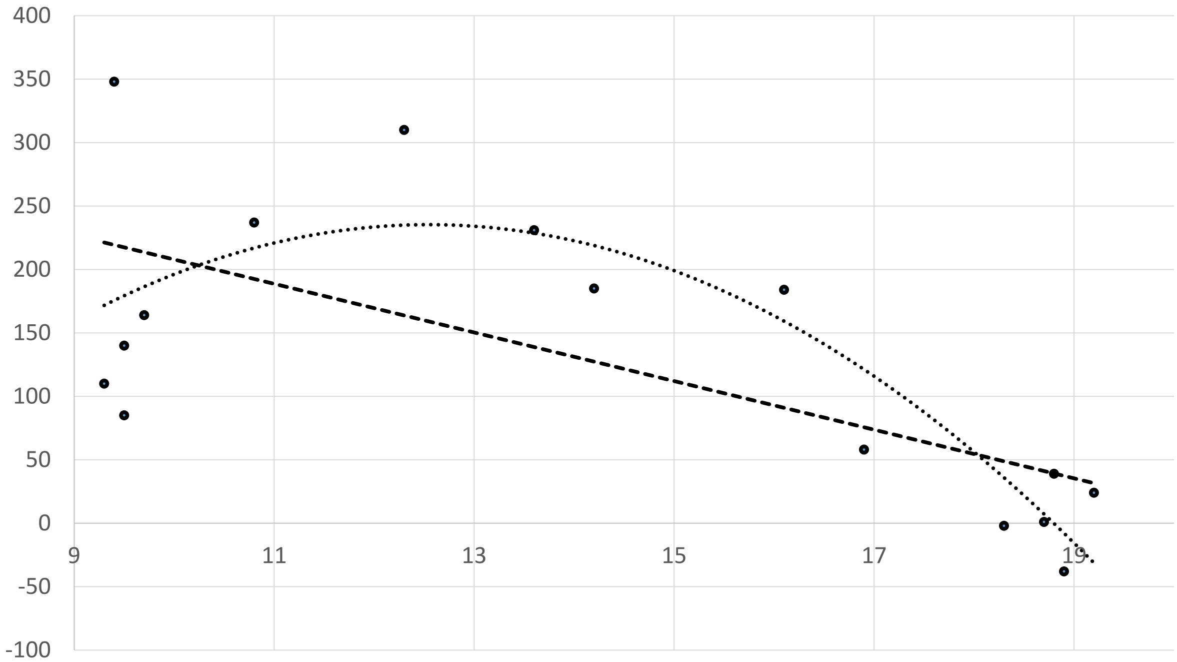
First offshore wind farms in Germany were installed in 2009, with 30 MW. Ever since, the average annual growth rate of installed capacity is 126%. Offshore wind projects are very expensive, since they have excessive initial investment costs. And the project makes sense only if it is of bigger scale, that is why we see such big growth rates of installed capacities. This type of RES showed incredible growth, with only 30 MW installed in 2009, 3283 MW were installed in 2015 alone. Growth of more than 10 000 % in 6 years.

Figure 9 is a scatter plot for biomass RES. Y-axis and X-axis are same as in Figure 5. Equation of the dotted line is

$$\widehat{MW} = \underset{(82.6653)}{399.44} - \underset{(5.66)}{19.16}FIT_t$$

That is, one cent of FIT corresponds to decrease of 19.16 MW of installed capacity. For instance, if in year t+1 FIT will be increased by one cent, then installed capacity will be decreased by 19.16 MW in comparison to year t. Constant and independent variables are statistically significant at 5% significance level. R-squared of this equation is 0.4501, i.e. independent variable explains 45.01% of variability of dependent variable. Likewise, when we add a polynomial of second order R-squared increases to the level of

Figure 9: German biomass



BMWi and own computations

0.6808. Coefficients remain statistically significant at 5% significance level, but p-value of constant is 0.075, thus constant is statistically significant only at 10% significance level. The equation of the model – dotted line – is:

$$\widehat{MW} = \underset{(1.966)}{-6.027}FIT^2 + \underset{(55.77982)}{151.2494}FIT - \underset{(368.9966)}{713.6272}$$

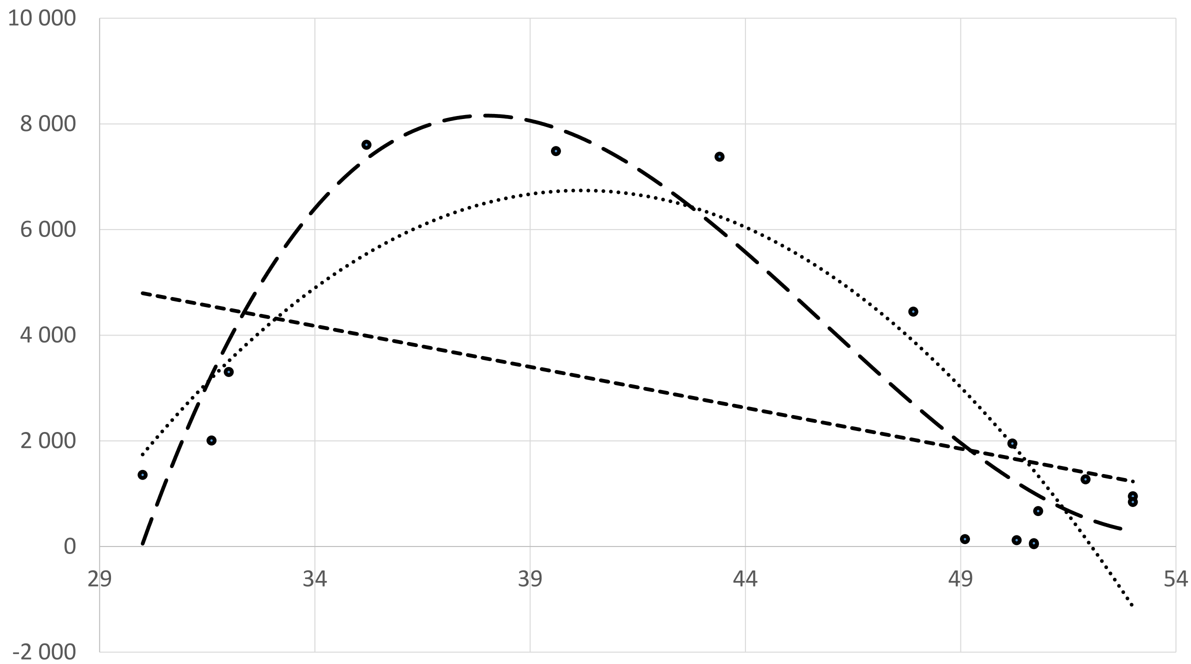
The maximum of the parabola is the optimum FIT, i.e. maximum annual installed capacity is achieved under this FIT. The maximum is at 12.5476, consequently FITs higher than 12.5476 are inefficient, since they will result in lower installed capacities at higher costs. In addition, FITs set below 6.29957 will result in negative installed capacities. Therefore, FITs should be set inside (6.29957;12.5476] interval. Average growth rate of FIT between 2001 and 2015 is 5% and average annual growth rate of installed capacity is 16%. Nevertheless, in recent years the growth slowed down to average of 0.62%[20]. The boom of installations of this type of RES was between 2001 and 2006

[20] Average annual growth rate between 2010 and 2015.

with average annual growth rate of 33%.

No regression was run for the Czech Republic due to lack of data.

Figure 10: German solar energy



BMWi and own computations

Figure 10 is a scatter plot for solar RES in Germany. Y-axis and X-axis are same as in Figure 5. Equation of the line is

$$\widehat{MW} = \underset{(3542.484)}{9441.76} - \underset{(77.53)}{154.9}FIT_t$$

Constant is statistically significant at 5% significance level and independent variable is statistically significant only at 10% significance level as well as whole regression is significant only at 10% significance level. R-squared of this equation is 0.2219, i.e. independent variable explains 22.19% of variability of dependent variable. With one cent increase in FIT, installed capacity will decrease by 154.9 MW. But, Ramsey RESET test concludes that we have omitted variables. Thence, we add a polynomial of second order. All coefficients and constant become statistically significant even at 1% significance level and regression is overall significant even at 1% significance level. R-squared increases to the level of 0.7148. The equation of the model – dotted line – is:

$$\widehat{MW} = -\underset{(10.138)}{48.062}FIT^2 + \underset{(849.1176)}{3863.828}FIT - \underset{(17096.32)}{70916.21}$$

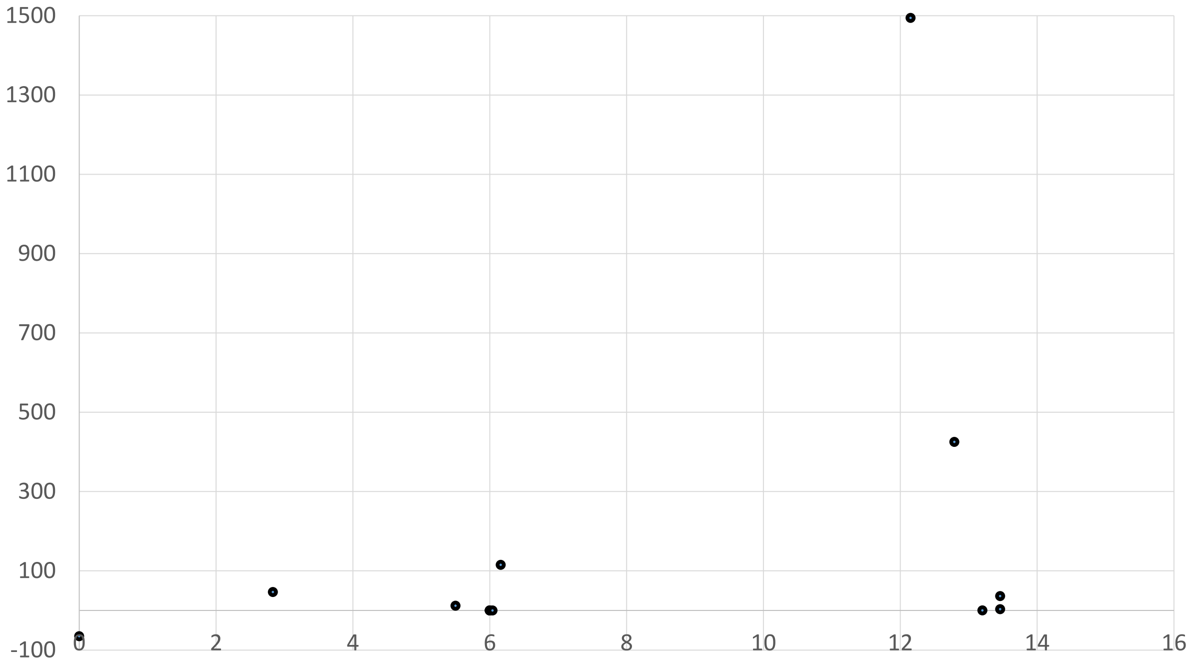
The optimum FIT for this model is where parabola has its maximum. The maximum is at 40.1963, consequently, FITs higher than 40.1963 are inefficient. Furthermore, FITs set below 28.3546 result in negative installed capacities. Therefore, FITs should be set inside (28.3546;40.1963] interval. Yet, Ramsey RESET test still concludes that we have omitted variables. Thus, we add polynomial of third order and Ramsey RESET test does not conclude that we have omitted variables. It slightly changes our intervals. Likewise, R-squared increases to the level of 0.8531, all coefficients and constant remain statistically significant at 1% significance level. The equation of the model – wide dashed line – is:

$$\widehat{MW} = \underset{(1.19885)}{4.0298}FIT^3 - \underset{(150.8367)}{554.4399}FIT^2 + \underset{(6223.685)}{24675.01}FIT - \underset{(84994.61)}{350005}$$

There are two points where derivative is zero: 37.9719 and 53.7514. Inside the interval of these values marginal returns are negative, thus, it is inefficient to set FIT between 37.9719 and 53.7514. In addition, FITs set below 29.9764 will result in negative installed capacities. Therefore, FITs should be set inside the following intervals: (29.9764;37.9719] and $(61.6409; +\infty)$. We excluded interval (53.7514; 61.6409), since values inside [30.0824;37.9719] result in the same installed capacities but at lower FITs. This is the only type of RES for which average FIT has been steadily decreasing since 2006, average decrease rate of 5% between years 2006 and 2015. Nonetheless, average annual installed capacity growth rate for the same period is 16%, with boom in 2009 with 128% annual growth rate. Moreover, now there are 3 consecutive years of negative annual growth rates of installed capacity.

Figure 11 is a scatter plot for Czech solar energy. Y-axis and X-axis are same as in Figure 7. As it has already been written, in 2010 Czech government introduced a retroactive legislation. Therefore, data after 2010 is very biased. Moreover, in 2010

Figure 11: Czech solar energy



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there was an unexpected boom of photovoltaic installations, which led to stoppage of connections into the grid for new PV installations. That is why, I added a dummy variable "D", which was equal 1 only for 2010 year and 0 for all others years. Only after adding polynomial of fourth order regression was moreless successful. Ramsey RESET test still concluded that there is an omitted variable, though at 4% significance level did not. Breusch-Pagan test for heteroskedasticity did not detect any heteroskedasticity. Regression equation is:

$$\widehat{MW} = \underset{(0.1704983)}{-0.698}\,FIT^4 + \underset{(4.298)}{16.12}FIT^3 - \underset{(35.039)}{107.27}FIT^2 + \underset{(101.4919)}{228.829}FIT + \underset{(137.984)}{913.9}\,D - \underset{(74.32)}{64.49}$$

Constant here is statistically insignificant. Function for FITs has three values where derivatives are zero: 1.57; 4.72; 11.026. Inside (1.57;4.72) interval marginal returns are negative, i.e. it is inefficient to set FITs inside this interval. Inside [4.72;11.026) marginal returns are positive. However, FITs should be set inside the following intervals: (0;1.57] and (6.64;11.026]. We excluded [4.72;6.64] interval because FITs set inside [0.1858;1.57] result in same installed capacities.

Table 1: Summary of optimal FITs

Type of RES	Interval for optimum FITs
German onshore wind	(8.52; 9.65]
German offshore wind	(14.56; 15.14] and (16.55; $+\infty$)
German biomass	(6.29; 12.55]
German solar	(29.98; 37.97] and (61.64; $+\infty$)
Czech solar	(0; 1.57] and (6.64; 11.03]*

Note: for Czech solar intervals include shortages explained before.

Table 1 summarizes all found optimum intervals for feed-in tariffs. We did not find optimum intervals for FITs in cases of: hydro RES of both countries, landfill,sewage and mine gas RES of both countries, Czech wind RES and Czech biomass. Moreover, optimum interval of FITs for Czech solar includes some shortages explained before. Therefore, we have optimum intervals for FITs in 5 cases. Thereby, we believe that if feed-in tariff scheme to be continued and governments want to maximize their installed capacities of RES, they should set feed-in tariffs inside these intervals. For Germany, FITs are measured in euros and for the Czech Republic FITs are measured in Czech korunas.

4 Conclusion

The main purpose of this paper was to determine what are the growth opportunities of renewable energy and how renewable energy is financed in the Czech Republic and Germany. After reviewing German and Czech renewables policies we conclude that support for renewable energy is mainly covered by end-customers. End-customers of both countries have additional costs related to support of RES included in their bills. Additional costs related to RES include: feed-in tariffs and other financial types of support, grid development costs and grid balancing costs. All these costs are firstly borne by TSOs and DSOs but then they are passed onto end-customers. However, not all additional costs are borne by end-customers, in the Czech Republic, there is a subsidy, which covers the costs of market operators associated with FITs. In addition, RES producers have some tax benefits. This support resulted in significant increase of installed capacities in all types of RES excluding hydro, since it has already been very developed. However, since feed-in tariff scheme is regarded as a very costly method and moreover, European Commission has approved the removal of all feed-in tariff schemes from 2017, Germany has already started to shift towards auction scheme.

Various shortcomings related to renewables are discussed and some ways of how to resolve these shortcomings are provided. We estimated relation between GHG abatement and share of RES. We also analyse the dependence between annual installed capacities of RES and respective feed-in tariffs. We took the empirical data of annual installed capacities and regressed it on respective FITs and/or their polynomials. The analysis resulted in optimum intervals for some types of RES, they are summarised in our paper. We could not collect most of the data for the Czech Republic, since the Energy Regulatory Office of the Czech Republic does not publish the time series for RES, unlike Germany, which publishes a comprehensive database regarding RES.

Optimum intervals in our paper indicate at which values of FIT the biggest amount of installed capacities is anticipated. Thus, if FIT schemes are to be continued after 2017, FITs should be set inside these intervals. These intervals assume that there are not any caps and restrictions. Nonetheless, there were regressions with statistially insignificant results, for instance, hydro RES in Germany and the Czech Republic. In this case, we conclude that size of FITs do not really plays a big role in decision making of investors, i.e. investors are more concerned about other factors rather than about FITs. Likewise, regressions resulted in insignificant results in case of Czech wind RES.

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Appendix A – Regression Outputs

Table 2: Stata output for German GHG abatement by RES-E

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(1, 14)	18.21
Model	3.54E+08	1	3.5E+08	Prob >F	0.0008
Residual	2.72E+08	14	1.9E+07	R-squared	0.5653
				Adj R-squared	0.5343
Total	6.27E+08	15	4.2E+07	Root MSE	4410.9
GHGEDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
RESEshareDE	3609.046	845.7903 4.27	0.001	1795.007	5423.086
_cons	-317.18	1820.415 -0.17	0.864	-4221.58	3587.222

Note: ovtest Prob >F = 0.7104; hettest Prob >chi2 = 0.1165;
swilk Prob >Z = 0.0911

Table 3: Stata output for German GHG abatement by RES-H/C

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(1, 14)	14.65
Model	1.08E+08	1	1.1E+08	Prob >F	0.0018
Residual	1.04E+08	14	7393880	R-squared	0.5113
				Adj R-squared	0.4764
Total	2.12E+08	15	1.4E+07	Root MSE	2719.2
GHGHCDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
RESHCshareDE	3132.254	818.3969 3.83	0.002	1376.967	4887.541
_cons	-290.566	818.1411 -0.36	0.728	-2045.3	1464.172

Note: ovtest Prob >F = 0.1388; hettest Prob >chi2 = 0.5004;
swilk Prob >Z = 0.92334

Table 4: Stata output for German GHG abatement by RES-H/C

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(1, 14)	923.55
Model	13027681	1	1.3E+07	Prob >F	0
Residual	197484.9	14	14106.1	R-squared	0.9851
				Adj R-squared	0.984
Total	13225166	15	881678	Root MSE	118.77
GHGTDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
RESTshareDE	951.2398	31.30108 30.39	0	884.1057	1018.374
_cons	-6.63744	31.26193 -0.21	0.835	-73.6876	60.41274

Note: ovtest Prob >F = 0.3923; hettest Prob >chi2 = 0.9475;
swilk Prob >Z = 0.13027

Table 5: Stata output of German regression for hydro RES

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(1, 14)	0.39
Model	4526.865	1	4526.865	Prob >F	0.5426
Residual	162676.1	14	11619.72	R-squared	0.0271
				Adj R-squared	-0.0424
Total	167202.9	15	11146.86	Root MSE	107.79
MWHydroDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITHydroDE	-18.1088	29.01279 -0.62	0.543	-80.33507	44.11741
_cons	211.4045	236.0032 0.90	0.386	-294.7721	717.5811

Note: no tests were done, since regression is insignificant.

Table 6: Stata output of Czech regression for hydro RES

Source	**SS**	**df**	**MS**	**Number of obs**	**8**
				F(1, 6)	0.33
Model	41.81111	1	41.81111	Prob >F	0.5845
Residual	751.9777	6	125.3296	R-squared	0.0527
				Adj R-squared	-0.1052
Total	793.7888	7	113.3984	Root MSE	11.195
MWhydroCZ	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FIThydroCZ	7.676342	13.29032 0.58	0.585	-24.84389	40.19658
_cons	-15.9082	38.97599 -0.41	0.697	-111.279	79.46259

Note: no tests were done, since regression is insignificant.

Table 7: Stata output of German regression for landfill, sewage and mine gas RES

Source	SS	df	MS	Number of obs	12
				F(1, 10)	3.9
Model	85677.72	1	85677.72	Prob >F	0.0765
Residual	219624	10	21962.4	R-squared	0.2806
				Adj R-squared	0.2087
Total	305301.7	11	27754.7	Root MSE	148.2
MWlandfillDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITlandfil~E	643.8705	325.9901 1.98	0.076	-82.48075	1370.222
_cons	-4239.11	2325.79 -1.82	0.098	-9421.292	943.0728

Note: ovtest Prob >F = 0.6085; hettest Prob >chi2 = 0.8844; swilk Prob >Z = 0.18622

Table 8: Stata output of German regression for geothermal RES

Source	SS	df	MS	Number of obs	12
				F(1, 10)	1.01
Model	15.53274	1	15.53274	Prob >F	0.3396
Residual	154.4673	10	15.44673	R-squared	0.0914
				Adj R-squared	0.0005
Total	170	11	15.45455	Root MSE	3.9302
MWgeoDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITgeoDE	0.282413	.2816304 1.00	0.34	-0.3450982	0.909925
_cons	-3.40822	5.511267 -0.62	0.55	-15.68808	8.871653

Note: no tests were done, since regression is insignificant.

Table 9: Stata output of German regression for onshore wind RES

Source	SS	df	MS	Number of obs	16
				F(1, 14)	6.61
Model	3314183	1	3314183	Prob >F	0.0222
Residual	7015292	14	501092.3	R-squared	0.3208
				Adj R-squared	0.2723
Total	10329475	15	688631.7	Root MSE	707.88
MWonshoreDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITonshoreDE	1090.021	423.8435 2.57	0.022	180.9671	1999.075
_cons	-7703.76	3906.02 -1.97	0.069	-16081.33	673.8246

Note: ovtest Prob >F = 0.0522; hettest Prob >chi2 = 0.0080; swilk Prob >Z = 0.67288

Table 10: Stata output of German regression for onshore wind RES with polynomial of 2nd order

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(2, 13)	8.02
Model	5706569	2	2853284	Prob >F	0.0054
Residual	4622906	13	355608.2	R-squared	0.5525
				Adj R-squared	0.4836
Total	10329475	15	688631.7	Root MSE	596.33
MWonshoreDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITonshoreDE	49620.89	18714.03 2.65	0.02	9191.685	90050.1
FITonshore~q	-2570.46	991.0165 -2.59	0.022	-4711.42	-429.498
_cons	-236184	88149.72 -2.68	0.019	-426620	-45747.7

Note: ovtest Prob >F = 0.2548; hettest Prob >chi2 = 0.0984; swilk Prob >Z = 0.80035

Table 11: Stata output of German regression for offshore wind RES

Source	**SS**	**df**	**MS**	**Number of obs**	**7**
				F(1, 5)	7.56
Model	2325630	1	2325630	Prob >F	0.0403
Residual	1538064	5	307612.9	R-squared	0.6019
				Adj R-squared	0.5223
Total	3863694	6	643949	Root MSE	554.63
MWoffshoreDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FIToffshor~E	438.4589	159.4633 2.75	0.04	28.54531	848.3724
_cons	-6702.93	2616.775 -2.56	0.051	-13429.57	23.69948

Note: ovtest Prob >F = 0.0027; hettest Prob >chi2 = 0.0994; swilk Prob >Z = 0.29774

Table 12: Stata output of German regression for offshore wind RES with polynomial of 2nd order

Source	**SS**	**df**	**MS**	**Number of obs**	**7**
				F(2, 4)	219.9
Model	3828870	2	1914435	Prob >F	0.0001
Residual	34823.56	4	8705.889	R-squared	0.991
				Adj R-squared	0.9865
Total	3863694	6	643949	Root MSE	93.305
MWoffshoreDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FIToffshor~E	-11207.8	886.7051 -12.64	0	-13669.7	-8745.96
FIToffshor~q	353.0522	26.86775 13.14	0	278.4554	427.649
_cons	88725.89	7275.592 12.20	0	68525.61	108926.2

Note: ovtest Prob >F = 0.1291; hettest Prob >chi2 = 0.5067; swilk Prob >Z = 0.37329

Table 13: Stata output of German regression for offshore wind RES with polynomial of 3rd order

Source	**SS**	**df**	**MS**	**Number of obs**	**7**
				F(3, 3)	736.62
Model	3858456	3	1286152	Prob >F	0.0001
Residual	5238.035	3	1746.012	R-squared	0.9986
				Adj R-squared	0.9973
Total	3863694	6	643949	Root MSE	41.785
MWoffshoreDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FIToffshor~E	72632.58	20371.35 3.57	0.038	7801.834	137463.3
FIToffshor~q	-4656.33	1216.998 -3.83	0.031	-8529.36	-783.305
FIToffshor~u	99.41284	24.15052 4.12	0.026	22.55512	176.2706
_cons	-377268	113251.5 -3.33	0.045	-737685	-16851.2

Note: ovtest Prob >F = 0.5667; hettest Prob >chi2 = 0.5080;
swilk Prob >Z = 0.65274

Table 14: Stata output of German regression for biomass RES

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(1, 14)	11.46
Model	89203.11	1	89203.11	Prob >F	0.0044
Residual	108981.9	14	7784.421	R-squared	0.4501
				Adj R-squared	0.4108
Total	198185	15	13212.33	Root MSE	88.229
MWbiomassDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITbiomassDE	-19.1608	5.660266 -3.39	0.004	-31.30086	-7.02074
_cons	399.4383	82.66532 4.83	0	222.1388	576.7378

Note: ovtest Prob >F = 0.0544; hettest Prob >chi2 = 0.1122;
swilk Prob >Z = 0.61289

Table 15: Stata output of German regression for biomass RES with polynomial of 2nd order

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(2, 13)	13.86
Model	134919.1	2	67459.55	Prob >F	0.0006
Residual	63265.91	13	4866.608	R-squared	0.6808
				Adj R-squared	0.6317
Total	198185	15	13212.33	Root MSE	69.761
MWbiomassDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITbiomassDE	151.2494	55.77982 2.71	0.018	30.74439	271.7543
FITbiomass~q	-6.02677	1.966364 -3.06	0.009	-10.2748	-1.7787
_cons	-713.627	368.9966 -1.93	0.075	-1510.8	83.54147

Note: ovtest Prob >F = 0.6864; hettest Prob >chi2 = 0.3743;
swilk Prob >Z = 0.19820

Table 16: Stata output of German regression for solar RES

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(1, 14)	3.99
Model	25337064	1	25337064	Prob >F	0.0655
Residual	88859997	14	6347143	R-squared	0.2219
				Adj R-squared	0.1663
Total	1.14E+08	15	7613137	Root MSE	2519.4
MWpvDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITPVDE	-154.907	77.53224 -2.00	0.066	-321.1972	11.38301
_cons	9441.761	3542.484 2.67	0.018	1843.888	17039.63

Note: ovtest Prob >F = 0.0000; hettest Prob >chi2 = 0.0711;
swilk Prob >Z = 0.05059

Table 17: Stata output of German regression for solar RES with polynomial of 2nd order

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(2, 13)	16.29
Model	81632652	2	40816326	Prob >F	0.0003
Residual	32564409	13	2504955	R-squared	0.7148
				Adj R-squared	0.671
Total	1.14E+08	15	7613137	Root MSE	1582.7
MWpvDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITPVDE	3863.828	849.1176 4.55	0.001	2029.421	5698.235
FITpvDEsq	-48.0617	10.13821 -4.74	0	-69.9639	-26.1594
_cons	-70916.2	17096.32 -4.15	0.001	-107851	-33981.9

Note: ovtest Prob >F = 0.0005; hettest Prob >chi2 = 0.5904;
swilk Prob >Z = 0.61751

Table 18: Stata output of German regression for solar RES with polynomial of 3rd order

Source	**SS**	**df**	**MS**	**Number of obs**	**16**
				F(3, 12)	23.23
Model	97424828	3	32474943	Prob >F	0
Residual	16772233	12	1397686	R-squared	0.8531
				Adj R-squared	0.8164
Total	1.14E+08	15	7613137	Root MSE	1182.2
MWpvDE	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITPVDE	24675.01	6223.685 3.96	0.002	11114.76	38235.25
FITpvDEsq	-554.44	150.8367 -3.68	0.003	-883.085	-225.795
FITpvDEcu	4.029787	1.198853 3.36	0.006	1.417711	6.641863
_cons	-350005	84004.61 -4.17	0.001	-533035	-166974

Note: ovtest Prob >F = 0.0611; hettest Prob >chi2 = 0.8394;
swilk Prob >Z = 0.56411

Table 19: Stata output of Czech regression for solar RES with polynomial of 4th order

Source	**SS**	**df**	**MS**	**Number of obs**	**13**
				F(5, 7)	74.82
Model	2067825	5	413565.1	Prob >F	0
Residual	38692.84	7	5527.548	R-squared	0.9816
				Adj R-squared	0.9685
Total	2106518	12	175543.2	Root MSE	74.347
MWpvCZ	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
FITpvCZqu	-0.69811	.1704983 -4.09	0.005	-1.101274	-0.29495
FITpvCZcu	16.12037	4.297576 3.75	0.007	5.958221	26.28252
FITpvCZsq	-107.27	35.03922 -3.06	0.018	-190.1249	-24.4157
FITpvCZ	228.8294	101.4919 2.25	0.059	-11.16089	468.8196
CZdummy	913.9999	137.9842 6.62	0	587.7191	1240.281
_cons	-64.4934	74.32014 -0.87	0.414	-240.2327	111.2458

Note: ovtest Prob >F = 0.0412; hettest Prob >chi2 = 0.8321; swilk Prob >Z = 0.06579