Are the recent changes in renewable energy support schemes harming adoption?

A study of solar PV in Germany

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Abstract

As governments understand it more and more just how devastating the effects of climate change and global warming can be, there is an increase in initiatives to reduce CO_2 emissions in all areas of our lives. One if these areas – and one of the main culprits behind green-house gasses – is the energy sector, which still mainly relies on conventional energy sources. However, with the recent technological developments, renewable energy sources are becoming more and more competitive, which means that more and more countries include renewable energy support in their policy mix. Solar photovoltaics is one of these energy sources, that had been responsible for a very significant part of the recent growth in renewable energy share. Solar PV is often supported by policy mechanism, feed-in tariff being one of the most often employed one. But lately more countries have decided to significantly decrease feed-in tariffs for solar PV – such as Germany – or completely dismantle the system – such as the United Kingdom. In this paper I will investigate the effects of feed-in tariff contribution changes in order to see whether these policy changes are taking countries on the right path, towards a renewable-rich future. I will discuss relevant policies world-wide and in Germany, and analyse time-series data from Germany in order to reach my conclusion, which is that while decreasing feed-in tariff do affect solar PV adoption, the slowdown could be necessary to avoid any long-lasting damage to consumers or utilities. Finally, I will advise that any government considering an update to their renewable policy should follow Germany's example and create a long-term strategic plan to follow.

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Introduction

Even if some parts – or, rather, political leaders – of the world are in denial about climate change, science has proven that it – and consequently global warming – is the reason behind most of the extreme weather events that have happened recently, and that if we do not change our behaviour, things are only going to get worse.

The main reason behind climate change is the increased CO_2 emissions in the atmosphere, and one of the main sources of CO_2 emissions are the burning of fossil fuels such as oil, coal and gas (Le Quéré et al., 2013), which are still the main sources of energy in the global energy mix (Afonso et al., 2017). With the world's energy demand growing fast due to population expansion and technological advancements (Kannan & Vakeesan, 2016), this energy mix has devastating consequences for the environment. Global energy-related carbon dioxide emissions rose by 1.6% in 2017 and while there is no clear consensus yet, but it is expected that the 2018 data will show continued growth as well; far from the trajectory of climate goals (IEA, 2018). Energy-related air pollution continues to result in millions of premature deaths each year (IEA, 2018). Clearly this is a problem we cannot ignore further, but the solution is far from a quick and easy fix.

Electricity demand is relatively inelastic; therefore, production levels must be maintained. However, there are alternatives to conventional electricity generation methods that have been gaining traction in the recent years. Renewable energy is considered as one of the key elements with which we can address climate change and its consequence, global warming. Policies concerning it are included in the energy policies of major countries (Sisodia et al., 2015; Rosenow et al., 2017; Del Rio, 2007).

Germany is one of the earliest adopters with its first renewable electricity law dating back to 1991 (Paraschiv et al., 2014); and they have not abandoned the cause since then either.

Germany's main energy policy when it comes to renewable targets is the Renewable Energy Sources Act (EEG). It is the main tool in the country's aim of reaching at least 80% electricity generation via renewable energy sources by 2050 (Rogge & Johnstone, 2017). The EEG was introduced in 2000, and it has established a feed-in tariff guaranteed over a period of 20 years (Rogge & Johnstone, 2017). Over the years the EEG has been regularly amended, leading to many changes such as the lowering of feed-in tariffs based on technological improvements and deployments success for it to become more cost-effective (Rogge & Johnstone, 2017). The changes in EEG has not been always welcome, and the German government has been accused of slowing the *Energiewende* – roughly translated as energy transition – and standing against the initial values and targets they set out in the beginning of the process (Amelang et. al., 2016).

But is the lowering of the feed-in tariffs truly harmful for adoption, or is it a necessary step that must be taken to protect consumers, encourage competition and facilitate developments that would help the transition? In the following paper, I am going to analyse the effects of feed-in tariff changes on renewable energy adoption to answer this question by looking at time series data on average feed-in tariff prices and net energy production by solar energy generators in Germany between 2010 - 2018. My focus will be on solar photovoltaics – solar PV – as that is the renewable energy source that has been the main driver of the previously unprecedented growth the renewable energy market has experienced (IEA, 2017). I will also present an overview of renewable and solar PV trends, policies and blockers to ensure that we are not examining solar PV in isolation. By the end of the essay I aim to prove that while feed-in tariff changes affect solar adoption, there are situations where this slowdown is essential to prevent long-term issues.

The remainder of the paper is organized as follows. In **Section 2**, I present a summary of the theoretical concepts regarding renewables, the main policies, and I review the advantages and disadvantages of investing in renewable energy generation. I also provide a summary of

German policies and trends in renewables with an emphasis on solar photovoltaics. In **Section 3**, I describe the data in solar PV adoption and solar PV feed-in tariff that I am using for my analysis and discuss the econometric issues and potential limitations arising from the use of time-series data. In **Section 4**, I report my regression results and discuss future research options or policy recommendations that might arise from them.

2. Renewable Energy: A Review

As the introduction alluded to it, the electricity sector is experiencing its most dramatic transformation since its creation. Electricity is becoming more and more popular as a "fuel" choice in countries, with its share of global consumption approaching 20% and expected to rise further (IEA, 2018) due to population growth and technological advancements (Kannan & Vakeesan, 2016). Electricity's generation mix and corresponding infrastructure is also undergoing an update with the growth of renewable share. In 2016, more than 25% of the total production of primary energy within the EU came from renewable sources. The increase in primary production using renewable sources was also more than the share of total primary energy production from other sources (Eurostat, 2017).

Based on current trends, during the time period leading up to 2022, wind and solar is expected to represent more than 20% of global renewable growth (IEA, 2017). By 2022, global renewable electricity generation is expected to grow to over 8,000 TWh; close to the total consumption of China, India and Germany combined (IEA, 2017). The share of renewables in electricity generation is expected to reach 30% in 2022 (IEA, 2017). While coal is still expected to remain the largest source of electricity generation in 2022, renewables will have halved the gap between them, from 34% to 17% (IEA, 2017). And not a moment too soon; if we are to reach our long-term climate targets, the European electricity sector must be completely free from carbon by mid-century (Patt, 2015; EC, 2011).

To facilitate this transition, the European Parliament called for the use of energy from renewable sources. It has suggested to the Commission in June 2016 to increase the EU's target on energy consumption from renewable energy sources up to 30% so that it can be reached through individual targets of the member states (Soava et al., 2018). Most member states have some sort of renewable energy policy active, and it's not without a good reason: it has been a long-established fact that even cost-effective energy efficiency measures are often not taken up by businesses or consumers. Renewable energy has a particularly difficult time competing with conventional electricity, even though it has many economic, environmental and societal benefits as well as development and employment opportunities (Del Rio, 2007). Therefore, policy is required to support their adoption (Sorell, 2015).

There are a wide range of renewable support schemes that can be considered, but renewable promotion has been based on three main mechanisms: feed-in tariffs, tradable green certificates and bidding/tendering systems (Del Rio, 2007). These are often supplemented with other subsidies such as fiscal and financial incentives, investment subsidies or green pricing (Del Rio, 2007). In numerous countries, renewable policies are moving from feed-in tariffs to bidding/tendering systems to encourage competition (IEA, 2017), making them more cost-effective. In this paper I will be analysing the effects of changes in feed-in tariffs on solar PV adoption.

But what is a feed-in tariff? A feed-in tariff is a subsidy on output, usually measured per kWh generated, paid by the utilities. The utilities are obliged to purchase this output and the tariff comes with a guaranteed premium price, usually for a specific number of years. World-wide, feed-in tariffs have aided the deployment of 64% of all wind and 87% of all solar PV capacity since 2010 (Jacobs, 2014). The cost of feed-in tariff is usually borne by consumers (Del Rio, 2007; Farell & Lyons, 2015), usually in the form of a surcharge that is applied to their electricity bill. With the basics of renewable policies explained, I will continue by discussing the benefits and drawbacks of renewable energy.

2.1 The benefits and drawbacks of renewable energy

On top of fighting climate change, supporters of renewable energy also see it as a tool to encourage the decrease of dependency of traditional energy sources (Würzburg et al., 2013; Del Rio, 2007; Gasparatos et. al, 2017), which is important as conventional energy sources are a decreasing commodity. The fact that unlike conventional energy sources, renewable energy is not limited to particular geographical areas means that by investing in renewables, countries can make themselves more resilient to politics of conventional energy production or transmission (Kannan & Vakeesan, 2016; Kabir et al., 2018; Gasparato et al., 2017).

Renewables also avoid distribution costs if the electricity is generated at the place of consumption (Klein & Noblet, 2017) or as close to it as possible (Pitt & Michaud, 2015). This is possible if we consider the model when the producer is also the consumer and the excess electricity is driven towards other nearby consumers. Given that renewables have a flexibility when it comes to installation size – an advantage conventional energy sources don't have – it is possible to install producers that can supply their surrounding region, and if this installation is done alongside local energy storage or locally concentrated grids, this model is viable (Lilliestam & Hanger, 2016).

Investment in renewable energy can also become an economic development driver, creating construction jobs and manufacturing opportunities (Pitt & Michaud, 2015), especially if we consider not only the small installations but the large, sometimes GW-sized farms (Lilliestam & Hanger, 2016). This could potentially – dependent on opportunity size – counteract the popular reason government use for continuing to promote reliance on fossil fuel systems. They often state that the transition towards more environmentally friendly options would come with massive job losses and negative economic impacts (Delina & Janetos, 2018).

Renewable energy projects are generally considered to be cost-effective compared to conventional energy systems in many areas of production (Noel, 2017). They have shown to have the significantly fewer number of cost escalations when compared to conventional energy projects with solar PV having the largest number of total underruns; which is an unlikely happening in traditional energy projects (Sovacool et al., 2014). And even though the current technologies are far from perfect, they still represent a great increase in efficiency as well as a decrease in costs (Kabir et al., 2018).

Since 2010, costs of new solar PV have come down by an average of 70%, while battery costs have decreased by an average 40% (IEA, 2018). Based on the data available for us, it is not unlikely to expect solar PV to become even more affordable in the long run. And once they have been implemented, they are very low-cost from an operations point of view as they have very low or even zero marginal costs (Paraschiv et al., 2014; Kabir et al., 2018), which is another point in their favour. However, while these factors are positives in favour of renewables, they are not without drawbacks either.

When it comes to the relationship between renewables and consumer electricity prices, there is no clear consensus. Due to their low or zero marginal costs, researchers tend to expect a decrease in electricity prices when the renewable share of market increases (Paraschiv et al., 2014), however, the results of research is far from unanimous. There are some studies that have found a negative relationship (Azofra et al., 2014), while others have found that the increase of renewable present has led to increased electricity prices (Dinica, 2011). The introduction of renewable energy sources can lead to reduced power prices – e.g. spot prices – as less conventional energy is produced (Del Rio, 2007), however, it is not certain that this will result in an overall consumer electricity price decrease, due to the added costs specified in the promotion policy (Jensen & Skytte, 2002). If there is an increase in customer prices, it is often associated with increased distribution and supply costs (Sisodia et al., 2015), which are increasing due to the unconcentrated nature of solar PV producers – which means that if the renewable electricity is not consumed locally, more grid needs to be upgraded – and the added burden of having to pay for the feed-in tariff, often in the form of a surcharge that is distributed amongst the entire consumer-base, respectively.

In addition to the increase in costs, solar PV performance is only semi-predictable from a grid operator's point of view, as they might have a difficulty keeping up with the increase in small-scale solar PV producers, which could result in voltage fluctuations or outages (Klein & Noblet, 2017). Additionally, the loss in revenue utilities suffer due to more people using renewable energy sources could mean that the utilities might not have enough revenue for the upkeep of the grid (Klein & Noblet, 2017; Pitt & Michaud, 2015). Utilities are concerned that the growing number of customer-owned, distributed solar energy systems will create costs that they will have to pass onto their ratepayers (Pitt & Michaud, 2015). They argue that it is unfair that customers who own solar PV only pay for the times their PV panels do not generate electricity, as the retail electric rate is meant to cover fixed costs like wires, poles, substations and centralised electricity generation as well (Pitt & Michaud, 2015). According to this argument, solar PV customers are effectively subsidised by the rest, as prices will have to go up for them in order to cover the fixed costs. And price increases would hit those the hardest who are not users of the technology, which are often the groups that are the most vulnerable to electricity price increases.

After all, even though the price of renewable installations has been on the decrease, renewable energy comes with very high installation costs (Kabir et al., 2018) that not everyone can afford. Domestic solar PV panels are a good example of this. Even with recent developments, renewable technology such as domestic solar panels, batteries and inverters are still in need of significant further development (Kabir et al., 2018). They are also not very efficient when it comes to space requirements, which limits the areas where they can be deployed. And space requirements are not the only issue (Mormann, 2018); there are also a question of availability when it comes to the economic benefits. After all, even though feed-in tariffs are seen to provide incentives for small producers such as households and SMBs (Meyer, 2003) and are hailed as bringers of a wide array of economic policies, if we examine the participants, often they end up being highly educated and in good financial standing (Mormann, 2018).

Overall, some studies have shown that the benefits of energy development are unevenly distributed across different groups (Miller & Richter, 2014). In addition to that, these benefits come with strong costs to others. As renewable energy technologies continue to gain traction in the world, the social impacts of their promotional policies are starting to show. Ratepayers and taxpayers all over the world are fearing being left behind by the clean energy transition, and they question just how fair are today's energy policies are (Mormann, 2018). In the following section, I am going to describe the history of renewable energy policies in Germany and expand upon how the changes in policies affected the support for solar PV.

2.2 Renewable energy in Germany

Germany has been called the world's first major renewable energy economy (Burgermeister, 2009). With its first renewable energy law dating back to 1991, the country was an early mover in steering electricity markets towards an environmentally-friendly direction (Paraschiv et al., 2014). The current government policy is a well-structured, long-term integrated policy to develop an energy system that is based on renewables and energy efficiency called the *Energiewende*, which roughly translates as energy transition. The policy defines various targets, one main points being the phase-out of nuclear power by 2022 (Agora, 2017). The electricity generated by nuclear power is meant to be replaced by electricity generated by renewables, making the phase-out policy a good example of the substitution pathway (Kelsey & Meckling, 2018). The *Energiewende* also sets targets on how much energy consumption should decrease to increase energy efficiency, and defines that by 2025, renewables should have a 40-45% share in gross electricity consumption and a 18% share of final electricity consumption. Its targets for 2050 are even more impressive; it sets a minimum 80% share in gross electricity consumption and a minimum 60% share in final electricity consumption.

One of the main tools used to reach these targets is the feed-in tariff for solar PV, established by the Renewable Energy Sources Act, the EEG. The EEG was introduced in 2000, and the feed-in tariff it established is guaranteed over a period of 20 years (Rogge & Johnstone, 2017). The longevity of the EEG surcharge is seen as a guarantee on returns, as one can use it to plan ahead and take on projects that require larger investment volume (Reichardt & Rogge, 2016). But the steadiness of the surcharge doesn't only affect producers; manufacturers of technology also use it to anticipate how much demand is going to be there for their product (Reichardt & Rogge, 2016). The feed-in tariff surcharge is set to degress from one time period to another to encourage early participation in the scheme. With this method, Germany could begin developing renewables when they were relatively expensive, creating costs that will be borne by German consumers during years to come. However, this early commitment to renewables has contributed to their declining cost worldwide (Paraschiv et al., 2014). Under the directions of the EEG, the Transmission System Operators (TSOs) are obliged to accept the delivery of power from independent producers of wind and PV-based electricity into their own grid and must pay feed-in tariffs (Paraschiv et al., 2014). To cover the losses grid operators would make due to feed-in tariffs, consumers must pay an EEG surcharge (Frondel et al, 2010).

In the first phase of Germany’s implementation of the EEG, a considerable increase in solar PV was observed (Paraschiv et al., 2014), but it was not without costs to German households. The unexpected growth of the first phase made the feed-in-tariffs unbearable, which meant that they had to be reduced. However, at the same time, because of the increased number of implementations, the EEG surcharge had to be increased (Paraschiv et al., 2014). This meant that those who just missed the first phase of solar PV investment could expect tariffs that were further reduced than the originally proposed degression over time, while at the same time, the surcharge added to consumers electricity bills increased further. Over the years the EEG has been regularly amended, leading to several changes such as the further lowering of feed-in tariffs based on technological improvements and deployment successes in order for it to become more cost-effective (Rogge & Johnstone, 2017).

The changes in EEG affected consumer electricity prices, although contrary to what researchers tend to expect, the increase of renewable shares did not bring the prices down (Agora, 2017). While spot-prices have indeed decreased, the increase in taxation and other levies meant that the overall price levels were upward trending (Frondel et al., 2010). They have levelled off in the recent years and have been relatively stable since 2013; even if they are still the second highest in Europe with Denmark taking the first place. The recent stability in price is due to the fact that new renewable plants are now comparable in cost to new conventional power plants (Agora, 2017). Nevertheless, the effects of renewables were not felt the same way across Germany; low-income households were and are more affected by high electricity prices (Grösche & Schröder, 2014), which can take up to 5% of household expenditures, even though German households are more energy efficient and consume less electricity than their European counterparts (Agora, 2017). Meanwhile, energy intensive industries in Germany pay one of the lowest electricity prices in Europe, benefiting from exemptions and falling wholesale electricity prices (Agora, 2017), which is one of the most critiqued part of EEG as a whole.

Over the years, the aims of the EEG were shifted from the promotion of renewable power plants to creating an electricity grid that was capable of handling the volatile electricity renewables generate (Paraschiv et al., 2014), and not without a good reason. Germany's main supply of wind and solar is concentrated in the Northern part of the country, but the majority of the consumption of electricity is concentrated in the south, which makes it difficult for grid operators to balance things out, especially since there are limited efficient storing capacities (Paraschiv et al., 2014). Just how much a delayed grid expansion can hurt a renewable project can be seen in the example of "Riffgat", an off-shore wind park in the German North. While the construction of the park itself was completed, the grid expansion to the shore fell behind, which meant that in order to avoid deterioration of the installations, the controllers of the park had to burn 22,000 litre of Diesel each month (Paraschiv et al., 2014) before it could be finally connected to the grid in 2014. It is clear that ensuring grid efficiency is an essential part of the German energy transition, and while my example is one of a large-scale project, as the literature has demonstrated prior, small-scale solar PV installations require similar considerations as well.

There are two options for grid infrastructure expansion: it can be done either by updating the existing grids by laying parallel lines (Bayer et al., 2018), or by creating new ones (Agora 2018). But in order for either method to be successful, it is important to anticipate this expansion as early on as possible as grid expansions are quite costly and time consuming (Agora 2018). It is also essential that with the upgrades, intelligent operating equipment is installed, e.g. voltage regulators or voltage-regulated distribution transformers (Bayer et al., 2018), for the grid to be able to react to the fluctuations created by renewables. And in this case, predicting the growth of small-scale, decentralised solar PV installations is even harder than tracking the development of large-scale projects, which means that in the case of Germany, the early growth stimulated by the high feed-in tariffs actually gave utilities plenty of things to worry about. And with the current level of growth, it is clear that investments in solar PV and wind power cannot be considered in isolation, only in connection with developing an efficient electricity grid (Paraschiv et al., 2014). But that means having to allocate additional funds for grid development, which was only possible if the feed-in tariffs were further reduced. This means that even though the reduction of feed-in tariffs was not welcomed by renewable energy advocates (Armelang et. al., 2016), it was in fact essential in order for the continuation of stable electricity supply.

Overall, we can see that Germany's relationship with feed-in tariffs is far from straight forward. While the system allowed for a fast uptake of the technology, it came with hefty costs for both utilities and consumers. Nevertheless, the German public remains strongly in support of renewable energy developments. Based on the responses to a survey circulated in 2018 October, over 90% of the respondents think that the expansion of renewable energies is important (Amelang et al., 2019). At the same time, there was no similarly strong majority on the question of how the energy transition costs should be distributed. Nearly half of the respondents were on the opinion that those that use more energy should pay more, but the other half was divided between the opinions of everyone contributing equally or those with higher incomes contributing more (Amelang et al., 201). It is uncertain whether there will be any changes in the distribution of the EEG surcharge in the future, but for now, the German government seems to be satisfied with growth level of renewables, both in wind and solar PV. As of 2016, the cumulative installed capacity of solar PV and wind exceeded 89 GW (onshore wind: 44.8 GW, offshore wind: 4.1 GW, photovoltaics: 40.4 GW), thus comprising approximately 15% of national power consumption. At current growth rates, renewable energy sources will be able to more than compensate for the changes in energy policy, including the nuclear phase-out (Agora, 2017). But in order to be able understand whether we can expect the same growth rates, we need to be able to understand how feed-in tariff prices relate to adoption. In the next segment, I will introduce my datapoints and discuss any trends they display, as well as any data manipulation that had to be done on them in order to ready them for analysis.

3. Data and trends

For my analysis, I used aggregated time-series data for Germany in 2010 to 2018. The aggregation was done by month in order to enrich the otherwise small sample. Given that installed capacity for solar PV is collected on an annual basis, I chose to express solar PV adoption – my dependent variable – by the net electricity generation via solar energy which I collected from Fraunhofer Research Institute, who have compiled them various sources. Solar energy is economically less competitive than wind, meaning that even where solar resources are strong, solar is unlikely to be installed without additional drivers (Kelsey & Meckling, 2018). This means that solar deployment patterns are less about the resource availability and more about the additional drivers present (Kelsey & Meckling, 2018), which suits my purposes perfectly. The changes in renewable energy support – my independent variable – were expressed by the feed-in tariffs that were in force during the period of analysis, which I collected from the the BMWi – The Federal Ministry for Economic Affairs and Energy.

Germany's solar energy is solely solar PV, and once a PV installation is online they are unlikely to be turned off for any other reason than a fault in the system or an update. We have yet to hit the stage in time where old panels have become obsolete enough to need an update – on average they come with 20-year warranties –, so that lowers the likelihood of turn-offs due to updates. Therefore, any increases in net electricity generation by via solar energy can only be due to either seasonal changes – which have been taken into consideration in the analysis – or to an increase in the number of installations.

As a net value, the dependent variable does not count self-generation, only what is produced for public consumption, which I thought fitting given that feed-in tariff is a public levy as well.

Figure 1 displays net electricity generation via solar energy over time while Figure 2 displays the ACF plot. From them we can see that there is an upward trend present as well as a strong multiplicative seasonality.

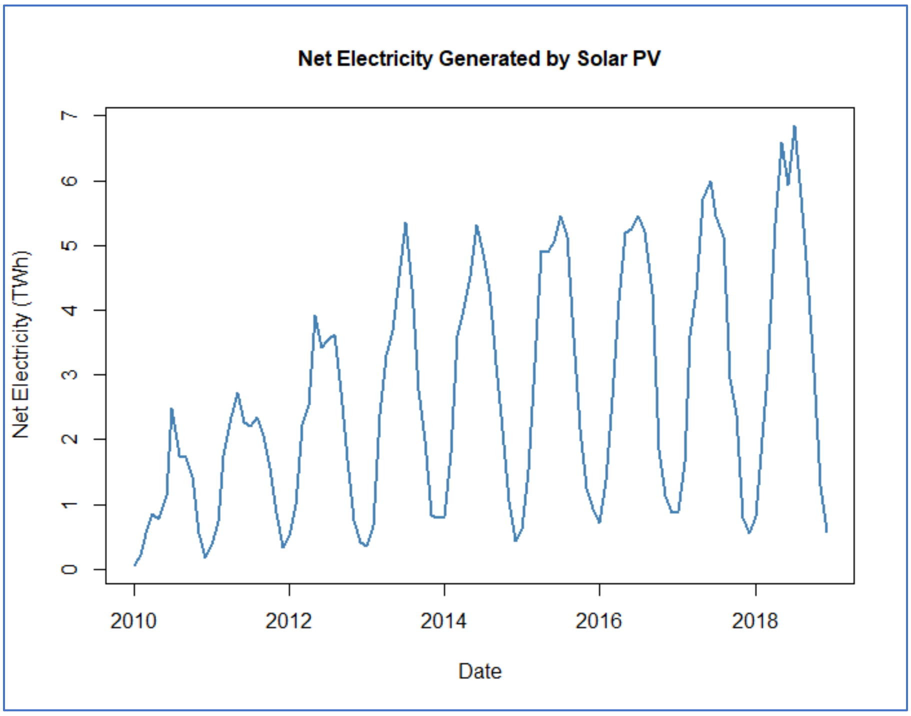

Figure 1 - Net Electricity Generated by Solar PV

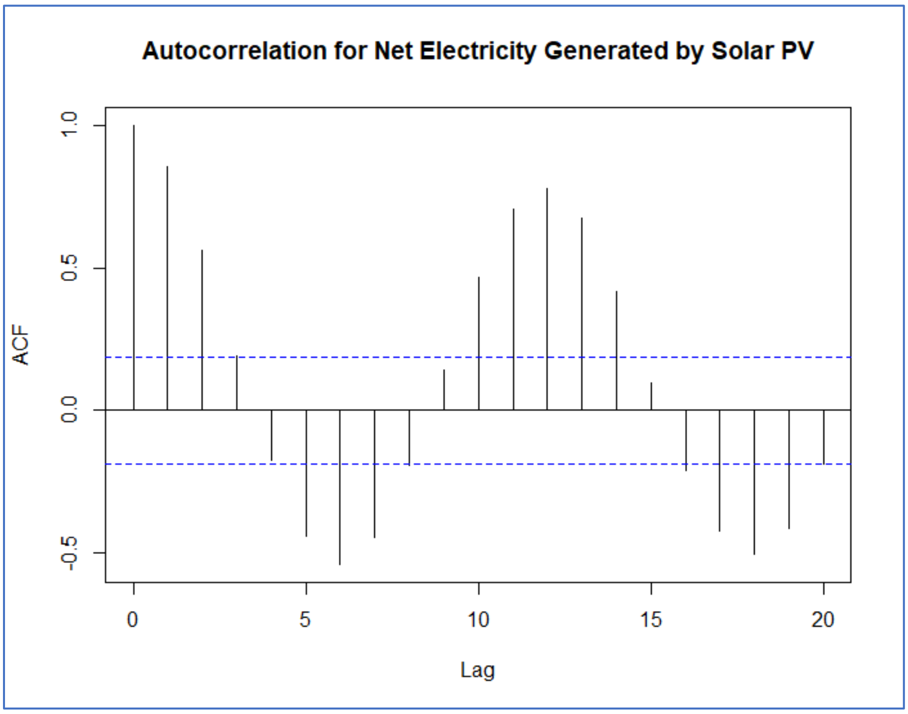

Figure 2 - ACF for Net Electricity Generated by Solar PV

To be able to perform a regression analysis, the dependent variable had to be transformed. First, I performed a seasonal adjustment to mitigate the effects of seasonality. This was done by using the *Ecdat* R package and resulted in the time series object graphed in Figure 3.

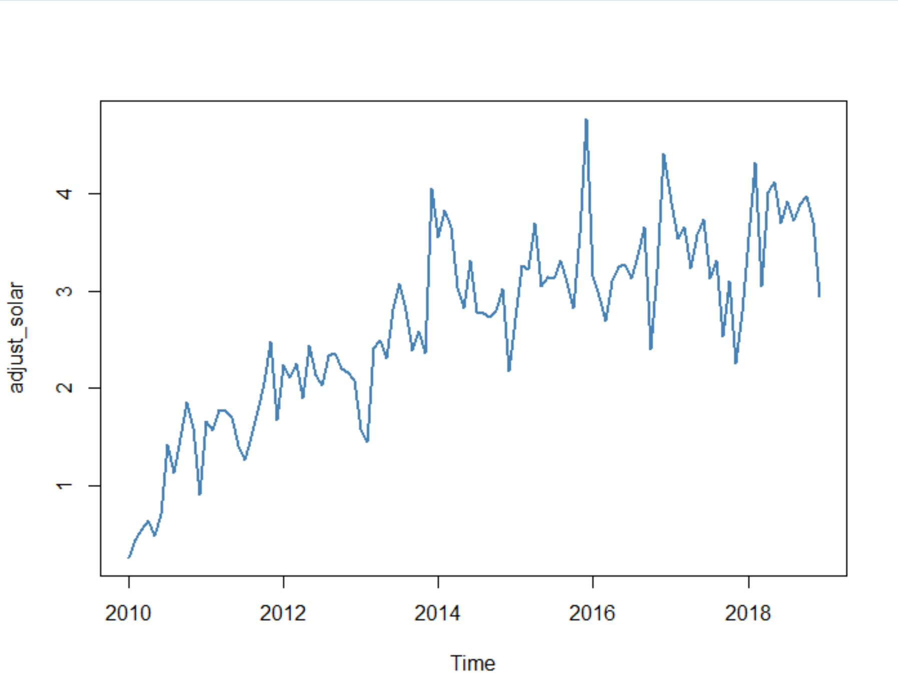

Figure 3 - Seasonally adjusted net electricity generated by solar PV

However, once the seasonality has been dealt with, it became obvious that the dependant variable was displaying an increasing trend. Just to make sure that there was correlation present between the dependent variable and time, I have performed another ACF analysis, graphed in Figure 4. This shows that the trend is indeed present.

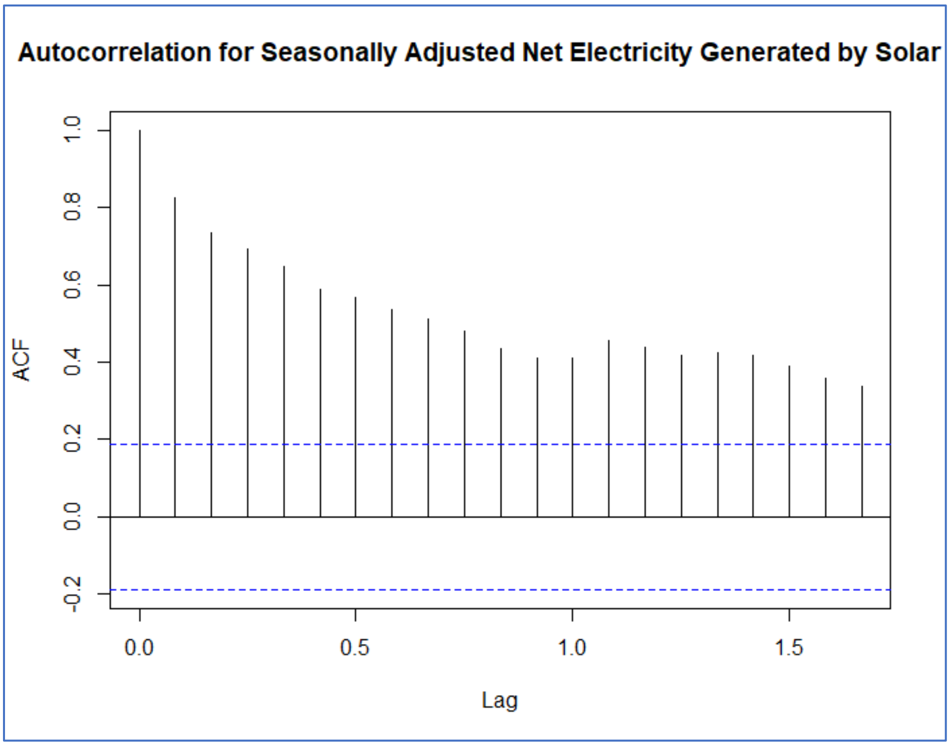

Figure 4 - ACF for Seasonally Adjusted Net Electricity Generated by Solar PV

As such, I treated the dependent variable by taking its log, which resulted in its final form, displayed in Figure 5. After the transformations the dependant variable used going forwards was the seasonally adjusted log of net electricity generation by solar PV.

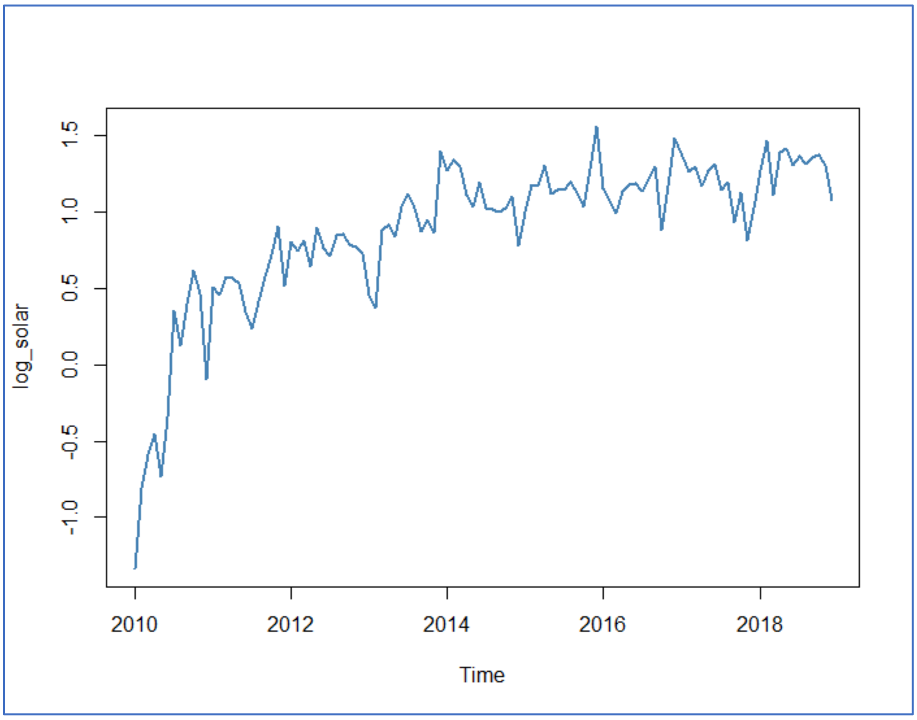

Figure 5 - Seasonally Adjusted Log of Net Electricity Generation by Solar PV

The independent variable of feed-in tariffs also needed some adjustments and transformations. First, there are separate tariffs for solar PV based on the capacity of the installed panels. There are four categories for rooftop PV, while originally there were three for ground-based PV, but by now only the smallest category – which is incidentally the largest category in rooftop – is supported. Unfortunately, there was no historical data available on the split of installations based on PV capacity, therefore I could not create a weighted average for feed-in tariffs. I could not find any variable that was present throughout the entire time series that could be used to weight the average of PV tariffs with, therefore in the end I had to contend with a simple, unweighted average of the feed-in tariffs, which created the initial independent variable.

Figure 6 displays the average of feed-in tariffs over time, while Figure 7 displays the ACF plot. In both of them, a clear downward trend is visible, which means that in order to make the independent variable a stationary variable, I had to take its log.

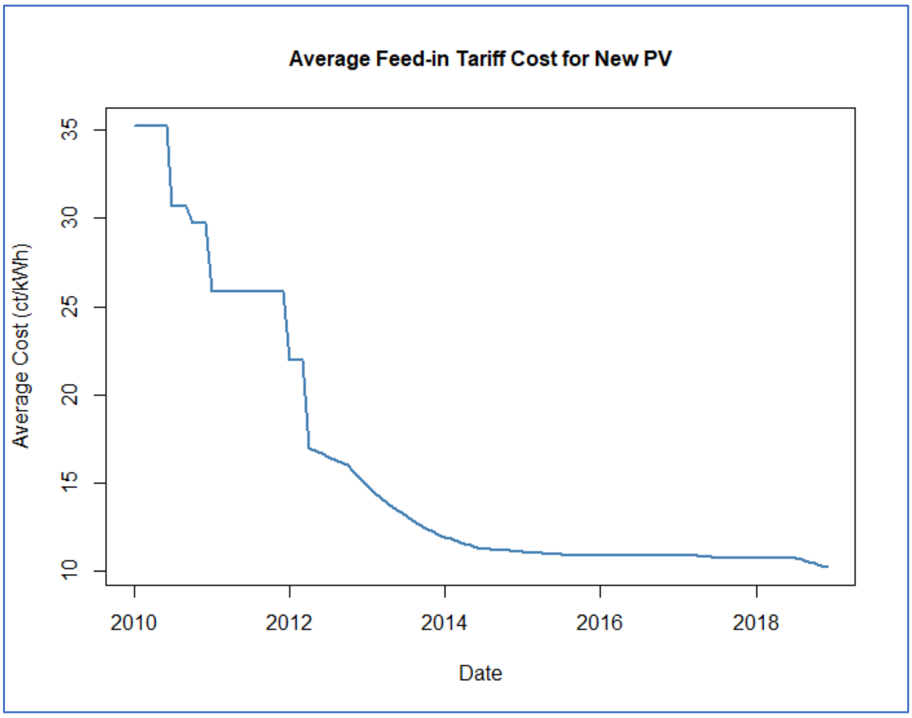

Figure 6 - Average Feed-in Tariff Cost for New PV (ct/kWh)

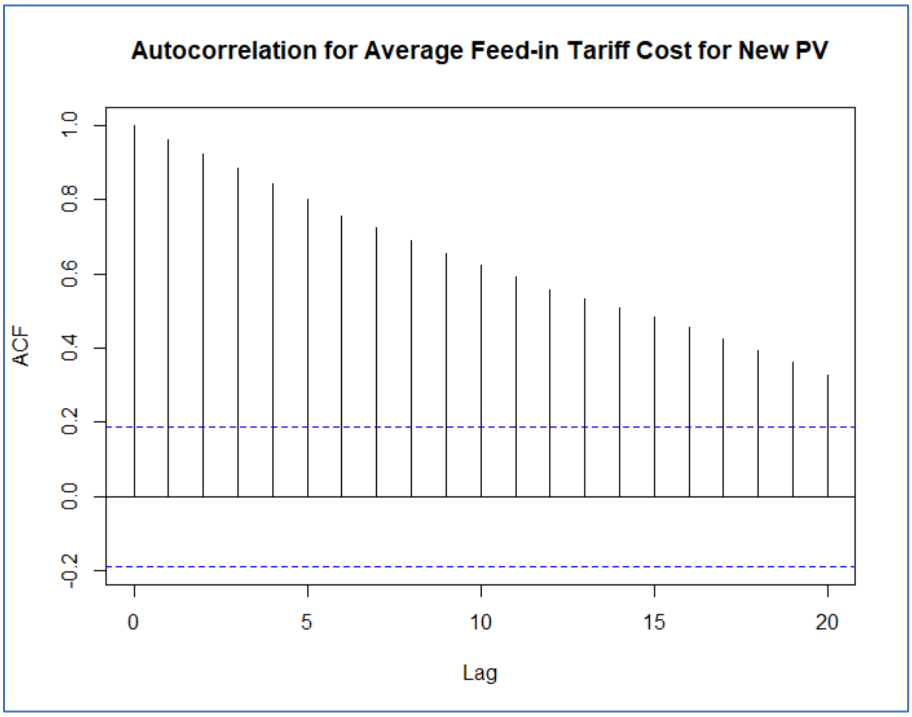

Figure 7 - ACF for Average Feed-in Tariff Cost for New PV (ct/kWh)

Figure 8 shows the final independent variable, which is log average feed-in tariff cost for new solar PV.

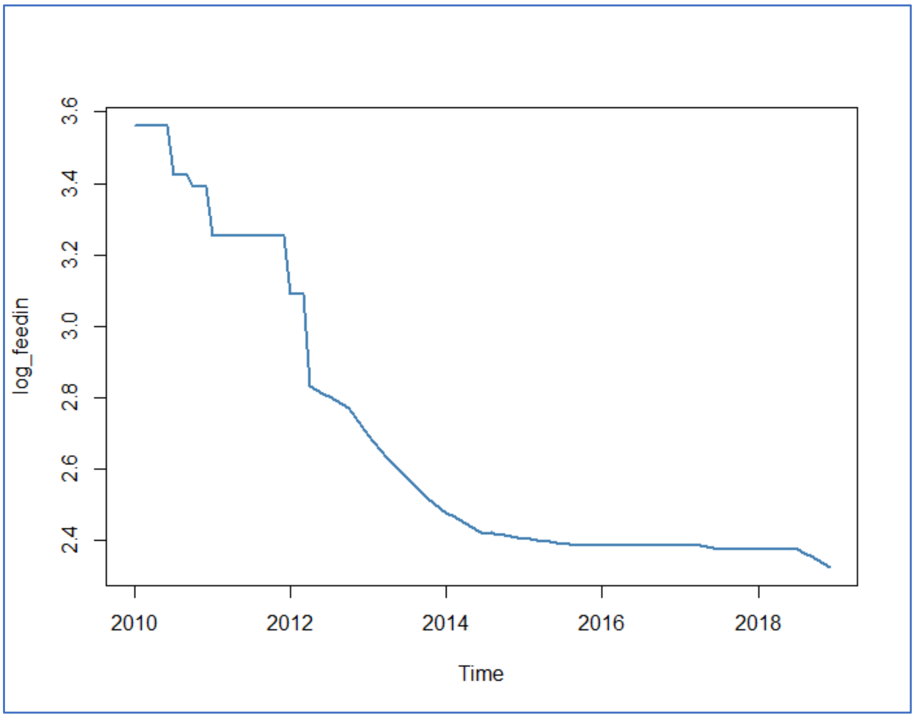

Figure 8 - Log Average Feed-in Tariff Cost for New PV

In order to have a better idea where the results fall in context of typical variation, I ran the basic statistics of both variables. As the summary statistics table shows below, the typical month-to-month variation is quite high for both. For seasonally adjusted solar electricity generation it is 51%, while for feed-in tariffs it is 41%. This can be explained by the history of the two variables, so it's not unusual in this situation, but it is well worth to remember when interpreting results.

Minimum	1st Quantile	Mean	SD	3rd Quantile	Maximum
1.34	0.73	0.73	0.51	1.18	1.56

Table 1 - Summary of Dependent Variable

Minimum	1st Quantile	Mean	SD	3rd Quantile	Maximum
2.33	2.39	2.43	0.41	2.90	3.56

Table 2 - Summary of Independent Variable

Given that I was interested in how the changes in feed-in tariffs affect the changes in net electricity generation via solar PV, e.g. whether a % increase in feed-in tariffs causes a % increase in net solar electricity generation, I have decided to regress the first differences of the two variables on each other.

I have created a "visual regression" graphing the **Δlog of net solar electricity generation**$_t$ and **Δlog of feed-in tariff**$_t$ in Figure 9, but the graph didn't show any clear correlation.

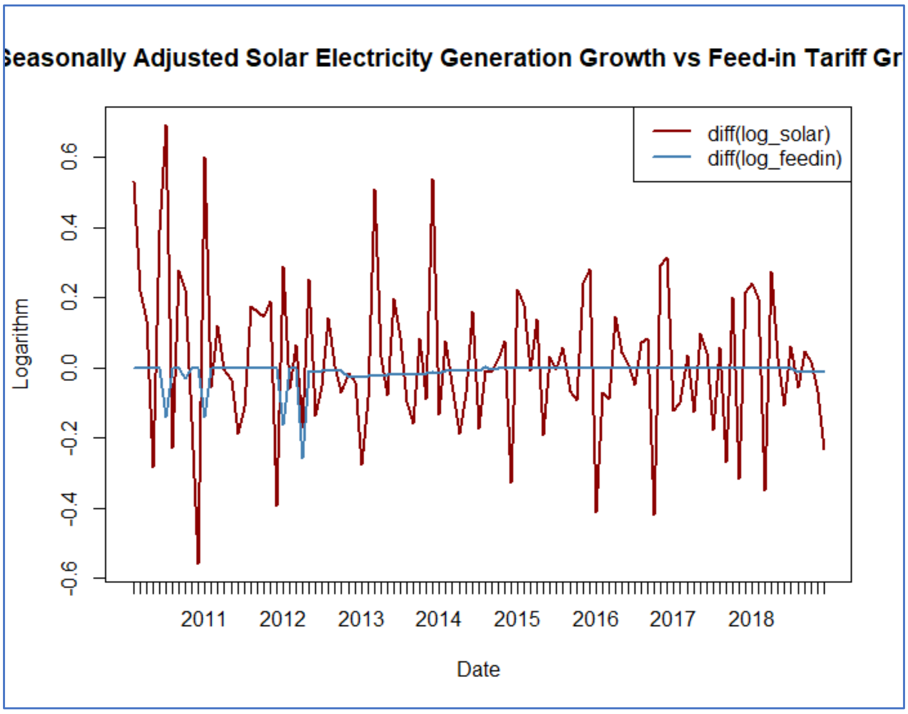

Figure 9 - Seasonally Adjusted Solar Electricity Generation Growth vs Feed-in Tariff Growth

While the changes in feed-in tariff were quite close to constant, the changes in in solar electricity generation fluctuated a lot. Neither of them showed any trends or seasonality though, which meant that both variables were stationary enough for analysis

Another factor I considered was whether the effects of feed-in tariff changes on solar electricity generation were delayed. Given that the installation of solar PV models take time, it was reasonable to expect delays, which is why I decided to take a lag of the right-hand-side variable, making my base regression the following:

$$\boldsymbol{E[\Delta ln\mathrm{solar}_t|\Delta ln\mathrm{feedin}_{t-1}] = \alpha + \beta\Delta ln\mathrm{feedin}_{t-1}}$$

However, before I ran any regressions, I also considered potential confounders which are especially important in this case as I am was not working with randomised experiments. First, I considered reverse causality and anticipation effects. Reverse causality in this case would mean that changes in solar electricity generation would make politicians change the feed-in tariff rates. While according to the literature the changes happened due to the cost burdens placed on consumers, it makes sense to test whether the data shows any potential effects. Anticipation effect in our case would be that prospective solar PV owners realise that the feed-in tariff is about to decrease, and they invest in solar PV to ensure they have the best deal possible. Based on the literature and the idea behind degression, I expected to see anticipation effects present in the data.

Based on the literature available I highlighted two other covariates as well: price of solar PV and consumer electricity price.

The cost of a solar PV panel directly influences the overall costs of an investment in PV. As Figure 10 shows, the average price of solar PV panels has a downward trend, which could then encourage more people to install PV as the change in price would greatly reduce the burden. This behaviour could interfere with our analysis on the effects of feed-in tariffs on solar adoption, therefore we should be controlling for the solar PV panel price.

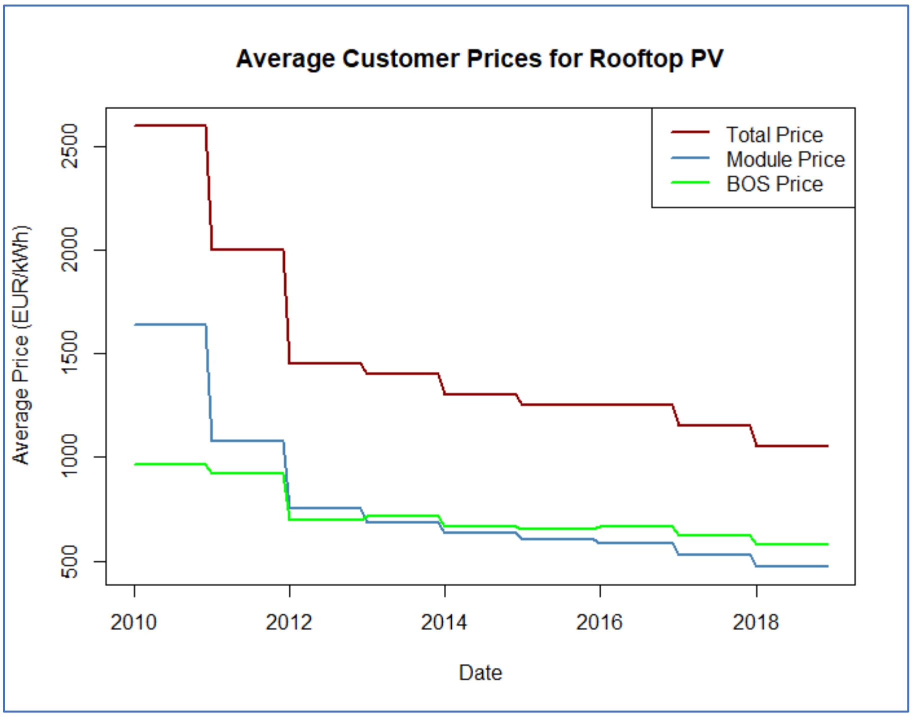

Figure 10 - Average Customer Proces for Rooftop PV

Interestingly, the two components of the solar PV price – the price of the module and the balance of system price that incorporates all other components – show slightly different downwards trends which is why I decided to use them as separate confounders. Given that I only included the feed-in tariffs for rooftop elements, I made sure to do so with the prices as well.

Because of the downwards trend, I had to take the log of the solar PV price variables to avoid having a non-stationary variable in the regressions.

The last covariate is the price of consumer electricity, collected from Eurostat. Unfortunately, electricity prices are only reported bi-annually, and there were no reports on seasonality that I could use to transform them into monthly prices, so I had to keep them as bi-annual ones. As Figure 11 shows, the overall price of consumer electricity shows an increasing trend, which I believed could encourage more people to install solar PV as they could then decrease their electricity expenditures on the long run. Therefore, we must control for electricity prices when analysing the effects of feed-in tariffs on solar PV adoption.

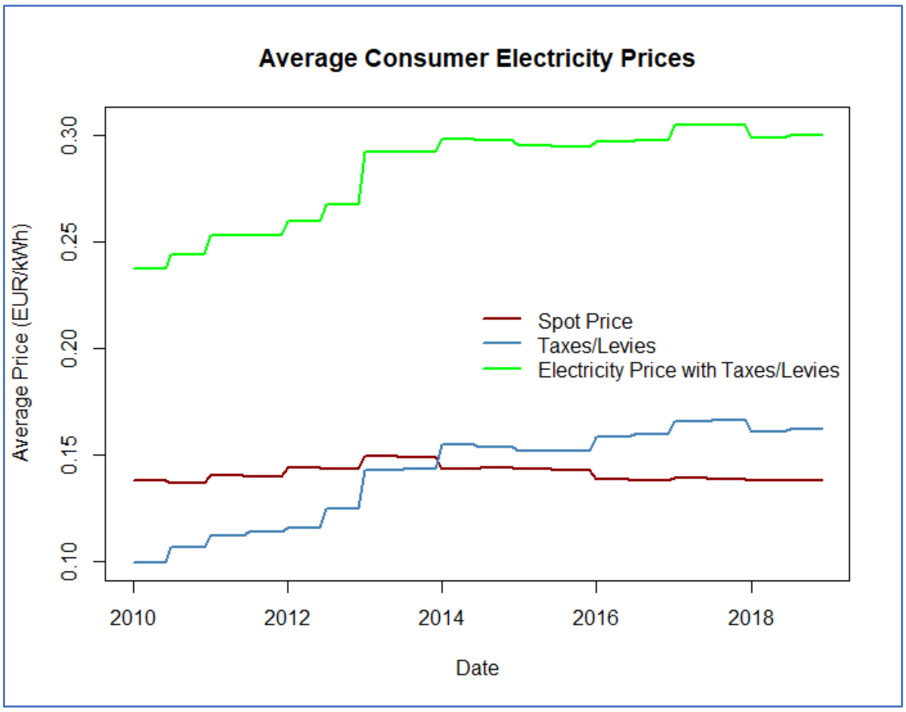

Figure 11 - Average Consumer Electricity Prices

Interestingly, while the overall electricity price and the taxes/levies that are associated with consumer electricity show an increasing trend, spot prices have been decreasing in the last four years. This could be the result of the increase in renewables in electricity production as per the literature I have discussed previously, and similarly, the increase in taxes/levies could also be due to the EEG surcharge operators charge consumers. However, unfortunately there was no analysis available on the price components of these two prices, so I couldn't draw any solid conclusions. Nevertheless, given that they are moving in different directions, I decided to use them as control variables separately.

Because of the trends present, I had to take the log of the consumer electricity price variables to avoid having a non-stationary variable in the regressions.

The last thing I needed to do before running my regressions was to compute HAC standard errors. As the regressions were going to be ran on time series data, this was an essential step. I chose to compute Newey-West estimators, for which I first had to calculate the truncation parameter *m*.

Due to my small data sample I did not use the formula

$$\mathbf{m=\lceil 0.75 \cdot T^{1/3} \rceil}$$

where T is the number of observations in the sample, as the result I got from it was 4, which does not cover the usually suggested exceeding periodicity of data, which would be 12 in my case since I was working with monthly data.

Therefore, I selected **m = 12** instead.

The Newey-West estimators were added to the *stargazer* output of the regressions, which I will discuss in the next section.

4. Results and Policy Implications

In my first batch of regressions, I computed two regressions,

$$E[\Delta ln\text{solar}_t|\Delta ln\text{feedin}_{t-1}] = \alpha + \beta\Delta ln\text{feedin}_{t-1}$$

that is, my base regression of first differences of log solar electricity generation and log feed-in tariff with a lag on the feed-in tariff, and

$$E[\Delta ln\text{solar}_t|\Delta ln\text{feedin}_{t-1}] = \alpha + \beta_1\Delta ln\text{feedin}_{t-1} + \beta_2\Delta ln\text{feedin}_{t-2} + \beta_3\Delta ln\text{feedin}_{t-3} + \beta_4\Delta ln\text{feedin}_{t-4} + \beta_5\Delta ln\text{feedin}_{t-5} + \beta_6\Delta ln\text{feedin}_{t-6} + \beta_7\Delta ln\text{feedin}_{t-7} + \beta_8\Delta ln\text{feedin}_{t-8} + \beta_9\Delta ln\text{feedin}_{t-9} + \beta_{10}\Delta ln\text{feedin}_{t-10} + \beta_{11}\Delta ln\text{feedin}_t + \beta_{12}\Delta ln\text{feedin}_{t+1}$$

where I added nine more lags, as well as the confounders for reverse causality and anticipation effect. The results were the following:

	Dependent variable: Solar PV Growth Rate	
	(1)	(2)
diff(L(log_feedin, 1))	0.085	-0.091
	(0.603)	(0.655)
diff(L(log_feedin, 2))		-0.793
		(0.704)
diff(L(log_feedin, 3))		0.765
		(0.704)
diff(L(log_feedin, 4))		-0.653
		(0.703)
diff(L(log_feedin, 5))		1.306
		(0.644)**
diff(L(log_feedin, 6))		-0.684
		(0.644)
diff(L(log_feedin, 7))		-0.021
		(0.644)
diff(L(log_feedin, 8))		-0.497
		(0.598)
diff(L(log_feedin, 9))		0.683
		(0.598)
diff(L(log_feedin, 10))		0.127
		(0.598)
diff(log_feedin)		-0.945
		(0.655)
diff(L(log_feedin, -1))		1.269
		(0.655)*
Constant	0.019	0.015
	(0.022)	(0.028)
HAC truncation	12	12
Observations	106	96
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3 - Regression 1 & 2

Table 3 shows the results of the first two regressions, and when I interpreted the results I could see that first of all, there was a slight anticipatory effect present in the data, but since the Confidence Interval was only at 90%, it is not significant enough for my purposes. However, I could also see that instead of the expected one-month lag, 5 months had to pass from the change in feed-in tariff to see any statistically significant result, that is one with a 95% confidence interval. The result of the second regression states that if we compared different months, months that had a 10% increase in feed-in tariffs five months prior would have approximately 13% higher net solar electricity generation.

Interestingly, none of the other lags showed any statistically significant results, but that could also have been due to the uncontrolled presence of the two other covariates. Therefore, I proceeded with my second group of regressions, in which I included the covariates log electricity and PV price. The regressions were the following:

In regression 3 I included the 10 lags while controlling for pv price (module and balance of system price):

$$E[\Delta ln\textbf{solar}_t|\Delta ln\textbf{feedin}_{t-1}, \Delta ln\textbf{module\_price}_t] = \alpha + \beta_1\Delta ln\textbf{feedin}_{t-1} + \beta_2\Delta ln\textbf{feedin}_{t-2} + \beta_3\Delta ln\textbf{feedin}_{t-3} + \beta_4\Delta ln\textbf{feedin}_{t-4} + \beta_5\Delta ln\textbf{feedin}_{t-5} + \beta_6\Delta ln\textbf{feedin}_{t-6} + \beta_7\Delta ln\textbf{feedin}_{t-7} + \beta_8\Delta ln\textbf{feedin}_{t-8} + \beta_9\Delta ln\textbf{feedin}_{t-9} + \beta_{10}\Delta ln\textbf{feedin}_{t-10} + \beta_{11}\Delta ln\textbf{module\_price}_t + \beta_{12}\Delta ln\textbf{bos\_price}_t$$

In regression 4 I included the 10 lags while controlling for electricity price (spot price and taxes/levies):

$$E[\Delta ln\textbf{solar}_t|\Delta ln\textbf{feedin}_{t-1}, \Delta ln\textbf{bos\_price}_t] = \alpha + \beta_1\Delta ln\textbf{feedin}_{t-1} + \beta_2\Delta ln\textbf{feedin}_{t-2} + \beta_3\Delta ln\textbf{feedin}_{t-3} + \beta_4\Delta ln\textbf{feedin}_{t-4} + \beta_5\Delta ln\textbf{feedin}_{t-5} + \beta_6\Delta ln\textbf{feedin}_{t-6} + \beta_7\Delta ln\textbf{feedin}_{t-7} + \beta_8\Delta ln\textbf{feedin}_{t-8} + \beta_9\Delta ln\textbf{feedin}_{t-9} + \beta_{10}\Delta ln\textbf{feedin}_{t-10} + \beta_{11}\Delta ln\textbf{el\_spot\_price}_t + \beta_{12}\Delta ln\textbf{el\_tax}_t$$

And in regression 5 I included the 10 lags while controlling for both pv price and electricity price:

$$E[\Delta ln\textbf{solar}_t|\Delta ln\textbf{feedin}_{t-1}, \Delta ln\textbf{price}_t] = \alpha + \beta_1\Delta ln\textbf{feedin}_{t-1} + \beta_2\Delta ln\textbf{feedin}_{t-2} + \beta_3\Delta ln\textbf{feedin}_{t-3} + \beta_4\Delta ln\textbf{feedin}_{t-4} + \beta_5\Delta ln\textbf{feedin}_{t-5} + \beta_6\Delta ln\textbf{feedin}_{t-6} + \beta_7\Delta ln\textbf{feedin}_{t-7} + \beta_8\Delta ln\textbf{feedin}_{t-8} + \beta_9\Delta ln\textbf{feedin}_{t-9} + \beta_{10}\Delta ln\textbf{feedin}_{t-10} + \beta_{11}\Delta ln\textbf{module\_price}_t + \beta_{12}\Delta ln\textbf{bos\_price}_t + \beta_{13}\Delta ln\textbf{el\_spot\_price}_t + \beta_{14}\Delta ln\textbf{el\_tax}_t$$

The results were the following:

	Dependent variable: Solar PV Growth Rate		
	(1)	(2)	(3)
diff(L(log_feedin, 1))	-0.157	-0.089	-0.213
	(0.649)	(0.650)	(0.629)
diff(L(log_feedin, 2))	-0.308	-0.251	-0.360
	(0.644)	(0.646)	(0.624)
diff(L(log_feedin, 3))	0.191	0.030	-0.385
	(0.647)	(0.669)	(0.662)
diff(L(log_feedin, 4))	-0.685	-0.656	-0.666
	(0.696)	(0.698)	(0.674)
diff(L(log_feedin, 5))	1.236	1.289	1.244
	(0.637)*	(0.638)**	(0.616)**
diff(L(log_feedin, 6))	-0.201	-0.826	-0.047
	(0.667)	(0.640)	(0.680)
diff(L(log_feedin, 7))	-0.079	-0.036	-0.094
	(0.637)	(0.638)	(0.616)
diff(L(log_feedin, 8))	-0.659	-0.599	-0.655
	(0.591)	(0.592)	(0.572)
diff(L(log_feedin, 9))	0.696	0.918	-0.005
	(0.597)	(0.687)	(0.738)
diff(L(log_feedin, 10))	0.028	0.099	0.063
	(0.592)	(0.594)	(0.573)
diff(log(module_price))	-1.168		-1.745
	(0.548)**		(0.695)**
diff(log(bos_price))	0.380		0.952
	(1.002)		(1.016)
diff(log(el_spot_price))		7.126	1.187
		(2.768)**	(3.376)
diff(log(el_tax))		-1.690	-3.584
		(1.228)	(1.365)**
Constant	-0.005	0.013	-0.007
	(0.027)	(0.026)	(0.027)
HAC truncation	12	12	12
Observations	97	97	97
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 4 - Regression 3 & 4 & 5

Table 4 shows the results of the second group of regressions. The results show that in order to see any statistically significant effects, 5 months must pass from the change in feed-in tariff prices, which could either mean that it takes quite a long time to set up a solar PV system, or that potential solar PV investors are slow to react to feed-in tariff price changes.

The impacts of the changes in feed-in tariff changes in the two statistically significant regressions are quite similar to that of regression 2. The result of regression 4 states that if we compared different months, months that had a 10% increase in feed-in tariffs five months prior would have approximately 13% higher net solar electricity generation, provided that consumer electricity prices didn't change. The result of regression 5 states that if we compared different months, months that had a 10% increase in feed-in tariffs five months prior would have approximately 12% higher net solar electricity generation, provided that consumer electricity and solar PV prices didn't change. If we recall, the typical month-to-month variation for feed-in tariff increase is 41% while for solar electricity generation it is 51% so the results are not unusual.

We can also see from the results that net solar electricity generation is sensitive to changes in PV module price changes. An increase in this variable would result in a decrease in energy generation, which is not surprising if we consider that increased module prices would make investment in solar PV more expensive. The effects of solar PV price module changes are large, larger than the effects of feed-in tariff changes, which means that solar adoption is more sensitive to solar PV price changes than to changes in feed-in tariff. Interestingly, balance of system price changes do not have a statistically significant effect.

Solar adoption – measured by solar electricity generation in our case – is also sensitive to changes in electricity prices. If it is the spot price that changes, adoption increases massively, while if the taxes and levies associated with electricity prices increase, then the effect is the opposite, even though to a smaller degree. This could be due to potential producer's behaviour, i.e. them wanting to reduce their costs by producing their own electricity when spot prices raise and not wanting to further increase their costs by investing in renewables when taxes increase, as they would still need to pay the fixed taxes when not using renewables. But I also think that the bi-annual nature of electricity data and the small sample size could also be at least partially blamed for the extreme effects and polarisation. Nevertheless, we have found correlation between the datapoints, and again, the effects of changes in electricity prices are significantly more than that of the feed-in tariff.

Of course, we must keep in mind that we are working with a small sample size and using an approximate value for solar adoption, therefore we cannot exclude the possibility that there are omitted variables that we have no data of. However, I believe that the results support casual effects of feed-in tariffs on solar adoption. However, as the data indicates, this relationship cannot be examined in a bubble. Other factors such as solar PV module and electricity prices also heavily influence adoption, more so than feed-in tariffs.

And while there was no way to quantify it due to lack of data, based on the available literature, both grid access and public opinion of renewables can affect adoption rates. Unfortunately, we cannot compare their effects to that of prices and feed-in tariffs due to lack of data, but I think it would be unwise to forget about their presence.

Therefore, I would be hesitant to suggest that reinstating higher lever feed-in tariffs would be the best course of action, even though within the renewable camp in Germany, that is a popular idea. Knowing the negative effects feed-in tariffs can have on vulnerable people's living standards – due to the increase in electricity prices they bring – as well as their effect of increasing inequality, I am on the opinion that for a mature resource like solar PV that is well-supported amongst the population, the costs – social and economic – associated with this kind of promotion might be too high.

Adding to this is the fact that just like how insufficient grid access cause serious damages in solar adoption; too high growth rate in solar adoption could pose a serious threat to the

German electricity grid, as discussed in the literature. I believe that slowdown created by the degression of feed-in tariff gives the German utilities the opportunity to enforce and update their grid in order to increase its efficiency with solar energy and renewables in general. Overall, I am in support of the continuing phase out of feed-in tariffs in Germany.

Of course, this does not mean that no other policy should take its place, but I am in favour of the policy mix that instead of just focusing on one aspect of energy policies, such as price, governments should approach renewable integration with a cost-efficient mindset that incorporates incentives for R&D – to ensure that the newest, more efficient technologies hit the market as soon as they can –, demand-side management as well direct supporting systems such as feed-in tariffs or tax credit incentives (Sisodia et al., 2015; Rosenow et al., 2017). Germany has already applied this method to some areas of energy policy, for example the off-shore wind developments (Reichardt. & Rogge, 2016) and the nuclear phase-out policy (Rogge Johnstone, 2017), so the methodology should already be familiar. Germany has been very successful in leading an efficient and – somewhat – fair energy policy so far, now the time has come to focus not on promotion but maintenance and inclusion. The historical consistency in their policies should give them the credibility (Reichardt & Rogge, 2016), while meeting the long-term targets should give confidence to investors in market growth, as long as they are updated regularly (Reichardt & Rogge, 2016).

Conclusion

In this paper I described the current renewable trends with a special focus to Germany and solar PV. I have analysed the effects of changes in feed-in tariffs on solar adoption in order to find out whether they are actually harming the growth of solar PV or not. And while the data supports that the decrease of feed-in tariffs can indeed effect solar adoption negatively, I am on the opinion that this step is necessary in order to avoid causing social and economic damage to consumers and utilities, which is why my recommendation would be to keep up with the current policies in Germany.

I also believe that future energy policies should be approached from a cost-effective, holistic mindset in order to ensure that the support of one policy aspect is not damaging the other. And while this approach and particular mix have worked out well for Germany, I caution against blindly applying their policies to anyone in need of some guidance in renewables. I am on the opinion that the success of Germany's renewable policies is heavily dependent on public support as well as their preparedness for renewable development, which is not a feature many other countries share. Overall, I believe the best approach would be for governments who are planning on updating their current renewable policies or establishing new ones is to first assess the strengths and weaknesses of the renewable industry in their countries, then devise a long-term strategic plan with multiple KPIs, and commit to keeping as close to it as possible. Finally, I would urge policy adapters to be patient, as based on the results in Germany, a consistent , long-term approach is necessary in order to facilitate truly meaningful change.

Appendices

Appendix 1 – R code

```
# CLEAR MEMORY
rm(list=ls())


install.packages("tidyr")
install.packages("plm")
install.packages("gridExtra")
install.packages("xts")
install.packages("zoo")
install.packages("magrittr")
install.packages("anytime")
install.packages("quantmod")
install.packages("dynlm")
install.packages("nlme")
install.packages("AER")
install.packages("orcutt")
install.packages("dyn")
install.packages("dummies")
install.packages("Ecdat")
install.packages("gtools")



library(stringr)
library(pastecs)
library(readr)
library(dplyr)
library(tidyr)
library(ggplot2)
library(gridExtra)
library(plm)
```

```
library(stargazer)
library(DataCombine)
library(xts)
library(zoo)
library(magrittr)
library(anytime)
library(quantmod)
library(dynlm)
library(nlme)
library(AER)
library(orcutt)
library(dyn)
library(dummies)
library(Ecdat)
library(gtools)


# Setting the working directory
rm(list = ls())
getwd()
setwd("C:/Users/Detti/Desktop/Uni/CEU (Masters)/Year2/Thesis/Data")
# Program applies additional functions from here
source("C:/Users/Detti/Desktop/Uni/CEU (Masters)/Year1/Data Analysis/Project 2/da_helper_functions.R")

# Data manipulation ----------------------------------------------------------

# Reading solar data & formatting columns/datapoints
solar_raw <- read.csv('solar_data.csv')

solar_raw$FixedDate <- as.Date(solar_raw$month.year,format="%Y-%m-%d")
```

```
solar_raw$month.year <- NULL

colnames(solar_raw) <- c("sunshine", "renewable_opinion", "avg_pv_price",
"avg_module_price",
                   "avg_bos_price", "el_price_no_tax", "el_price_tax,", "feedin", "el_total",
"el_solar", "el_wind", "el_others", "el_gas",
                   "el_oil", "el_hcoal", "el_bcoal", "el_uran", "el_bio", "el_hydro", "date")

solar_raw$percent_of_tax <- (solar_raw$el_price_tax-
solar_raw$el_price_no_tax)/solar_raw$el_price_tax

solar_raw$el_tax <- solar_raw$el_price_tax - solar_raw$el_price_no_tax

# creating time series objects (level and when necessary log)

FeedIn <- xts(solar_raw$feedin, solar_raw$date)["2010-01-01::2019-04-01"]

FeedInGrowth <- xts(log(FeedIn/lag(FeedIn)))

ElectricityNoTax <- xts(solar_raw$el_price_no_tax, solar_raw$date)["2010-01-01::2019-04-
01"]

ElectricityNoTaxGrowth <- xts(log(ElectricityNoTax/lag(ElectricityNoTax)))

ElectricityTax <- xts(solar_raw$el_price_tax, solar_raw$date)["2010-01-01::2019-04-01"]

ElectricityTaxGrowth <- xts(log(ElectricityTax/lag(ElectricityTax)))

Tax <- xts(solar_raw$el_tax, solar_raw$date)["2010-01-01::2019-04-01"]

TaxGrowth <- xts(log(Tax/lag(Tax)))

PercentOfTax <- xts(100*solar_raw$percent_of_tax, solar_raw$date)["2010-01-01::2019-04-
01"]
```

```
TotalPrice <- xts(solar_raw$avg_pv_price, solar_raw$date)["2010-01-01::2019-04-01"]

TotalPriceGrowth <- xts(log(TotalPrice/lag(TotalPrice)))

ModulePrice <- xts(solar_raw$avg_module_price, solar_raw$date)["2010-01-01::2019-04-
01"]

ModulePriceGrowth <- xts(log(ModulePrice/lag(ModulePrice)))

BOSPrice <- xts(solar_raw$avg_bos_price, solar_raw$date)["2010-01-01::2019-04-01"]

BOSPriceGrowth <- xts(log(BOSPrice/lag(BOSPrice)))

Solar <- xts(solar_raw$el_solar, solar_raw$date)["2010-01-01::2019-04-01"]

SolarGrowth <- xts(log(Solar/lag(Solar)))

Sunshine <- xts(solar_raw$sunshine, solar_raw$date)["2010-01-01::2019-04-01"]

solar_raw$solar_of_total <- solar_raw$el_solar/solar_raw$el_total*100

SolarTotal <-  xts(solar_raw$solar_of_total, solar_raw$date)["2010-01-01::2019-04-01"]

# visualising time series objects

par(mfrow = c(1, 1))

# plot the series
plot(as.zoo(SolarTotal),
     col = "steelblue",
     lwd = 2,
```

```
    ylab = "Percent",
    xlab = "Date",
    main = "% of Net Electricity Generated by Solar PV",
    cex.main = 1)

# plot the series
plot(as.zoo(Sunshine),
    col = "steelblue",
    lwd = 2,
    ylab = "Hours",
    xlab = "Date",
    main = "Median Hours of Sunshine",
    cex.main = 1)

# plot the series
plot(as.zoo(Solar),
    col = "steelblue",
    lwd = 2,
    ylab = "Net Electricity (TWh)",
    xlab = "Date",
    main = "Net Electricity Generated by Solar PV",
    cex.main = 1)

# plot the series
plot(as.zoo(SolarGrowth),
    col = "steelblue",
    lwd = 2,
    ylab = "Logarithm",
    xlab = "Date",
    main = "Solar PV Growth Rates",
    cex.main = 1)
```

```
# plot the series
plot(as.zoo(PercentOfTax),
     col = "steelblue",
     lwd = 2,
     ylab = "Percent",
     xlab = "Date",
     main = "Tax and Levies as % of Electricity Price",
     cex.main = 1)



plot(merge(as.zoo(ElectricityNoTax),as.zoo(Tax), as.zoo(ElectricityTax)),
     plot.type = "single",
     col = c("darkred", "steelblue", "green"),
     lwd = 2,
     xlab = "Date",
     ylab = "Average Price (EUR/kWh)",
     main = "Average Consumer Electricity Prices")

legend("right",
       legend = c("Spot Price", "Taxes/Levies", "Electricity Price with Taxes/Levies"),
       col = c("darkred", "steelblue", "green"),
       lwd = c(2, 2),
       box.lty=0)

# plot the series
plot(as.zoo(FeedIn),
     col = "steelblue",
     lwd = 2,
     ylab = "Average Cost (ct/kWh)",
     xlab = "Date",
     main = "Average Feed-in Tariff Cost for New PV",
     cex.main = 1)
```

```
# plot the series
plot(as.zoo(FeedInGrowth),
     col = "steelblue",
     lwd = 2,
     ylab = "Logarithm",
     xlab = "Date",
     main = "Feed-in Tariff Growth Rates",
     cex.main = 1)

plot(as.zoo(TotalPrice),
     col = "steelblue",
     lwd = 2,
     ylab = "Average Price (EUR/kWp)",
     xlab = "Date",
     main = "Average Customer Price for Rooftop PV",
     cex.main = 1)

plot(as.zoo(TotalPriceGrowth),
     col = "steelblue",
     lwd = 2,
     ylab = "Logarithm",
     xlab = "Date",
     main = "PV Price Growth Rates",
     cex.main = 1)

plot(as.zoo(ModulePrice),
     col = "steelblue",
     lwd = 2,
     ylab = "Average Price (EUR/kWp)",
     xlab = "Date",
     main = "Average Customer Price for Rooftop PV Modules",
```

```
    cex.main = 1)

plot(merge(as.zoo(TotalPrice), as.zoo(ModulePrice), as.zoo(BOSPrice)),
    plot.type = "single",
    col = c("darkred", "steelblue", "green"),
    lwd = 2,
    xlab = "Date",
    ylab = "Average Price (EUR/kWh)",
    main = "Average Customer Prices for Rooftop PV")

legend("topright",
      legend = c("Total Price", "Module Price", "BOS Price"),
      col = c("darkred", "steelblue", "green"),
      lwd = c(2, 2))

plot(as.zoo(ModulePriceGrowth),
    col = "steelblue",
    lwd = 2,
    ylab = "Logarithm",
    xlab = "Date",
    main = "PV Module Growth Rates",
    cex.main = 1)

plot(as.zoo(BOSPrice),
    col = "steelblue",
    lwd = 2,
    ylab = "Average Price (EUR/kWp)",
    xlab = "Date",
    main = "Average Customer Price for Rooftop PV BOS",
    cex.main = 1)

plot(as.zoo(BOSPriceGrowth),
```

```
    col = "steelblue",
    lwd = 2,
    ylab = "Logarithm",
    xlab = "Date",
    main = "PV BOS Growth Rates",
    cex.main = 1)


# testing for autocorrelation
acf(na.omit(Solar), lag.max = 12, plot = F)
acf(Solar, main = "Autocorrelation for Net Electricity Generated by Solar PV",) # seasonality

acf(na.omit(FeedIn), lag.max = 12, plot = F)
acf(FeedIn, main = "Autocorrelation for Average Feed-in Tariff Cost for New PV") #
correlation --> linear trend

acf(na.omit(ModulePrice), lag.max = 12, plot = F)
acf(ModulePrice, main = "Autocorrelation for Average Customer Price for Rooftop PV
Modules") # correlation --> linear trend

acf(na.omit(BOSPrice), lag.max = 12, plot = F)
acf(BOSPrice, main = "Autocorrelation for Average Customer Price for Rooftop PV BOS") #
correlation --> linear trend

# therefore we should regress log differences on each other
# we also need to adjust solar for seasonality

solar<-ts(solar_raw$el_solar,start=2010,frequency=12)

decompose_solar = decompose(solar, "multiplicative")
adjust_solar = solar / decompose_solar$seasonal

plot(adjust_solar, col = "steelblue", lwd = 2)
```

```
acf(na.omit(adjust_solar), lag.max = 12, plot = F)

acf(adjust_solar, main = "Autocorrelation for Seasonally Adjusted Net Electricity Generated
by Solar PV") # correlation --> linear trend



log_solar <- log(adjust_solar)


plot(log_solar, col = "steelblue", lwd = 2 )


feedin<-ts(solar_raw$feedin,start=2010,frequency=12)

log_feedin <- log(feedin)



plot(log_feedin, col = "steelblue", lwd = 2 )


# summary statistics

summary(log_solar)

sd(log_solar)

summary(log_feedin)

sd(log_feedin)


# graph the log values of feed-in and solar pv


plot(merge(as.zoo(diff(log_solar)), as.zoo(diff(log_feedin))),

     plot.type = "single",

     col = c("darkred", "steelblue"),

     lwd = 2,

     xlab = "Date",

     ylab = "Logarithm",

     main = "Seasonally Adjusted Solar Electricity Generation Growth vs Feed-in Tariff
Growth")
```

```
legend("topright",
       legend = c("diff(log_solar)", "diff(log_feedin)"),
       col = c("darkred", "steelblue"),
       lwd = c(2, 2))

price <- ts(solar_raw$avg_pv_price,start=2010,frequency=12)
log_price <- log(price)

module_price <- ts(solar_raw$avg_module_price,start=2010,frequency=12)
log_module_price <- log(module_price)

bos_price <- ts(solar_raw$avg_bos_price,start=2010,frequency=12)
log_bos_price <- log(bos_price)

el_spot_price <- ts(solar_raw$el_price_no_tax,start=2010,frequency=12)
log_el_spot_price <- log(el_spot_price)

el_tax <- ts(solar_raw$el_tax,start=2010,frequency=12)
log_el_tax <- log(el_tax)

el_price <- ts(solar_raw$el_price_tax,start=2010,frequency=12)
log_el_price <- log(el_price)

# first difference log - 1 lag first difference log regression
solar1 <- dynlm(diff(log_solar) ~ diff(L(log_feedin, 1)))
coeftest(solar1, vcov. = vcovHAC)
summary(solar1)

# first difference log - first difference log with contemporaneous, lead and lags
solar2 <- dynlm(diff(log_solar) ~ diff(L(log_feedin, 1)) + diff(L(log_feedin, 2)) +
diff(L(log_feedin, 3)) + diff(L(log_feedin, 4)) + diff(L(log_feedin, 5)) + diff(L(log_feedin,
6)) + diff(L(log_feedin, 7)) + diff(L(log_feedin, 8)) + diff(L(log_feedin, 9)) +
diff(L(log_feedin, 10)) + diff(log_feedin) + diff(L(log_feedin, -1)))
```

```
coeftest(solar2, vcov. = vcovHAC)

summary(solar2)



length(log_feedin)


SEs <- list(sqrt(diag(NeweyWest(solar1, lag = 12, prewhite = F))),
            sqrt(diag(NeweyWest(solar2, lag = 12, prewhite = F))))



stargazer_r(
        list(solar1, solar2),
        digits = 3,
        model.names = FALSE,
        dep.var.labels.include = FALSE,
        dep.var.caption = 'Dependent variable: Solar PV Growth Rate',
        header = FALSE,
        se = SEs,
        no.space = T,
        add.lines = list(c("HAC truncation","12", "12")),
        omit.stat = c("rsq", "f","ser"),
        out="graph_1.html")



# first difference log - first difference log with lags and pv price controls

solar3 <- dynlm(diff(log_solar) ~ diff(L(log_feedin, 1)) + diff(L(log_feedin, 2)) +
diff(L(log_feedin, 3)) + diff(L(log_feedin, 4)) + diff(L(log_feedin, 5)) + diff(L(log_feedin,
6)) + diff(L(log_feedin, 7)) + diff(L(log_feedin, 8)) + diff(L(log_feedin, 9)) +
diff(L(log_feedin, 10)) + diff(log(module_price)) + diff(log(bos_price)))

coeftest(solar3, vcov. = vcovHAC)

summary(solar3)
```

```
# first difference log - first difference log with lags and electricity price controls

solar4 <- dynlm(diff(log_solar) ~ diff(L(log_feedin, 1)) + diff(L(log_feedin, 2)) +
diff(L(log_feedin, 3)) + diff(L(log_feedin, 4)) + diff(L(log_feedin, 5)) + diff(L(log_feedin,
6)) + diff(L(log_feedin, 7)) + diff(L(log_feedin, 8)) + diff(L(log_feedin, 9)) +
diff(L(log_feedin, 10)) + diff(log(el_spot_price)) + diff(log(el_tax)))

coeftest(solar4, vcov. = vcovHAC)

summary(solar4)


# first difference log - first difference log with lags and both pv modul and electricity price
controls

solar5 <- dynlm(diff(log_solar) ~ diff(L(log_feedin, 1)) + diff(L(log_feedin, 2)) +
diff(L(log_feedin, 3)) + diff(L(log_feedin, 4)) + diff(L(log_feedin, 5)) + diff(L(log_feedin,
6)) + diff(L(log_feedin, 7)) + diff(L(log_feedin, 8)) + diff(L(log_feedin, 9)) +
diff(L(log_feedin, 10)) + diff(log(module_price)) + diff(log(bos_price)) +
diff(log(el_spot_price)) + diff(log(el_tax)))

coeftest(solar5, vcov. = vcovHAC)

summary(solar5)



length(log_feedin)


SEs2 <- list(sqrt(diag(NeweyWest(solar3, lag = 12, prewhite = F))),
          sqrt(diag(NeweyWest(solar4, lag = 12, prewhite = F))),
          sqrt(diag(NeweyWest(solar5, lag = 12, prewhite = F))))



stargazer_r(
      list(solar3, solar4, solar5),
      digits = 3,
      model.names = FALSE,
      dep.var.labels.include = FALSE,
      dep.var.caption = 'Dependent variable: Solar PV Growth Rate',
      header = FALSE,
      se = SEs2,
      no.space = T,
```

```
add.lines = list(c("HAC truncation","12", "12", "12")),
omit.stat = c("rsq", "f","ser"),
out="graph_2.html")
```

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