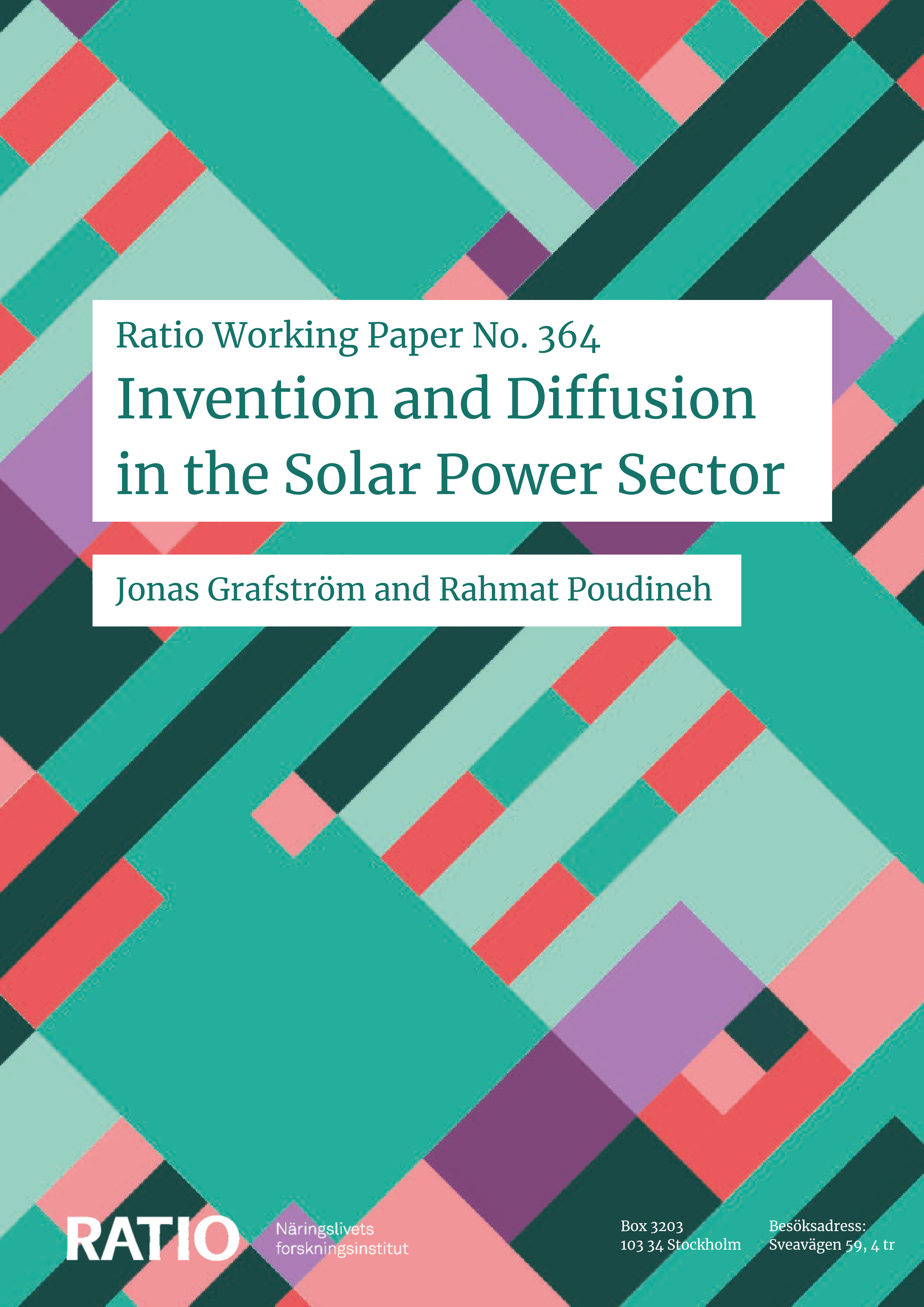

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Invention and Diffusion in the Solar Power Sector

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Invention and Diffusion in the Solar Power Sector

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Abstract

There is an increasing interest in policies that promote invention and diffusion in solar energy technologies. In this paper the question of how does support policies affect inventions and diffusion of solar PV technology and is the effect heterogeneous and counteracting is investigated. The policies investigated are Feed-in-tariffs, Public R&D stock and flow, Environmental tax, and Environmental Policy Stringency Index. A Schumpeterian technological development approach is utilized on a panel dataset covering 23 European countries between 2000 and 2019. Two econometric approaches are employed, a negative binomial regression model is used to assess inventions and a panel data fixed effect regression is used for the diffusion model. The empirical findings suggest that FITs, Public R&D stock and flow, Environmental tax and Environmental Policy Stringency Index have no statistically significant negative effect on either inventions or diffusion. In most cases for invention the policies had a statistically significant positive effect. Policy crowding out does not seem to have been present.

Keywords: solar PV, Invention, diffusion, Schumpeter, policy.
JEL classification: Q55, Q58, Q48, Q42.

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1. Introduction

There is an increasing interest in policies that promote invention and diffusion in solar energy technologies (Peters et al., 2012; Johnstone et al., 2012; Rubin et al., 2015; Elshurafa et al., 2018). Global photovoltaic solar capacity (hereinafter PV) has increased from 1.25 GW in 2000 to 23 GW in 2009 and 704 GW in 2020. The PV price, in terms of levelized cost of electricity has declined from around 80 USD (in 2013 USD) per KWh in 1976 to average 0.38 USD per KWh in 2019 (IRENA, 2020). A multitude of policies promotes solar inventions and diffusion contributing to a rapid development (Popp, 2002; Johnstone, 2010; Hosenuzzaman, et al., 2015; Jimenez et al., 2016; Ding et al., 2020).

However, while there are numerous studies that evaluate policy induced innovation and diffusion separately – how the same policy affects both have not been considered. Not evaluating a policy on several dimensions is unfortunate since there is a risk that a policy can promote one aspect of technological progress such as invention but derail diffusion. Different support policies can have heterogeneous effects in different technologies (Popp, 2002; Brunnermeier and Cohen, 2003; Palage et al., 2019). The same policy can also affect different renewable energies differently (Pitelis et al., 2020).

For instance, feed-in-tariffs (FITs) combined with an underestimation of cost reductions led to an uninhibited PV market boom in Spain in 2008 and in France in 2010 (del Río and Mir-Artigues, 2012; de La Tour et al., 2013). The boom ensued a sharp policy alteration where a payment cap for installations and a cut in the FITs lead to a bust since a generous deployment policy can incentivize higher cost production and technology lock-in (Böhringer et al., 2017; Kim and Tang, 2020). A policy at the wrong moment can impede a successful development and thus can prompt bankruptcies and job losses, therefore the question of how different policies reinforce or counteract each other is a concern in policy analysis (Strambo et al., 2015).

The purpose of this paper is to establish if policies (*Feed-in-tariffs, Public solar RD&D stock and flow, Environmental tax,* and *Environmental Policy Stringency Index*) have a simultaneous effect on invention and diffusion in solar PV and if these effects are counteracting. The contribution to the research literature is twofold. First, the research extends the understanding of how policies affect invention and diffusion simultaneously i.e., our understanding of possible unintended policy effects is enhanced. Second, time and country dimension for solar pv development are somewhat extended which is important considering fast development of solar energy. The following research question is investigated:

- How does support policies affect inventions and diffusion of solar PV technology and is the effect heterogeneous and counteracting?

The empirical strategy is based on a framework from Grafström and Lindman (2017) derived from the Schumpeterian view on invention, innovation, and diffusion (Schumpeter, 1934; 1942). The theoretical foundation concerning technological change is based on the induced innovation concept (Hicks, 1932; Acemoglu, 2002). According to the induced innovation concept policies can induce both desired and undesired outcomes (Guidolin and Mortarion, 2010; Evans, 2016). The evolutionary economics literature is also considered where technological change is a complex, non-linear, and highly iterative process (Foray, 2009).

A panel data set covering 23 European countries between 2000 and 2019 is utilized.[1] Two econometric methods are used – a knowledge production function and a diffusion model (Ruttan, 1959; Kline and Rosenberg, 1986; Jaffe and Stavins, 1995). The econometric results are used to consider whether a policy had negative or positive effects on invention and diffusion of solar PV technology, point estimates will not be commented on.[2] The policy choices were limited by data availability and country coverage. For example, there is not good, and relevant, price data from many smaller countries with few installations especially two decades ago when the solar technology was immature.

Why would any negative effects be expected? An example would be if firms are incentivised to reduce invention efforts (slightly) to focus more on diffusion due to a policy program that under a limited time make significant tax breaks for installations. As seen in previous studies, energy policy affects inventive, innovative and diffusion activity on renewable energy technologies (Popp, 2002; De Vries and Withagen, 2005; Johnstone et al., 2010a; Johnstone et al., 2012; Johnstone et al., 2010b; Rao and Kishore, 2010; Tang, 2018; Lin and Chen, 2019).

A caveat is that cross-country policy compression creates challenges on several levels. Firstly, a policy with the same name can be constructed vastly different and have amendments attached to it beyond the fiscal paid out, e.g., demands that the recipient should act in a certain way or that a package of policies is meant to support each other. Secondly, we have tried to assemble policies that was in effect or implemented in most countries, this excluded some policies. The policies tested in this paper are to a large extent aggregate that should represent a policy

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[1] Due to data availability issues the invention model have data up until 2016 while the diffusion model has it to year 2019, the issue is elaborated upon in Section 4. Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Slovak Republic, Spain, Sweden, United Kingdom.

[2] Since the policies are expected to differ in construction among the countries point estimates are not of value, but the direction of the effect is interesting.

direction. If just a few countries were studied as in some previous research, then more specific policies can be studied but here a more overarching European approach is chosen.

The paper is organized as follows. Section 2 presents literature regarding support policies for solar PV and invention and diffusion. Section 3 introduces the method and model specifications and econometric issues; Section 4 describe the data, definitions, and sources while Section 5 presents the empirical results Section 6 synthesizes and discusses the empirical results. Section 7 presents some concluding remarks.

2. Previous literature

2.1 Policy for PV

Governmental energy policies are meant to influence energy industry development into a certain trajectory for example, sustained capacity growth, new categories of energy generation, delivery, and consumption (Guidolin and Mortarion, 2010). Energy policies may involve legislation, investment promotion, or international agreements (Solangi et al., 2011). Policy can also mitigate uncertainty. Renewable energy initially had a significant cost disadvantage against fossil fuel. Few firms can finance decades of uncertainty and it has taken decades to develop cost competitive renewable energy.

A non-trivial part of many European countries' current energy policies is related to the development of renewable energy technologies. The policies can be in the form of FITs, quotas with Tradable green certificates (TGCs), bidding/ tendering schemes, low-interest loans, investment subsidies, net metering, and fiscal incentives. Both support policies and energy prices can influence inventive, innovative and diffusion activity on renewable energy technologies (Popp, 2002; De Vries and Withagen, 2005; Johnstone et al., 2010a; Johnstone et al., 2010b; Johnstone et al., 2012; Rao and Kishore, 2010; Tang, 2018; Lin and Chen, 2019).

The growth in the PV industry since 2004 has largely been driven by government support in the European and Asian countries (Jacobs et al., 2013; Wang et al., 2016; Xiong and Yang, 2016). The invention creating impact of various policies depends on technology maturity as showed by Johnstone et al. (2010b). A policies' effect on technological change depends on its stringency, predictability, and implementation. Longer policy engagement has a positive effect on innovation (Hille et al., 2020). Aldieri et al. (2020) further showed that renewable energy implementation costs depend on potential market size, geographical distances, labour cost differences, and institutional factors. Below follows a longer description of policies:

- *FITs* is longstanding an incentive program for renewable technologies (Solangiet al., 2011; Böhringer et al., 2017). The price can be set administratively or through market-based mechanism such as an auction. When a firm construct a renewable energy installation, they can receive a long-term contract which provides access to the electricity grid at an elevated guaranteed price (del Rio and Mir-Artigues, 2012). Johnstone et al. (2010) and Nicolli and Vona (2016) found that FITs was positive for solar PV innovation. Outside of Europe, FITs have been legislated in Australia, Canada, and in parts of the United States, as well as in many developing nations. According to Dong et al. (2021) the PV construction in China would virtually disappear without FITs. FITs have sometimes been costly because of exponential PV growth which generated a corresponding growth in costs (del Río and Mir-Artigues, 2012; de La Tour et al., 2013). Demand-pull policies, such as FITs, promote different learning processes, and can nurture innovation (Palage et al., 2019).
- *R&D supports* consist of a variety of grants, loans, and subsidies to help remedy technological spillovers and encourage future cost reductions. Public R&D can compensate for a firm's underinvestment caused by uncertainty and market failures (Söderholm and Klaassen, 2007; Goulder and Parry, 2008; Aschhoff and Sofka, 2009). Renewable energy technologies can be augmented by Public R&D expenditure on other technologies by knowledge spillovers (Cohen and Levinthal, 1989; Costantini and Crespi, 2008; Antonelli and Quatraro, 2010). Nemet and Baker (2009) found that cost reduction targets for solar PV could not be reached by subsidies alone and that R&D support was needed. Miremadi et al. (2019) found that R&D spending on renewable sources helped increase knowledge spillovers between the Nordic countries. Zhao et al. (2021) found that R&D support is a driver of renewable energy innovation.
- In the context of energy policy, *taxes* are intended to remedy negative externalities such as emissions and is a theoretically simple solution for correcting market imperfections (Menanteau et al., 2003; Zhao, 2010). Several tax policies exist where some European countries have energy taxes with renewable energy exemptions which allows renewable energy producers to exempt their production from tax payments (Freire-González and Puig-Ventosa, 2019). Property tax exemptions allow businesses and homeowners to exclude the added value of a solar system from the valuation of their property for taxation purposes. The Scandinavian countries and the Netherlands have used CO_2 taxes since 1990, and province in different Canadian and US states have enacted their own taxes. The recent rapid deployment of PV in the United States has been attributed in

significant part to a federal Investment Tax Credit which allows consumers to deduct 26 percent of the cost of installing a solar energy system from their federal taxes (Comello and Reichelstein, 2016).

- There are policies that directly promote renewable energy production which uses market-based incentives and quantity-based mandates to increase the share of electricity from renewable sources (Kim and Tang, 2020). *Renewable portfolio standards* (RPS) mandate firms to have a certain percentage of their total electricity production or delivery comes from renewable energy (Lauber, 2004). An alternative for the firms is to purchase renewable energy certificates. A downside found with RPS is that they can reduce trade performance in a country by inducing extra cost on its industries and encourage imports rather than own development by domestic firms where trade is free (Rickerson et al., 2007).
- *Production and investment subsidies* are intended to promote deployment of new installations. A commonplace practice is to pay for subsidies to renewables by taxing conventional electricity suppliers (Avril et al., 2012). Other investment support systems are loans for home installation of a PV system (Rai and Sigrin, 2013). Net metering systems have been introduced for small-scale renewable energy systems (Darghouth et al., 2011).
- The *European Union Emissions Trading System* (EU ETS) is currently the world's largest greenhouse gas emission trading program, governing emissions across 30 European nations covering emissions from more than 11,000 heavy energy-using installations (power stations & industrial plants) and airlines operating between these countries amounting to around 45 percent of the EU's greenhouse gas emissions (European Environmental Agency, 2019).

Over the past three decades, a literature around policy-induced inventions and innovation has emerged. The literature has assessed a "weak" version of the so-called "Porter hypothesis" which suggest that stringent environmental policies can spur innovation and lead to the growth of green technologies (Porter and van der Linde, 1995; Böhringer et al., 2017). Some policies create demand or expand markets, with positive side effects such as learning-by-doing and cost-competitiveness against other technologies where a market expansion increase returns to R&D investment for firms (Popp, 2006). The role of endogenous technological change and innovation have also been prominent in economic literature on environmental policy (Gillingham et al. 2008; Bergek and Berggren 2014).

2.2 Invention and diffusion

Policy can induce technological change in several ways and enable provision of both basic and applied knowledge. Policy intended to increase diffusion of a technology (e.g., construction subsidies) can stimulate a variety of learning by "moving down" the technologies' learning curves (Sagar and Zwaan, 2006). Popp (2019) highlight the value of public policy to promote technological development and adoption based on the "public good" nature of knowledge that creates positive externalities for the public and the innovator.

Invention and innovation are sometimes used synonymously while diffusion is treated independently. Schumpeter had a compelling argument regarding concept separation: "Innovation is possible without anything we should identify as invention, and invention does not necessarily induce innovation, but produces of itself ... no economically relevant effect at all" (Schumpeter, 1939, p. 81). Literature that concerns the development of new patents as invention research even when the authors call it innovations have bene considered. We follow the definition made by Rosenberg (1990) and Grant (2002) who defines *Invention* as: "The creation of new products and processes through the development of the new knowledge or from new combinations of existing knowledge. Most inventions are the result of novel applications of existing knowledge," (Grant, 2002, p. 333).

In the PV sector, Peters et al. (2012) found evidence of public policy-related invention. Johnstone et al. (2012) studied the determining factors of environmentally related patents and observed that both environmental policy stringency and general inventive capacity promoted environment related innovation. Kruse and Wetzel (2016) used PV patent data from the European Patent Office and a panel of 26 OECD countries over the period 1978–2009, they found that the existing knowledge stock was a significant driver of invention.

Johnstone et al. (2010a) studied patent propensity in several green energy fields and found that FITs induced innovation in solar power analyzing a patent panel data covering 25 countries over the period 1978–2003. They found that public policy significantly affects patent applications. Braun et al. (2010) studied solar and wind power technology for 21 OECD countries between 1978 and 2004 found that public R&D stimulates patent production. Lin and Chen (2019) studied China on a provincial level from 2006 to 2016 and found that invention was driven by R&D expenditures and in the long run electricity prices. Popp et al. (2011) used patent data to assess the role that technological advancement played in investment in renewable energy. Tradable green certificates induce more innovation in close to competitive technologies, whereas technology-specific policies induced innovation in technologies further away from grid-parity, such as PV (Chowdhury et al., 2014).

Diffusion occurs after invention and innovation through adoption by firms or individuals (Grant, 2002). Policy and prices affect the diffusion rate (Hansen et al., 2015). The diffusion of solar PV is a process by which an invention is transmitted over time among PV industry members (Raso and Kishore, 2010). A technologies' diffusion rate is dependent on context specific factors such as institutions, technologies, and socio-economic situation (Aldieri et al., 2020).

Bollinger and Gillingham (2012) studied the owner-occupied homes diffusion of PV panels in California and found that an additional installation increases the probability of an adoption in the zip code by 0.78 percentage points. Similar peer-effects were found by Cho et al., (2019). Sovacool and Ratan (2012) reviewed adoption of residential solar panels in Germany and United States from investors' perspective and found that political commitment, favourable legal and regulatory frameworks, competitive prices, community, and individual ownership was facilitators for solar power adoption. Palm (2016) found that factors such as Peer effects (individuals influencing each other to adopt PV) and local organizations promoting PV were identified as explanatory factors for the high local PV diffusion rates. Mirzania et al., (2020) studied South Africa and the United States respectively and found that the main success factors for diffusion was consistent policy support, which bridged the gap between research and development and market diffusion. In South Africa, the main barriers were technical and economic problems, including a lack of technological expertise, resources, and funding.

Popp et al. (2011) found that technological advancement (measured as patents) leads to a greater investment in renewable energy. New technologies are often pricier than established technologies hence cost decrease for the newer technology is possible. A price decrease can increase market shares and outcompete technologies with less cost reduction opportunity. Cost reduction can originate in learning-by-doing and an energy policy that incentives inventions or innovations can also speed up technology diffusion (Söderholm and Sundqvist, 2007; Fischer and Newell, 2008). Kavlak et al., (2018) studied learning and development for solar PV and found that government and private R&D was the most important driver of development in the 1990s whereas after 2001 scale economies drove cost reductions.

3. Method: An invention and diffusion model of PV

3.1 Invention model specifications

Consistent with prior research on inventions, annual patent counts were used to proxy inventions (Popp, 2002; Johnstone et al., 2010a). A knowledge production function framework developed by Griliches was utilized (1979; 1992). The invention estimation approach used is common in previous studies (Klaassen et al., 2005; Aldieri and Cincera, 2009; Boschma and Iammarino, 2009; Corradini et al., 2014). The empirical approach is laid out with baseline equation (1):

$$\begin{gathered} PC_{nt} = \beta_0 + \beta_1 Cumulative\ capacity\ _{nt-2} + \beta_2 Human\ Capital_{nt-2}\ + \\ \beta_3 Wage\ rate_{nt-2} + \beta_4 Polysilicon\ Price\ _{nt-2} + \beta_5 Policy_{nt-2} + T_n + \alpha_n + \varepsilon_{nt}, \end{gathered} \tag{1}$$

The dependent variable, PC_{nt}, is PV patents approved in country *n* (*n* = 1, …, *N*) for year *t* (*t* = 1, …, *T*). Control variables normally observed in the literature is added such as polysilicon price, cumulative capacity, and researcher ratio in labour force; these control variables are lagged two years. The lag is utilized because public R&D spending at time *t* may render a patent application in period $t + x$ ($x = 2$) (Nicolli et al., 2012). Country-specific fixed effects, α_n, captures any unobservable country-specific heterogeneity. The error term captures the residual variation, ε_{nt}.

Model I introduced in equation (1) is the base which four other model specifications (II-IV) expands from. The period 2000 to 2016 is tested for the specifications (see Table 1).

Table 1 Invention specifications

Model	Estimated model specification	Description
I	$PC_{nt} = \beta_0 + \beta_1 Cumulative\ capacity\ _{nt-2} + \beta_2 controle\ variables_{nt-2} +\ \beta_3 FIT_{nt} + T_n + \alpha_n + \varepsilon_{nt}$	Base model with FIT 2000-2016.
II	$C_{nt} = \beta_0 + \beta_1 Cumulative\ capacity\ _{nt-2} + \beta_2 controle\ variables_{nt-2} + \beta_3 R\&D\ flow_{nt} + T_n + \alpha_n + \varepsilon_{nt}$	R&D flow 2000-2016.
III	$C_{nt} = \beta_0 + \beta_1 Cumulative\ capacity\ _{nt-2} + \beta_2 controle\ variables_{nt-2} + \beta_3 R\&D\ stock_{nt} + T_n + \alpha_n + \varepsilon_{nt}$	R&D Stock 2000-2016.
IV	$C_{nt} = \beta_0 + \beta_1 Cumulative\ capacity\ _{nt-2} + \beta_2 controle\ variables_{nt-2} + \beta_3 Env\ Tax_{nt} + T_n + \alpha_n + \varepsilon_{nt}$	Environmental Tax 2000-2016.
V	$C_{nt} = \beta_0 + \beta_1 Cumulative\ capacity\ _{nt-2} + \beta_2 controle\ variables_{nt-2} +\ \beta_3 EPS_{nt} + T_n + \alpha_n + \varepsilon_{nt}$	Policy Environmental Policy Stringency Index 2000-2016.

3.2 The diffusion model specification

Basic technology diffusion models, which were later extended, assumed that the adoption of an invention or innovation depend on market size and the rate of increase, expressed in the following equation:

$$\frac{dN}{dt} = bN(t)(N^u - N(t)) \tag{2}$$

Where $N(t)$ is the cumulative adoption at time t and N^u is the upper limit to growth, b is the coefficient of diffusion. Söderholm and Klassen's (2007) amended version of the theoretical rational choice model used by Jaffe and Stavins (1995) is employed which assumes that the PV owner maximizes the present value of PV production net benefits. The projected total benefits of a median PV installation in country n during period t, TB_{nt}, can be expressed as:

$$TB_{nt} = \alpha_0 (CC_{nt})^{\alpha 1} \left(\int_{t=0}^{T} P_{nt}^{F} e^{-rt} dt \right)^{\alpha 2} \left(\int_{t=0}^{T} P_{nt}^{G} e^{-rt} dt \right)^{\alpha 3} \tag{3}$$

Where CC_{nt} is total installed PV capacity in country n (n = 1, …, N) for year t (t = 1, …, T). In the baseline equation P_{nt}^{F} is a policy (like Feed-in-Tarrifs) in year t, and P_{nt}^{G} is a control variable (like human capital level or input prices). Capacity in MW is utilized; hence a fixed load factor is implicitly assumed over the PV installations lifetime. Where the (simplified) total cost for a given level of PV capacity is:

$$TC_{nt} = \beta_0 (CC_{nt})^{\beta 1} (C_{nt})^{\beta 2} (Human\ Capital_{nt})^{\beta 3} \tag{4}$$

were C_{nt} represents a cost measure of installing PV capacity. A PV owner maximizes profit of PV production where the marginal benefits equal marginal costs. By differentiating equations (3) and (4) with respect to CC_{nt}, the subsequent first-order condition for profit maximization is obtained:

$$\begin{aligned} &\alpha_0 * \alpha_1 (CC_{nt})^{\alpha_1 - 1} (P_{nt}^{F})^{\alpha_2} (P_{nt}^{G})^{\alpha_3} \\ &\qquad = \beta_0 * \beta_1 (CC_{nt})^{\beta_1 - 1} (C_{nt})^{\beta_2} (Human\ capital_{nt})^{\beta_3} \end{aligned} \tag{5}$$

After rearranging, the logarithmic form of equation (5) can be written as:

$$\begin{aligned} ln\, C\, C_{nt} = \lambda + \frac{\alpha_2}{(\beta_1 - \alpha_1)} ln\, P_{nt}^{F} + \frac{\alpha_3}{(\beta_1 - \alpha_1)} ln\, P_{nt}^{G} - \frac{\beta_2}{\beta_1 - \alpha_1} ln\, C_{nt} \\ - \frac{\beta_3}{(\beta_1 - \alpha_1)} \end{aligned} \tag{6}$$

where

$$\lambda = \frac{(ln\, \alpha_0 + ln\, \alpha_1 - ln\, \beta_0 - ln\, \beta_1}{(\beta_1 - \alpha_1)} \tag{7}$$

Equation (8) is the baseline PV diffusion equation tested:

$$ln\, C\, C_{nt} = a_0 + a_1\, ln\, Human\ capital_{nt}^{F} + a_2\, ln\, Policy_{nt}^{G} + a_3\, ln\, C_{nt} + a_4\, ln\, R\,\&D_{nt} \tag{8}$$

The specifications of the diffusion models are presented in Table 2. In model VI, PV diffusion is explained by several cost related control variables. The disturbance terms represent any unobserved influences on solar power diffusions.

Table 2 Diffusion specifications

Model	Estimated diffusion equation	Comments
VI	$ln\, C\, CN_{nt} = \beta_0 + \beta_1\, ln\, C_{nt} + \beta_2\, ln\, FIT_{nt}^{G} + \beta_{3-n}\, ln\, Control\ variables_{nt}^{F} + \phi_{nt}$	Feed-in-tariff
VII	$ln\, C\, CN_{nt} = \beta_0 + \beta_1\, ln\, C_{nt} + \beta_2\, ln\, R\&D\ flow_{nt}^{G} + \beta_{3-n}\, ln\, Control\ variables_{nt}^{F} + \alpha_{nt}$	R&D flow
VIII	$ln\, C\, CN_{nt} = \beta_0 + \beta_1\, ln\, C_{nt} + \beta_2\, ln\, Solar\ R\&D\ stock_{nt}^{G} + \beta_{3-n}\, ln\, Control\ variables_{nt}^{F} + \mu_{nt}$	R&D Stock
IX	$ln\, C\, CN_{nt} = \beta_0 + \beta_1\, ln\, C_{nt} + \beta_2\, ln\, Env\ Tax_{nt}^{G} + \beta_{3-n}\, ln\, Control\ variables_{nt}^{F} + o_{nt}$	Environmental tax
X	$ln\, C\, CN_{nt} = \beta_0 + \beta_1\, ln\, C_{nt} + \beta_2\, ln\, EPS_{nt}^{G} + \beta_{3-n}\, ln\, Control\ variables_{nt}^{F} + \omega_{nt}$	Environmental Policy Stringency

3.3 Econometric issues

Patent data is binomial, and the dependent variable is count data (Baltagi, 2008; Greene, 2012). Either a negative binomial or Poisson estimators is appropriate for a count data regression (Hausman et al., 1984). The Poisson model has issues, the key issue is equi-dispersion, i.e., the variance is equal to the mean. Equi-dispersion is a problem, and models handling over-dispersion is preferred when the variance is larger than the mean. Negative binomial models can accommodate over-dispersion (Blundell et al., 1995). A common concern when handling patent data is the presence of many zero (0) (Blundell et al., 2002; Hu and Jefferson, 2009). Numerous zeros are either the result of no inventive activity, or failed efforts. The dependent variable is maintained in its original form instead of taking logs since the presence of a significant portion of zeros causes a drop of data when a logarithmic transformation is applied (Nicolli et al., 2012).

The occurrence of other endogenous policies is present, so a lag approach and fixed effects are used to mitigate endogeneity issues. Endogeneity issues can arise due to both reverse causality and omitted variables in a multi-country study. Endogeneity is concerning, especially when estimating of policy-induced effects (Nesta et al., 2014; Hille et al., 2020). Following Hille et al. (2020), given the research question regarding the heterogeneous effect different policies neither a propensity score matching, nor an instrumental variable approach was feasible or used. No statistically significant support for endogeneity was found by Hausman specification test for cumulative capacity in the invention equations. It is a possibility that other explanatory variables are endogenous in the invention and diffusion model specifications. The feed-in price and public R&D could be reduced by the government when solar PV cost falls. A point to consider is the additive error structure, where the error term, e_{nt}, is decomposed into two components so that:

$$e_{nt} = \lambda_n + v_{nt} \tag{1}$$

λ_n is a country-specific effect, while v_{nt} represent the residue stochastic disturbance term. Unobserved country-specific effects can exist in PV investment costs across the countries in the dataset related to, such as institutions and policies. Particularly institutions can be persistent thus country-specific effects are captured with a dummy variable for *N-1* (Baltagi, 2008).

4. Data sources, definitions, and descriptive statistics

4.1 The Dependent Variables

The dependent variable for the *invention model* is patent counts of granted PV patent applications based on priority year. Following an OECD approach Patent Cooperation Treaty patents were used (Hascic et al., 2008). In cases inventors from two different countries, each country obtains a count of 0.5 (Fischer et al., 2006). The geographical location for the invention is assigned after the formal inventor and not the formal applicant. The years covered are 2000 to 2016 due to data availability and reporting lags.

Bruns and Kalthaus (2020) highlighted several PV patent studies containing over 51 patent assembling methods, hence our considerations are the following. The patent data was derived from the OECD Environment Directorate who collaborate with the Directorate for Science, Technology, and Innovation. The OECD Environment Directorate have constructed patent-based innovation indicators to track developments in environment-related technologies. The statistic originates from the Worldwide Patent Statistical Database (PATSTAT) of the European Patent Office (EPO), the OECD developed and used algorithms to extract the data. Patents granted at more than one patent jurisdiction in the world were used to exclude lower value patents and to alleviate the possibility of unique patents rules.

Alternative sources for selecting patent data have become available in addition to the Green Inventory Classification, that is a rather old classification for example, IPC and EPO Y02E10/70 Cooperative Patent Classification class or the OECD ENVTECH Indicator. Since the research goal is to establish if the policies had a positive or negative effect on the variable, we are content with the more easily accessible variant of the variable selected, while if point estimates on elasticities would be made then a more precise dataset should be used.

There is an understandable criticism attached to the data source for a patent study apart from the usual pro-et-contra argument for patent data. There are good conceptual criticisms of patent data as output measure (Johnstone et al., 2017). A concern is non-patenting. (Pakes and Griliches, 1980). Not all inventions are patented, but not many substantial inventions are devoid of patenting (Johnstone et al., 2010a), but there is some degree of strategic non-patenting (Arundel, 2001). Another issue to consider is varying economic value of patents and depreciation over time (Pakes, 1985). The monetary returns of the top 10 percent capture most economic value (Scherer and Harhoff, 2000).

The dependent variable, in the *diffusion model* is installed electricity production capacities for PV derived from Eurostat. The data cover net maximum electrical capacity during the period 2000 to 2019. The variable represents existing generation capacity in a country and excluding decommissioned capacity. Electrical capacity for solar grew 700 times between 2000 and 2019 (Eurostat, 2021).

A weakness with using net maximum electrical capacity is that the output does not always contribute to the actual output of the system. For example, if subsidies are big enough then production capacity can be constructed where power output is not optimal but still give an economic profit. As showed in for example Grafström (2021) China had for a long-time incentive that encouraged firms construct wind power but not connecting the power plants to the electricity grid.

4.2 Policy and independent variables

To investigate the influence of policies on inventions and diffusion is collected and presented in Table 3. Five policy variables are tested. 1) *Feed-in tariffs;* 2,3) The stock and flow of *Public solar R&DD* spending; 4) *Environmental tax* and 5) *Environmental Policy Stringency Index.*

Table 3 Policy variables

Policy cluster	Policy instrument	Basic support mechanism
Feed-in tariffs	Fixed or premium feed-in-tariffs, Net metering, Public competitive bidding.	Market-pull
The stock and flow of Public solar R&DD spending	Research, development, and deployment programs, in million USD (2014 prices).	Technology-push
Environmental tax	Tax revenue, % of GDP.	Market-pull

Environmental Policy Stringency Index	The index covers the degree of stringency of 15 environmental policies.	Market- push and pull

FITs are based on prices, but policy designs can differ between countries and time. FITs are mostly a market-based economic instruments, which typically offer contracts of different lengths that guarantee a price to a producer of a pre-determined source of electricity per kWh fed into the electricity grid. An advantage is that the policy promotes actual energy production and not just installation. The data comes from the OECD who has cross-checked the data against other renewable energy policy databases (REN21, IEA/IRENA, OECD PINE database). The data is originally drawn from on government sources. The data include country-level values on the tariff (in USD/kWh), and length of the awarded power-purchasing agreement. Some countries use FITs with fixed rates, where the producers are assured a prearranged long-run reimbursement.

R&D-flow and *R&D-Stock* variable respectively represents a flow and stock variable of government expenditure on PV R&D in million USD (2014 prices). General- and specific purpose R&D is commonly considered when analysing a country's inventive capacity (Dechezleprêtre et al., 2013; Furman et al., 2002; Grafström, 2018a Grafström, 2018b; Wiser and Millstein, 2020; Grafström et al., 2020). The R&D data is derived from the International Energy Agency. There are issues to consider. The database could be incomplete and there can be consistency issues with respect to the geographical coverage (Arundel and Kemp, 2009; Bointner, 2014). Also, possible R&D spending from regional governments are not provided by all countries (IEA, 2012). Comprehensive R&D data from the private sector was not accessible.

The variable *Stock of public PV R&D* (K_{nt}) was built based on the perpetual inventory method (Ek and Söderholm, 2010):

$$K_{nt} = (1-\delta)K_{n(t-1)} + R_{n(t-x)} \tag{4}$$

K_{nt} is the knowledge stock in country *n* during time *t*. Additionally, δ is the knowledge stocks yearly depreciation rate ($0 \leq \delta \leq 1$), R_{nt} denotes new investments, and *x* is the years (lag) before new investments join the knowledge stock (Hall and Scobie, 2006). Following other studies (Griliches 1998; Corradini et al., 2014), a depreciation rate of 15 percent was applied.

Environmental tax (Tax revenue, percent of GDP) is supposed to capture overall climate for environmental action. A high level of environmental taxes should signal governmental priority of environmental issue and affect relative prices and investment incentives (Bovenberg and De

Mooij, 1997; Freire-González and Puig-Ventosa, 2019). Environmental taxes play a role in many European countries. In 2018, total environmental tax revenue in the EU amounted to €324.6 billion, representing 2.4 percent of EU GDP (Eurostat, 2020). The largest contributor of the environmental taxes was charged on energy which accounted for 77.7 of the total revenues from environmental taxes in 2018, well ahead of taxes on transport (19.1 percent) and pollution and resources (3.3 percent).

The *Environmental Policy Stringency Index* is constructed by the OECD. The index combines quantitative and qualitative factors related to environmental laws and regulations (Botta and Koźlak, 2014). The index covers the stringency of 15 environmental policies, primarily related to climate and air pollution. The stringency ranges from 0 (not stringent) to 6 (highest degree of stringency). The index is divided into two main subsets. There is a Market-based subset of instruments, for example, taxes on emissions, trading schemes, systems of deposit and refund and FITs (feed in tariffs). The Non-market subset includes for example the norms concerning emissions ceilings and the limit of sulphur content in diesel, and governmental subsidies for renewable energy. A policy index is valuable to investigate since according to the Porter hypothesis, stricter regulations create a scenario where firms and the environment can be winners (Porter and van der Linde, 1995). Firms get more competitive and innovative at the same time since strict regulations induce both product and process innovations which counteracts compliance cost. Furthermore, an index gives some advantages over using single policies seen in several studies who used dummy variables representing the existence of a policy. By paying more attention to the general effect of how instruments are designed, a better understanding of general policy effects is reached (Baudry and Bonnet, 2018).

Independent variables: Following economic theory, national technological development depends on three factors: (1) its invention infrastructure such as R&D employees or R&D expenditures as well as the stock of previous innovations (Grossman and Helpman, 1991), (2) its knowledge base in technology (Archibugi and Coco, 2005), and (3) its common infrastructure and industries (Jungmittag, 2006).

The variable *total researchers per thousand total employment* comes from OECD's Research and Development Statistics (RDS) database is based on the data reported to OECD and Eurostat in the framework of a co-ordinated collection. Human capital is an important input for economic growth (Romer, 1990). The research personnel variable captures human capital input in knowledge creation and country level ability to diffuse new technologies.

Polysilicon is an important input in a PV cell, which price has been on a downward path over the last decade. The input price should affect invention since a high price incentivise reduced product dependency. It is expected that a high input price decreases demand in the innovation part and incentivise cost reduction in diffusion part. Figure 1 shows the development of polysilicon price over the last two decades.

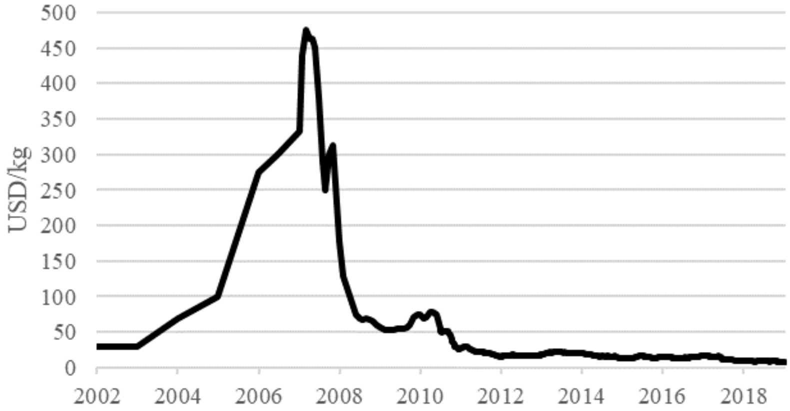

Figure 1 Polysilicon average price, USD/kg. Source: BNEF Survey.

Brent oil represent an alternative energy source and its price should affect implementation of other energy sources. The Brent price is from BP statistical review 2020.

The labour intensity of renewable energy is perceived to be higher than in conventional energy (del Río and Burguillo, 2008). Since any production, whether in research or actual construction phase, is dependent on some amount of labour input a variable that represent the *average annual wage* in 2018 USD PPPs and 2018 constant prices is used. The data contains data on average annual wages per full-time and full-year equivalent employee in the total economy and is obtained from the OECD. A rapid-developing technology usually have bottlenecks when it comes to key personnel. Solar power deployment is labour intensive, especially when it comes to installations and hence the wage rate in a country should matter.

The *real interest rate* on government bonds is utilized as proxy for the opportunity cost of public R&D expenses and other investments; these interest rates were compiled by the World Bank. Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator. A Caveat given by the World bank is that the terms and conditions attached to loans vary by country, which limit comparability to some extent (World bank, 2020). *GDP* (constant 2010 US$) is the gross domestic product. GDP sums the gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products (OECD, 2021). The *population* variable is derived from the OECD. **Table 4** presents variable statistics.

Table 4 Data descriptives and definitions

Variable	Description	Mean	Standard deviation	Minimum	Maximum
Patents granted	Number (counts) of granted PV patents.	28	77	0	663
Cumulative capacity	Installed electricity production capacities for PV (MW).	1433	5141	0	40679
R&D flow	Public expenditures on PV R&D in million USD (2014 prices and assuming purchasing power parity).	14	25	0	127
R&D stock	Stock of public expenditures on PV R&D in million USD (2014 prices and assuming purchasing power parity).	73	141	0	798
Solar Price	Weighted average total installed costs (2019 USD/kW).	2343	1239	766	5912
Environmental Policy Stringency Index (ER)	The stringency ranges from 0 (not stringent) to 6 (highest degree of stringency).	2.34	0.72	0.81	4.13
FIT	Feed-in tariff support level USD.	0.16	0.23	0	0.82
Environmental tax	Tax revenue, percent of GDP.	2.64	0.68	1.56	5.1
Human Capital	Total researchers per thousand in employment.	7.2	3.14	2.28	17.27
GDP	Gross Domestic Product, Million US$ (current PPP$)	719437	947459	13184	4644164
Average annual wage	In 2018 USD PPPs and 2018 constant prices.	37674	12218	11359	65891
Polysilicon price	Spot Polysilicon Overall Average Price USD/kg.	89.77	108.02	14.6	474
Interest rate	Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator	3.66	2.58	-0.51	22.49
Population	Persons, Thousands	20383	24141	436	83093

5. Empirical results and discussion

Five invention models are tested and presented in Table 5, with the baseline control variables and different policies that are added separately since many of these policies overlap, to some extent. For example, the environmental policy stringency consists of different support schemes such as FIT and government R&D.

Models I-IV analyse the development of patents in the PV field, between 2000 and 2016. Model V studies a slightly shorter period since data for the policy stringency index was lacking after year 2015 and some of the countries. In the case of R&D some countries did not report their spending (for example, Greece and Hungary so they were dropped in those regressions). A positive statistically significant result would indicate that the policy has a positive effect on inventions.

Table 5 Invention Models I -V

VARIABLES	**Model I** FIT	**Model II** R&D	**Model III** R&D Stock	**Model IV** Env. tax	**Model V** Policy index
Cumulative Capacity	0.0646**	0.0687***	0.0641***	0.0743***	0.00947
	(0.0240)	(0.0217)	(0.0187)	(0.0228)	(0.0278)
Human capital	-0.420	-0.351	-0.488**	-0.477	-0.546
	(0.387)	(0.250)	(0.189)	(0.372)	(0.409)
Average wage	-0.744	-0.966*	-1.142**	-0.764	-0.906
	(0.691)	(0.553)	(0.523)	(0.622)	(0.852)
Polysilicon Price	0.259***	0.307***	0.306***	0.288***	0.283***
	(0.0373)	(0.0361)	(0.0363)	(0.0415)	(0.0492)
Brent Oil	0.322**	0.299***	0.234**	0.364***	0.158
	(0.132)	(0.105)	(0.0990)	(0.120)	(0.172)
GDP	0.670	0.589	0.502	0.641	1.648*
	(0.730)	(0.573)	(0.428)	(0.667)	(0.845)
Population	3.251*	2.406*	0.695	3.473*	6.363***
	(1.771)	(1.253)	(0.673)	(1.693)	(1.718)
Interest rate	0.00637	0.0111	0.0270	0.0120	0.0360
	(0.0185)	(0.0195)	(0.0157)	(0.0190)	(0.0251)
FIT	0.466**				
	(0.220)				
Public Solar R&D		0.170***			
		(0.0584)			
Public Solar R&D Stock			0.295***		
			(0.0563)		
Environmental tax				0.200	
				(0.308)	
Env. Policy Stringency					0.269***
					(0.0915)
Constant	-24.13	-14.19	3.775	-26.28*	-56.20***
	(14.51)	(10.98)	(8.354)	(14.03)	(13.65)
Observations	371	371	371	371	252
Fixed Effects	YES	YES	YES	YES	YES
Year fixed effects	NO	NO	NO	NO	NO
R-squared	0.506	0.522	0.555	0.496	0.651
Number of country1	23	23	23	23	19

Statistically significant and positive results are found for all policies except for the environmental tax level.

For *diffusion* five models are tested with the baseline control variables and different policies added separately due to that they often contain elements of each other, such as that policy stringency contains taxes and R&D spending. The results are presented in Table 6. Observe that for some countries policy data was missing and those countries were dropped. The dependent variable is country level cumulative solar PV capacity between 2000 and 2019. Model X studies a slightly shorter period since data for the policy stringency index was lacking after 2015. A positive statistically significant result would indicate that the policy has a positive effect on diffusion.

Statistically significant results were found for the FITs, but not for the other policy variables.

Table 6 Diffusion Models VI - X

	Model VI	**Model VII**	**Model VIII**	**Model IX**	**Model X**
VARIABLES	FIT	R&D	R&D Stock	Env. tax	Policy index
Human capital	3.009**	3.049**	2.809**	2.894**	3.056*
	(1.310)	(1.310)	(1.212)	(1.196)	(1.671)
Average wage	-5.831	-6.298*	-6.255*	-5.864*	0.934
	(3.622)	(3.324)	(3.280)	(3.290)	(3.201)
Polysilicon Price	-0.685***	-0.535***	-0.552***	-0.580***	-0.431**
	(0.187)	(0.172)	(0.175)	(0.185)	(0.170)
Brent Oil	0.305	0.461	0.442	0.557	-0.763
	(0.500)	(0.501)	(0.462)	(0.472)	(0.728)
GDP	10.96***	11.24***	11.05***	11.25***	13.31***
	(2.595)	(2.354)	(2.381)	(2.554)	(2.355)
Population	-1.550	-2.727	-4.222	-2.55	12.56**
	(7.913)	(7.281)	(7.256)	(0.73)	(5.653)
Interest rate	0.00613	0.0496	0.0676	0.0655	0.386***
	(0.114)	(0.123)	(0.121)	(0.124)	(0.0976)
FIT	2.586**				
	(1.180)				
Public Solar R&D		0.273			
		(0.308)			
Public Solar R&D Stock			0.329		
			(0.316)		
Environmental tax				-0.552	
				(1.523)	
Env. Policy Stringency					0.655
					(0.391)
Constant	42.75	56.03	70.01	27.36	-170.8***
	(88.62)	(82.20)	(81.14)	(30.41)	(51.01)
Observations	414	414	414	414	254
Fixed Effects	YES	YES	YES	YES	YES
R-squared	0.744	0.733	0.733	0.730	0.791
Number of country1	23	23	23	23	19

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Several robustness checks were performed. Following Palage et al. (2019), the inclusion of the time-specific polysilicon price and Brent oil variable mean that the specifications cannot unequivocally control for other time-specific effects with yearly dummy variables. Lacking year dummy controls can be problematic because the estimated coefficients can also capture macroeconomic shocks correlated policies and patenting activity (Popp et al. 2011; Grafström, 2017). To check the robustness in the estimations, dummy variables for different time periods are included in robustness checks where the polysilicon price and Brent oil variable are excluded (Appendix B and C). The econometric analysis then includes time dummies T_n, and therefore a concern is remedied – that the coefficients on the variables of interest capture shocks correlated with both the level of R&D policies and the cumulative capacity, and innovation activity. Shocks could include any macroeconomic shocks and one can contemplate such unobserved variables that may cause the coefficients to be biased.

The diffusion specifications were run over a shorter period, 2008-2019 (Appendix C). The motivation for investigating the shorter period is that after 2008 there was a significant rise in solar installations in the countries compared to the relative sparse diffusion in the technology's relative infancy. The policy result remained significant and environmental taxes was also added to statistically significant policies that had a positive effect on solar diffusion. Polysilicon Price is statistically significant and negative. For invention a similar shorter time frame was tested with positive results for FIT and the R&D knowledge stock.

6. Discussion

Based on the findings presented in table 5 and 6, for invention and diffusion the policies investigated did not show negative counteracting effect on either invention or diffusion. A counteracting effect refers to a policy found to be statistically significant and positive for inventions are statistically significant and negative for diffusion (or the other way around). What is seen is positive effects of the policies and no negative effects. In Table 7 the results are summarised:

Table 7 Policy results

Policy	Invention	Diffusion
FIT	Positive significant	Positive significant
Public R&D	Positive significant	Not significant
Public Solar R&D Stock	Positive significant	Not significant
Environmental tax	Not significant	Not significant
Environmental Policy Stringency	Positive significant	Not significant

The positive and significant results for FITs indicate that the policy did not negatively affect the invention and diffusion process. Possible reasons for the policy being positive in both cases is that firms are either engaged in construction of solar parks or technology development. FITs are popular and have been found to be perceived by investors as one of the most effective policy (Bürer and Wüstenhagen, 2009). A large expansion of solar power could incentivise inventors and firms to invent and develop new technological solutions rather than expanding production.

For public R&D support the year-to-year spending did not affect diffusion which is not unexpected since research and development is a long run effort and some of the benefits could be adopted almost decades after the spending was initiated. As noted by Kavlak et al., (2018) in the 1990s R&D was more important and after 2001 scale economies was more important.

For invention, both the R&D flow and stock is a positive and statistically significant indicator. An argument for why the standard environmental policies (such as carbon taxes or permits) need to combine with R&D support in renewable energy technologies is that once the knowledge base in clean energy is large enough, firms will start innovating; rendering the need for public policy intervention only temporary (Acemoglu et al., 2012, Aalbers et al., 2013). In other words, the inventive capacity in the solar field was improved by long run knowledge accumulation (much in line with for example, Antonelli and Quatraro, 2010; Rennings, 2000). However, public R&D funding in both forms was insignificant for diffusion. One possible explanation is that technological change is a long run process where it takes a long accumulation period of knowledge before diffusion can be made. Imports from other countries that had R&D and production could also matter.

For Environmental tax and Environmental Policy stringency, the results are mixed. Environmental taxes do not affect neither invention nor diffusion. The result is in hindsight not unexpected. Different degrees of environmental taxes have existed in most countries for a long time, sometimes more for fiscal purposes than environmental objectives. An example would be if an energy tax is implemented then it will have environmental effects, but the true political purpose could have tax revenues. Since the variable measures tax revenue as percentage of GDP, tax efficient at tackling environmental harm would over time revenue should revenue leading to an equilibrium level of optimum externality at which the agent is indifferent between investing to reduce externality or pay taxes.

The Environmental policy stringency variable was statistically significant and positive for invention – indicating that the more emphasis a state places on environmental efforts (fiscal and legal) the higher output new solar technology will be in the country. Not surprisingly, a higher focus by public policy on mitigating and tackling climate issues will likely result in a better technological development for new solar energy.

Overall, the findings can be interpreted as a “weak” version of the so-called “Porter hypothesis” which argues that stringent environmental policies do spur inventions (Porter and van der Linde, 1995; Böhringer et al., 2017). The rise in cumulative PV-capacity can be explained two ways: first, the production costs for PV has declined sharply. Second, the expansion is the result of generous subsidies and other support policy measures in many countries (Wang et al., 2016; Xiong and Yang, 2016).

Based on the estimation results, policy crowding out effect are absent. It could be the case that politicians overall have implemented well thought true policies, at least on average. Th absents of policy crowding out does not exclude the possibility that during some stage policies in some countries could be counteracting.

7. Concluding Remarks and Directions for Future Research

The empirical findings suggest that FITs, Public R&D stock and flow, Environmental tax and Environmental Policy Stringency Index have no statistically significant negative effect on either inventions or diffusion. In most cases for invention the policies had a statistically significant positive effect. Policy crowding out does not seem to have been present.

It was not *a priori* clear whether different technological development steps would be affected differently by the same policy. Considering the solar PV technologies immaturity relative to other established technologies the answers should not be interpreted generally for all technologies. However, the method and the framework of analysis could be applied to other studies also.

The idea about crowding out policies originate in macroeconomic theories, on the other hand there are economic theories about that policies can create a “crowding in” effect. For example, post-Keynesian means that government activity could increase demand and thereby stimulate private expenditure as well.

There are several ways to improve the analysis if newer data could be obtained and enough time have elapsed to allow for a comprehensive analysis of the development in the last two decades. It could be the case that the coming decade is more important given the expectation about technological progress. At the turn of century solar power was a fringe phenomenon which have started to grow but it is yet to become a large part of the energy sector.

Outstanding questions include: How does these policies affect innovation? With sufficiently good installation price data, a broad investigation can be made to estimate a classic learning curve model where long run price change are evaluated. Future research should dedicate consideration to connected subjects to expand the knowledge of technological change and the environment.

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Appendix A: Correlation matrix and countries

Table A1: Correlation matrix

	CC	FIT	Pat	RND	FIT	Pindx	Tax	Inrest	Res	GDP	Wage	RnDS	BNP cap	Pop2	PP	Oil
CC	1,00															
FIT	0,09	1,00														
Pat	0,65	0,29	1,00													
RND	0,59	0,28	0,72	1,00												
FIT	0,09	1,00	0,29	0,28	1,00											
Pindx	0,24	0,35	0,30	0,32	0,35	1,00										
Tax	-0,07	-0,16	-0,22	-0,15	-0,16	0,17	1,00									
Inrest	-0,27	0,00	-0,25	-0,32	0,00	-0,44	0,01	1,00								
Res	0,03	-0,20	0,05	-0,06	-0,20	0,45	0,20	-0,33	1,00							
GDP	0,58	0,25	0,72	0,84	0,25	0,31	-0,27	-0,32	-0,05	1,00						
Wage	0,16	-0,01	0,26	0,35	-0,01	0,42	0,24	-0,45	0,45	0,32	1,00					
RnDS	0,76	0,31	0,75	0,91	0,31	0,39	-0,12	-0,36	-0,03	0,84	0,33	1,00				
BNP cap	0,30	0,10	0,31	0,36	0,10	0,62	0,12	-0,54	0,54	0,32	0,84	0,41	1,00			
Pop2	0,44	0,22	0,62	0,79	0,22	0,18	-0,31	-0,20	-0,16	0,96	0,20	0,73	0,13	1,00		
PP	-0,16	0,19	-0,01	-0,08	0,19	0,09	-0,05	-0,04	-0,02	-0,04	0,01	-0,06	0,10	-0,05	1,00	
Oil	0,26	0,29	0,23	0,19	0,29	0,62	-0,05	-0,12	0,25	0,16	0,14	0,29	0,48	0,05	0,26	1,00

Table A1: Countries

Austria	France	Italy	Portugal
Belgium	Germany	Lithuania	Slovak Republic
Czech Republic	Greece	Luxembourg	Slovenia
Denmark	Hungary	Netherlands	Spain
Finland	Ireland	Poland	Sweden

United Kingdom	Croatia	Malta	

Appendix B: Robustness check invention

Table B1: Models I-IV, time period 2000-2016.

Variable	**Model I** FIT	**Model II** R&D	**Model III** R&D Stock	**Model IV** Env. tax	**Model V** Policy index
Cumulative capacity	0.0609**	0.0613***	0.0568***	0.0653***	0.00684
	(0.0223)	(0.0193)	(0.0183)	(0.0213)	(0.0283)
Human capital	-0.715*	-0.609**	-0.629**	-0.743*	-0.786*
	(0.387)	(0.280)	(0.227)	(0.384)	(0.405)
Average wage	-1.049	-1.356*	-1.594**	-1.053	-1.412
	(0.816)	(0.712)	(0.664)	(0.804)	(0.980)
GDP	-0.160	-0.0378	0.253	-0.252	1.090
	(1.000)	(0.816)	(0.633)	(1.039)	(1.134)
Population	1.480	0.892	0.0199	1.022	4.975***
	(1.845)	(1.243)	(0.728)	(2.063)	(1.408)
Interest rate	0.00368	0.00749	0.0162	0.0107	0.0339
	(0.0176)	(0.0139)	(0.0117)	(0.0152)	(0.0224)
FIT	0.243				
	(0.218)				
Public Solar R&D		0.161***			
		(0.0477)			
Public Solar R&D Stock			0.256***		
			(0.0467)		
Environmental tax				-0.228	
				(0.356)	
Env. Policy Stringency					0.125
					(0.105)
Constant	0.215	8.116	17.66*	4.963	-33.65**
	(16.61)	(11.33)	(8.741)	(18.12)	(12.31)
Observations	371	371	371	371	252
Fixed Effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
R-squared	0.565	0.585	0.600	0.563	0.698
Number of country1	23	23	23	23	19

Table B2 Models I-IV, time period 2006-2016.

VARIABLES	(1) FIT	(2) R&D	(3) R&D Stock	(4) Env. tax	(5) Policy index
Cumulative capacity	0.0773***	0.0891***	0.0812***	0.0943***	0.0715*
	(0.0199)	(0.0195)	(0.0210)	(0.0185)	(0.0368)
Human capital	-0.583*	-0.553*	-0.690***	-0.642*	-0.869*
	(0.298)	(0.285)	(0.233)	(0.311)	(0.472)
Average wage	-0.248	-0.270	-0.466	-0.385	1.790

	(1.391)	(1.443)	(1.463)	(1.313)	(1.173)
Polysilicon Price	0.208***	0.259***	0.271***	0.195***	0.232***
	(0.0474)	(0.0437)	(0.0355)	(0.0596)	(0.0606)
Brent Oil	0.0528	0.0594	0.0544	0.0570	-0.133
	(0.0947)	(0.101)	(0.101)	(0.109)	(0.159)
GDP	0.182	0.128	0.117	-0.261	1.367
	(0.577)	(0.596)	(0.595)	(0.603)	(1.128)
Population	2.596	2.147	1.212	0.776	-1.344
	(1.733)	(1.548)	(1.282)	(1.660)	(3.353)
Interest rate	0.0260	0.0348*	0.0378**	0.0405*	0.0350
	(0.0206)	(0.0181)	(0.0174)	(0.0209)	(0.0238)
FIT	0.541**				
	(0.200)				
Public Solar R&D		0.106			
		(0.0687)			
Public Solar R&D Stock			0.246**		
			(0.0878)		
Environmental tax				-0.680	
				(0.443)	
Env. Policy Stringency					0.0608
					(0.0856)
Constant	-20.06	-16.02	-5.509	0.384	-6.928
	(14.54)	(15.38)	(15.41)	(18.65)	(28.07)
Observations	246	246	246	246	146
Fixed Effects	YES	YES	YES	YES	YES
R-squared	0.289	0.279	0.298	0.275	0.328
Number of country1	23	23	23	23	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C: Robustness check Diffusion

Table C1: Diffusion Models VI - X, Moving average on dependent variable, period 2000-2019.

	Model VI	**Model VII**	**Model VIII**	**Model IX**	**Model X**
VARIABLES	FIT	R&D	R&D Stock	Env. tax	Policy index
Human capital	3.189**	3.204**	3.029**	3.110**	3.240*
	(1.235)	(1.251)	(1.180)	(1.149)	(1.640)
Average wage	-5.835	-6.241*	-6.206*	-5.943*	0.751
	(3.425)	(3.207)	(3.190)	(3.143)	(3.397)
Polysilicon Price	-0.746***	-0.616***	-0.629***	-0.653***	-0.532***
	(0.189)	(0.172)	(0.175)	(0.183)	(0.164)
Brent Oil	0.308	0.474	0.465	0.549	-0.633
	(0.502)	(0.488)	(0.457)	(0.476)	(0.696)
GDP	10.62***	10.88***	10.75***	10.88***	12.67***
	(2.419)	(2.257)	(2.305)	(2.386)	(2.168)
Population	-0.908	-1.803	-2.834	-2.55	11.82**
	(7.488)	(7.003)	(7.124)	(0.75)	(5.508)
Interest rate	0.00992	0.0501	0.0630	0.0629	0.368***
	(0.110)	(0.119)	(0.116)	(0.119)	(0.0891)

FIT	2.360**				
	(1.133)				
Public Solar R&D		0.204			
		(0.283)			
Public Solar R&D Stock			0.234		
			(0.297)		
Environmental tax				-0.581	
				(1.543)	
Env. Policy Stringency					0.573
					(0.374)
Constant	37.70	47.96	57.56	29.13	-160.1***
	(83.26)	(78.20)	(78.54)	(29.20)	(47.33)
Observations	414	414	414	414	254
Fixed Effects	YES	YES	YES	YES	YES
R-squared	0.762	0.752	0.752	0.750	0.805
Number of country1	23	23	23	23	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C2: Models VI - X, period 2008-2019.

VARIABLES	**Model VI** FIT	**Model VII** R&D	**Model VIII** R&D Stock	**Model IX** Env. tax	**Model X** Policy index
Human capital	-0.281	-0.366	-0.716	-1.166	-1.085
	(1.362)	(1.431)	(1.319)	(1.472)	(1.609)
Average wage	1.671	2.297	2.469	3.296	-9.910*
	(6.703)	(6.821)	(6.908)	(7.068)	(5.329)
Polysilicon Price	-0.886***	-0.724***	-0.680***	-0.518***	-0.699***
	(0.150)	(0.148)	(0.149)	(0.156)	(0.199)
Brent Oil	-0.0748	0.0579	0.0568	0.503*	-0.202
	(0.315)	(0.339)	(0.336)	(0.280)	(0.529)
GDP	8.534***	9.080***	8.600***	9.975***	8.660
	(2.115)	(1.996)	(1.718)	(2.344)	(6.117)
Population	-19.82***	-22.41***	-23.87***	-2.59	-6.277
	(4.938)	(4.426)	(5.640)	(0.77)	(19.43)
Interest rate	-0.0254	0.0220	0.0203	-0.0283	0.0569
	(0.0970)	(0.0926)	(0.0891)	(0.0964)	(0.0852)
FIT	2.280**				
	(0.880)				
Public Solar R&D		0.235			
		(0.275)			
Public Solar R&D Stock			0.635		
			(0.418)		
Environmental tax				3.773*	
				(1.915)	
Env. Policy Stringency					0.805***
					(0.249)
Constant	149.7*	163.8*	176.2*	-59.53	151.3
	(81.10)	(88.20)	(93.98)	(74.72)	(184.9)
Observations	230	230	230	230	110
Fixed Effects	YES	YES	YES	YES	YES
R-squared	0.607	0.585	0.593	0.554	0.609
Number of country1	23	23	23	23	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C3: Diffusion Models VI - X, With year Fixed effects, period 2000-2019.

	Model VI	**Model VII**	**Model VIII**	**Model IX**	**Model X**
VARIABLES	FIT	R&D	R&D Stock	Env. tax	Policy index
Human capital	2.590*	2.648*	2.554*	2.596*	3.838**
	(1.381)	(1.495)	(1.457)	(1.485)	(1.724)
Average wage	-5.407	-6.311*	-6.387*	-5.923	-0.527
	(4.137)	(3.650)	(3.486)	(3.767)	(3.386)
GDP	9.064*	9.730**	9.905**	10.39**	15.75***
	(5.033)	(4.660)	(4.521)	(4.934)	(4.056)
Population	-3.960	-4.821	-6.238	-2.59	17.18**
	(8.268)	(7.630)	(7.160)	(0.77)	(7.945)
Interest rate	-0.0643	-0.0330	-0.0196	-0.0180	0.323***
	(0.132)	(0.150)	(0.150)	(0.143)	(0.0780)
FIT	2.415*				
	(1.269)				
Public Solar R&D		0.198			
		(0.316)			
Public Solar R&D Stock			0.348		
			(0.354)		
Environmental tax				-0.123	
				(1.610)	
Env. Policy Stringency					1.002*
					(0.538)
Constant	66.39	81.16	94.32	31.39	-212.3**
	(92.30)	(86.59)	(81.85)	(29.35)	(74.20)
Observations	414	414	414	414	254
Fixed Effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
R-squared	0.758	0.748	0.750	0.745	0.819
Number of country1	23	23	23	23	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1