Green industrial policies and domestic production of biofuels: an econometric analysis of OECD countries

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Abstract

The purpose of this paper is to investigate the relationship between green industrial policies and domestic biofuel production among OECD countries. The analysis builds on a data set including 24 OECD countries over the time period 2000–2016. This panel is estimated using a variant of the so-called Poisson pseudo-maximum-likelihood model and includes the mix of demand-pull (biofuel blending mandates) and technology-push policies (government R&D), as well as the interaction between these two types of instruments. The results suggest a positive relationship between blending mandates and domestic biofuel production. Thus, a more stringent blending mandate does not only increase the use of biofuels, but also domestic production (as a share of total fuel use). Government R&D has not, however, induced domestic biofuel industrialization processes. The results even suggest a negative interaction effect between government R&D and blending mandates, in turn implying that these two policies target different technological fields. The blending mandates tend to primarily favor commercialized first-generation biofuels, while government support to biofuel R&D has instead been focused on advanced biofuel technology.

Keywords Biofuel production · Ethanol · Blending mandates · Government R&D · Policy mix

1 Introduction

There is a rich literature addressing the relationship between environmental policy and technical change and innovation [see Popp (2019) for a recent overview]. This research has investigated the dynamics of the development and diffusion of zero-carbon technologies, including wind power, solar energy, and biofuels. During the last decade, this literature has increasingly raised the question of how policy can be introduced to ensure that the novel, sustainable technologies can grow into fully

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fledged industrial structures, which, besides greenhouse gas mitigation, also promote competitiveness, industrial growth and job creation. Governments increasingly pursue such green industrial policy ambitions (Rodrik 2014; Schmidt and Huenteler 2016; Gomel and Rogge 2020). Through green industrial policies, it is argued, the domestic industry could gain a first-mover advantage and, thus, tilt the future path of technological development closer to the country's initial comparative advantages (Altenburg and Assmann 2017). In this paper, we investigate the impact of various green industrial policies—and their interaction—on domestic industrialization processes in the empirical context of biofuel production in OECD countries.

The road transport sector is the largest contributor to global warming (EC 2016; Fuglestedt et al. 2008), and this has led to a strong push for climate policy interventions targeting this sector, including policies promoting the production and use of biofuels. Not only are biofuels considered carbon-neutral,¹ the support of domestic biofuel production could also, it is argued, help attain other political goals such as improved energy security, job creation in rural areas, and improved terms-of-trade (e.g., Ackrill and Kay 2014; Ng et al. 2010; Pilgrim and Harvey 2012; Stefanescu-Mihaila Olivia 2016; Tosun 2016; Uriá-Martínez et al. 2018). Ebadian et al. (2020) find energy security, rural development and job creation to be the main drivers behind the initial development of biofuels in countries around the world. These types of benefits are often emphasized in the various national bio-economy road-maps [see Bracco et al. (2018) for an overview], which tend to form the basis for the implementation of specific policy instruments.

Green industrial policies in the context of biofuel development have typically comprised a mix of so-called demand-pull and technology-push instruments (see further Sect. 2). In the former case, many countries have adopted so-called biofuel blending mandates requiring a minimum percentage of biofuels in transport fuels sold to the consumers at the pump (Hunsberger et al. 2017).² Such policies can be expected to stabilize the domestic demand for biofuels, something that in turn could encourage new investment in the sector (Charles et al. 2013). The technology-push instruments include government support for research and development (R&D), including pilot and demonstration projects (Hellsmark et al. 2016a; Palage et al. 2019a). This support facilitates the provision of basic and applied knowledge, which will be needed to progress novel biofuel technologies and improve their performance (Costantini et al. 2015). The link between this mix of policy instruments and domestic industrialization could in turn be strengthened by the presence of so-called

¹ Not all biofuel use is carbon neutral, and the climate impacts associated with substituting biofuels for fossil fuels vary with technology, inputs, and feedstock (Don et al. 2012; Williams et al. 2016). Even negative environmental effects of biofuels have been observed (Hoekman et al. 2018; Hoekman and Broch 2018). The focus of this paper is, however, on the impacts of policy on biofuel production, and not on the performance of this production in terms of carbon mitigation and/or other types of environmental footprints.

² A limited number of countries have instead introduced blending mandates at the production side. In this paper, however, we focus on blending mandates that regulate the use of biofuels (see further Sect. 3.2).

home bias in global trade and technology development (Bacchiocchi and Montobbio 2010).

Since the turn of the century, we have witnessed a substantial increase in the use of biofuels. Specifically, over the time period 2000–2016, global biofuel use increased by 668% reaching a total of 2.3 million barrels per day (EIA 2020a). Previous studies confirm that the biofuel blending mandates have contributed to this rapid growth (Hunsberger et al. 2017; Lamers et al. 2011; Swinbank et al. 2011). Moreover, existing literature also shows that both blending mandates and government R&D have assisted in inducing technological development in the biofuel field, typically measured through patenting activity (Costantini et al. 2015; Brolund and Lundmark 2014; Karmarkar-Deshmukh and Pray 2009; Palage et al. 2019a).

Nevertheless, while the above research has addressed the relationship between biofuel policies on technological change and innovation, there is a lack of studies addressing the policy impacts on industrialization per se. It should be clear that the nature of this relationship is far from clear. Biofuel blending obligations can typically be met by both domestic and imported biofuels, and while government R&D support has led to significant technological advancements, these may not necessarily be intertwined with the development of domestic industries. For this reason, the following research question is posed: have green industrial policy instruments influenced the development of domestic biofuel production?

The purpose of this paper is to investigate the influences of blending mandates and government R&D on the emergence of domestic biofuel producing industries. This is achieved in the context of biofuel development in 24 OECD countries over the time period 2000–2016. The empirical analysis relies on a panel data set, which is estimated using a variant of the so-called Poisson pseudo-maximum-likelihood model. The data include the mix of demand-pull and technology-push policies, as well as the *interaction* between these two types of policy instruments. This implies that we also investigate whether the impact generated by one of these policies will differ depending on the presence and the ambition level of the other policy. For instance, the impact of government R&D could differ at the margin depending on whether it is accompanied by ambitious blending mandates (and vice versa) (see Sect. 3.2 for further elaboration). In brief, the results suggest a positive relationship between blending mandates and domestic biofuel production, but there is no corresponding effect in the case of government R&D support. There is even evidence of a negative interaction effect between these two policy instruments.

In the next section, we outline a few key lessons from the literature, and with a special emphasis on the functioning of blending mandates. Section 3 displays the data sources and definitions, including an overview of the variables included in the empirical investigation. In Sect. 4, we outline the econometric model specifications. The empirical results are presented in Sect. 5 and discussed in Sect. 6. Finally, Sect. 7 provides some concluding remarks and points out a few important avenues for future research.

2 Green industrial policy: lessons from the literature

2.1 Demand-pull and technology-push instruments

The environmental and energy economics literature has devoted increased attention to the role of endogenous technological change and innovation (Gillingham et al. 2008; Popp 2019). This implies addressing the feedback mechanisms by which market signals and policy could change the direction of technological change towards cleaner technologies. In this paper, we focus on the role of policy in managing structural change in ways that account for both productivity and environmental (including climate) challenges in a coordinated way, i.e., green industrial policy (Rodrik 2014). Thus, while previous research has focused on the policy impacts on innovation, we address the corresponding effects on structural change and domestic industrialization.

The green industrial policy mix tends to build on two types of policy instruments. The first type includes so-called technology-push instruments that facilitate the provision of basic and applied knowledge. Examples include tax breaks for private R&D, direct government R&D subsidies, and the provision of public loans (Edler et al. 2013). Such policies can internalize technology market imperfections (i.e., knowledge spill-overs) and help promote an efficient level of R&D activity and basic knowledge generation (Popp 2019). The second policy type concerns so-called demand-pull instruments, which aim at the diffusion of new technologies and promote various learning processes by “driving down” the technologies learning curves (Sagar and Zwaan 2006). Examples include investment support to production (e.g., feed-in tariffs), quotas, and public procurement (Edler et al. 2013). Such (tacit) knowledge generation could also be associated with significant spill-overs (Lehmann and Söderholm 2018; Peters et al. 2012).

In this paper, we focus on the mix of government support to biofuel R&D and biofuel blending mandates, and it is important to acknowledge that these instruments could interact with each other in important ways. Demand-pull instruments promote the adoption of new technologies, and the experience (learning) gained through production and use could lead to the encountering of new problems and the discovery of new opportunities, in turn raising the rate-of-return of additional R&D (Rosenberg 1982).³ Hence, this feedback loop helps producers to optimize the production process and improve its economic performance even further. In other words, the learning that is encouraged by the demand-pull instruments will make additional R&D more productive. This is also in line with the literature on absorptive capacity, which recognizes that in order to benefit from learning processes, societies must invest in R&D, since it contributes to an ability to recognize and make use of the information generated through learning (Cohen and Levinthal 1990). This implies, thus, that demand-pull instruments, which are designed and implemented

³ This is also consistent with the so-called ‘chain-linked’ model of innovation (Rosenberg 1982).

in isolation from the government R&D programs, could be less effective (and vice versa) (Arrow et al. 2009).

Previous studies on the interaction between various energy policies have addressed—and in part corroborated—this positive feedback loop in the context of demand-pull and technology-push instruments and their impacts on innovation (e.g., patenting outcomes) [e.g., Palage et al. (2019b) for solar PV, Lindman and Söderholm (2016) for wind power, and Costantini et al. (2017) for energy-efficient technologies]. Still, if the government does not support R&D efforts that align with the problems encountered by firms in the production stage, the effect of demand-pull instruments on technological change (and ultimately on production) will be less profound. In other words, the specific nature and the magnitude of this policy interaction effect remain an empirical question.

This last remark, we argue, is relevant in the case of biofuel development. In contrast to both solar PV and wind power, biofuel technology is a more complex field, and unlike electricity, biofuels are heterogeneous products. Biofuels can be divided into two main categories: first-generation fuels and advanced biofuels (second, third, and fourth generations). First-generation biofuels are made from food crops grown on arable land, e.g., crop's sugar, starch, or oil content, and converted into ethanol and/or biodiesel. This conversion technology is relatively mature, and the feedstock is available in the world market. Close to all ethanol in the world has been derived from starch- and sugar-based feedstock (OECD 2019). However, due to a growing concern about the competition for arable land and rising food prices, policy efforts to develop non-food biofuel production, not least second-generation biofuels from lignocellulosic biomass, have been initiated (Ho et al. 2014; Panoutsou et al. 2013). These novel technologies have, however, not reached commercialized production scales.

For this reason, government R&D and biofuel blending mandates may promote different types of processes and biofuels (Bacovsky et al. 2013). This implies less scope for positive feedback loops, and even a more intense competition for the limited expertise in the field (e.g., process engineers). The sign and the magnitude of the policy interaction effect become uncertain; the (marginal) impacts of more stringent⁴ blending mandates on domestic biofuel production may be unaffected (or even more modest) in the presence of generous government R&D support.

Finally, while green industrial policies may help address technology and environmental market failures, they also risk leading to misallocation and regulatory capture (Altenburg and Assmann 2017). Policies that target specific sectors or technologies could be more prone to regulatory capture by different interest groups than more neutral (economy-wide) policies (Lerner 2009; Aalbers et al. 2013; Lehmann and Söderholm 2018). For this reason, Rodrik (2014) argues, the institutional design of green industrial policies needs to be characterized by embeddedness, discipline, and accountability. For our purposes, though, it is also important to note that since

⁴ In this paper, more stringent blending mandates refer to increases in the percentage ethanol share required in the fuel mix; it does not refer to requirements concerning the type of biofuel (e.g., advanced versus first generation).

biofuels come in many forms, some interest groups will lobby for certain technologies and fuels while other groups will instead promote competing alternatives (Oliveiraa et al. 2017).

2.2 The economics of biofuel blending mandates

A blending mandate is a demand-pull instrument that regulates the ratio of biofuels to total fuels sold to consumers at the pump. The motivations behind the adoption of such a blending mandate are often twofold: to replace fossil fuels with biofuels and stimulate the emergence of a domestic biofuel sector (Ebadian et al. 2020). The coupling of ethanol to the conventional transport fuel (petrol) stabilizes customer demand for ethanol by guaranteeing a market. This also reduces the price volatility originating from fluctuations in the ethanol feedstock prices; ethanol is mixed with petrol for which demand tends to be own-price inelastic. Moreover, without a blending mandate, biofuels and fossil fuels become close substitutes, which would lead to biofuels losing competitiveness during times of low oil prices and/or expensive feedstock prices (Arnold et al. 2019; Ghoddusi 2017a, b).

Previous research has often departed from the US biofuel fuel market, in turn assuming an endogenous price formation of oil and arable crops and that the blending mandate is (by default) met with domestically produced ethanol.⁵ De Gorter and Just (2009) (theoretically) and Wu and Langpap (2015) (empirically), predict decreasing petrol prices and increasing crop prices as a consequence of combining a blending mandate with ethanol subsidies. In the context of the 24 countries assessed in this study, though, policies cannot be expected to cause changes in world prices; countries are instead expected to compare the (exogenous) world price of ethanol to domestic ethanol production prices. The decisions that are taken based on this comparison will then determine the share of imported versus domestically produced fuels (Fabiosa et al. 2010; Feenstra and Taylor 2012). Domestic ethanol production costs will be influenced by national policies and feedstock prices. A blending mandate at the national level could affect domestic ethanol production costs through increased competition for the feedstock and/or economies of scale in production. In practice, however, such impacts are likely small since domestic ethanol can be replaced with imported ethanol and/or imported feedstock.

3 Data

In this paper, we employ data for 24 OECD countries over the time period 2000–2016, i.e., a total of 408 annual observations in the base model estimations. All countries in the sample are listed in Table 4 in the Appendix, and Table 5 provides descriptive statistics for all included variables. This choice of time period and countries has been based on the nature of the data, as well as on data availability and

⁵ The US blending mandate is implemented on the supply side (see also Sect. 3).

reliability. Prior to 2000, ethanol production was concentrated to a few countries in the world (e.g., Brazil), and so were policies supporting domestic biofuel production. Government biofuel R&D has, however, existed in several countries since the mid-1970s. Still, in this case, data availability is limited, in particular prior to 2000. Our data sample ends in 2016 due to lags in data reporting in some countries. All countries in the panel are OECD members, although eleven OECD countries had to be excluded: Chile, Estonia, France, Greece, Iceland, Israel, Luxembourg, Norway, Portugal, Slovenia, and the US. The US and France have been excluded since these countries have adopted supply-side blending mandates; i.e., their production of biofuels is predetermined. This should not be confused with the biofuel blending mandates implemented on the fuel users, which, as noted above, can be satisfied with both domestic and imported biofuels.⁶ The remaining countries were excluded (dropped in the estimation) due to being either singletons or separated by a fixed effect.⁷

The reason for focusing on OECD countries is twofold. First, they are all high-income countries and would naturally specialize in capital intensive economic activities. For this reason, they are likely to be impacted by specific policy instruments in similar ways (compared to any impacts on low-income countries). Second, harmonized data for ethanol production levels as well as government bioenergy R&D expenditures are available for all OECD member states (e.g., from the International Energy Agency and the US Energy Information Administration, respectively). It should also be noted that even if some countries had to be excluded due to data availability reasons, deliberate efforts have been made to obtain a data set consisting of both the most progressive nations in the biofuel field (e.g., Canada, Finland, and Germany), and countries with less-developed biofuel sectors (e.g., South Korea and Japan).

In sum, given this paper's focus on the policy impacts on domestic biofuel production, we have chosen a time period for which biofuel policies and ethanol production have emerged at a wider scale. Countries have been chosen based on comparability, both in terms of income level and data definitions, yet providing enough variation along the scale of industry maturity.

⁶ The US is also difficult to include since there is a lot of policy variation across states, and we want to avoid the intermingling of federal and state levels.

⁷ Singletons refers to the case where there is not enough within-group (e.g., within-country) variation to estimate the coefficients for the group, while separation occurs when a predictor variable (or set of predictor variables) perfectly predict the outcome variable. Both issues are magnified for models featuring many fixed effects and data samples with many zeros. Drops are, therefore, expected in our estimations. We employ Stata's statistical package PPMLHDFE (more about this estimator in Sect. 4.2), which drops the groups in a systematic and step-wise procedure that does not introduce any biases (Correia 2015; Correia et al. 2019a). For further explanation and discussion on the matter of singletons and separation by fixed effects, see Correia et al. (2019a, b, 2020), and Santos Silva and Tenreiro (2010, 2011).

3.1 The dependent variable

Our dependent variable is domestic ethanol production as share of total fuel use in the transport sector, i.e., the ethanol production share (EPS). The data needed to construct this variable were extracted from EIA (2020a). Ethanol production and aggregate fuel use are measured in average thousand barrels per day over 1 year. It is important to comment on one limitation of this variable. As noted above, biofuels are heterogeneous goods, and can be divided into two key categories: first-generation versus advanced biofuels. Figure 1 illustrates first-generation and advanced (i.e., second-, third- and fourth-generation) biofuel production in different regions of the world (in 2019). It displays how the first-generation fuels still dominate the world biofuel market, while the market shares for the advanced fuels remain low.

As for ethanol produced worldwide, about 60% comes from corn, 25% from sugar cane, 7% from molasses, 4% from wheat, and the remainder from other feedstock such as grains, cassava, sugar beets and lignocellulosic biomass (OECD 2019). In other words, in essence all ethanol produced in the world is derived from starch- and sugar-based feedstocks and, thus, belong to the category first-generation biofuels. However, our data do not distinguish between ethanol based on different feedstock. This will affect the interpretation of some of the empirical results, e.g., with respect to the role played by government R&D support (see also Sect. 3.2).

In the early 1990s, total production of ethanol in the OECD countries was virtually non-existent, but it has grown consistently since then. Apart from the USA, the three countries with the largest volumes of domestic ethanol production in the OECD region are (in descending order) Canada, Germany, and Spain. Nevertheless, in 2016, about a quarter of the total use of ethanol was imported, primarily from Brazil (EIA 2020a). Figure 2 illustrates the development of the ethanol production share (EPS) in our 24 sample countries over the time period 2000–2016.

In the early 2000s, EPS was close to zero for all sample countries, but it has since then grown at a fairly rapid pace in some parts of the world (e.g., Hungary, Belgium), at a more moderate pace in others (e.g., Spain, Poland), and not at all in a few other ones (e.g., Denmark, Japan).

3.2 The independent variables

3.2.1 Green industrial policy variables

The focus of this paper is the role of policy for stimulating the production of ethanol, and we address both demand-pull and technology-push policies. As noted above, the key demand-pull instrument in the case of ethanol production has been the blending mandate. In our sample, many countries have introduced separate mandates for ethanol and biodiesel, respectively. Our blending mandate variable, BLEND, incorporates the respective ethanol mandates, but also a few “open” mandates for which the biofuel type is not specified in advance.

Fig. 1 Production of biofuels (PJ) from first-generation and advanced biofuels by world region, 2019. Data limitations prevent us from showing ethanol separated from biodiesel, as well as disaggregated by country. Source: OECD/FAO (2019)

The BLEND data were collected mainly from ePURE (2018), and USDA (2018) (Beckman and Nigatu 2017), but have also been complemented with data from various government webpages. Figure 3 illustrates how the respective blending mandate shares have developed over the chosen time period, and how they differ across the 11 sample countries that introduced a blending mandate during the period. Among these, Germany was first out to adopt a blending mandate (4.4% in 2009), followed by Belgium (7%), Canada (5%), Latvia (4.5%), and Japan (0.6%) in 2010. The mandates typically stayed stable at the introduction level or increased over the six remaining sample years, except for Spain that eliminated its blending mandate in 2016, and Belgium that, in 2014, reduced its mandate from the highest level in the sample to a level closer to the sample average.⁸

Our technology-push policy variable builds on government biofuel R&D expenditures. Such support to R&D has historically played a key role for the fast growth of first-generation biofuels produced from arable crops. Today, these biofuels are associated with developed production technologies and supply chains and are produced commercially in several countries. During the last two decades, therefore, government support to biofuel R&D has been heavily focused on the advanced biofuels (Palage et al. 2019a; IRENA 2013; Kumar et al. 2013; Toivanen and Novotny 2017).

Governments of countries, which do not possess a comparative advantage in first-generation biofuel production, may be more likely to invest in building up an advanced biofuel sector. This has been especially evident among the Nordic countries, such as Finland and Sweden, which face a strong demand for zero-carbon

⁸ There are indications that some countries have had years during which they were not successful in complying with their blending obligations (Ebadian et al. 2020). Nevertheless, these deviations have overall been small, and we do not expect these to alter the interpretation of the empirical results.

Fig. 2 The development of the ethanol production share (EPS) in 24 OECD countries, 2000–2016. Source: EIA (2020a)

Fig. 3 The development of blending mandates (percentage shares) in 11 OECD countries, 2000–2016. The countries in our sample that did not have a blending mandate at any point in time during the chosen period are not shown. These are Australia, Denmark, Finland, Ireland, Italy, Netherlands, New Zealand, Poland, Slovakia, South Korea, Sweden, Switzerland, and the UK

transport fuels and with low production volumes of first-generation biofuel production. These countries focus on the development of second-generation production based on the conversion of forest biomass (residues) into biofuels (Hedeler et al. 2020). However, since Finland and Sweden are pioneers in advanced biofuel technology, they may not necessarily be able to fully appropriate the spill-over benefits of past R&D efforts in terms of domestic production (Miremadi et al. 2019). In other

words, countries that invest a lot in government biofuel R&D support are not necessarily large producers of biofuels.

Government R&D expenditures will have long-lasting impacts on knowledge accumulation and technological change, and it is therefore important to abstain from a sole emphasis on annual changes in government expenditures. Instead, we assume that lagged government biofuel R&D outlays add to a knowledge stock (see also Palage et al. 2019b). Specifically, we have:

$$\text{R\&Dstock}_{i,t} = \text{R\&Dexp}_{i,t-x} + (1 - \delta)\text{R\&Dstock}_{i,t-1}, \quad (1)$$

where $\text{R\&Dstock}_{i,t}$ denotes the government R&D-based knowledge stock; i indexes the sample countries and t years. Equation (1) builds on the so-called perpetual inventory model in which a given fraction of the previous year's stock adds to this year's stock. This is in turn an outcome of the rate of knowledge depreciation, δ ($0 \geq \delta \leq 1$). Furthermore, $\text{R\&Dexp}_{i,t-x}$ denotes the annual government expenditures to biofuel R&D, and x is the number of years it takes before these expenditures generate new knowledge, and thus add to the stock. In other words, through this specification, we acknowledge that government R&D support does not have instantaneous effects on knowledge generation, and any acquired knowledge depreciates in the sense that the knowledge generated through past government R&D efforts gradually become outdated.

To construct the R&D-based knowledge stock, in the baseline case, we assume a time lag of six (6) years, and a depreciation rate of 10% ($\delta=0.10$). The choice of depreciation rate builds on Nordhaus (2002), and this assumption reflects the relatively rapid development of bioenergy technologies during the last decades. Popp (2015) shows that the time lag between government R&D expenditures in the energy field and private energy patents can be both longer and shorter. In the specific case of biofuels, there appear to be discernable impacts already after 1–2 years, but the most profound impacts occur after 6–7 years. For this reason, we employ time lags of 2, 4, 6 and 8 years in the R&D-based knowledge stock (i.e., $x=2, 4, 6, 8$). The 6-year lag is used as the baseline assumption.

The International Energy Agency provides “Detailed Country RD&D Budgets” (code 34, “Biofuels incl. liquids, solids, and biogases”) in IEA Data Services (2020) for the year 1974 and onwards. In 1974, the respective domestic R&D expenditures were close to zero, and these low numbers represent our initial conditions when constructing the R&D-based knowledge stock.⁹ The data on government expenditures used in the calculations are in million USD based on 2017 prices and exchange rates.

Figure 4 shows the resulting knowledge stocks for our sample countries over the period 2000–2016. Overall, Japan has the largest R&D-based biofuel knowledge stock, followed by Canada, the Netherlands and Sweden, while the developments of this stock have been significantly more modest in countries such as, for instance, Turkey, Mexico, and Latvia.

⁹ For instance, the R&D knowledge stock reported in 1990 for a specific country is (in the baseline case), a function of the accumulated R&D expenditures during the period 1974–1989, and with a 10% depreciation rate attached to the stock.

To address the potential policy interaction between the demand-pull and the technology-push instrument, we also introduce an interaction variable. The BLEND variable is multiplied with the R&Dstock variable, and the resulting variable, R&D_BLEND, will be used to test the null hypothesis that a marginal increase in, for instance, the mandated biofuel share will have the same impact on the ethanol production share regardless of the magnitude of the R&D-based knowledge stock. We also test an alternative specification of this interaction effect in which we take the product between the R&D variable, R&Dstock, and a dummy variable taking the value of one (1) if a blending mandate is in place, i.e., if BLEND > 0, and zero (0) otherwise. This alternative interaction variable is denoted R&D_BLEND_D.

As noted above, previous research has tested the hypothesis that demand-pull and technology-push policies reinforce one another in a positive manner. In our context, this would imply that whereas a blending mandate stabilizes the domestic demand for biofuels, government R&D helps enabling the growth of a domestic biofuel sector to meet that demand. Still, as noted in Sect. 2.1, such a positive interaction is far from certain. This interaction may even be negative if, for instance, more stringent blending mandates primarily promote the use of first-generation biofuels while at the same time crowding out the domestic interest in advanced biofuels. The sign and the statistical significance of this interaction variable, therefore, remain an empirical question.

3.2.2 Control variables

In addition to the above policy factors, we also test a set of control variables. First, we address the role of end-user petrol prices (including any taxes). The domestic petrol price can influence the incentives to invest in domestic ethanol production through two channels: consumer's fuel choices, and/or the optimization of the produced quantity. The impact of changes in the petrol price on ethanol use depends on the presence of blending mandates, i.e., a decrease if a blending mandate is in place (ethanol and petrol are complements), and an increase in the absence of a blending mandate (fuels are substitutes). In the case of the 24 countries assessed in this paper, the two fuels are predominantly complements due the increasing trend of blending mandates, and because flexi-fueled cars so far remain relatively few. We also anticipate low transmission from changes in total fuel demand induced by changes in the petrol price to domestic production of ethanol, this since overall fuel demand tends to be own-price inelastic.

In terms of production, domestic ethanol producers should in principle be able to take advantage of domestic price fluctuations in the relative prices between various feedstock and fuels in the world market. In practice, however, due to international trade, the domestic arable crop prices are often correlated with world crop prices, and this reduces the gains from intertemporal price optimization (Bakucs et al. 2008; Olper and Raimondi, 2008; Vasciaveo et al. 2013).¹⁰ The coupling of ethanol

¹⁰ Domestic policies and location are factors that can both increase and decrease price integration. Differences in econometric method and time period studied also influence the findings, see Ghoshray (2011) for a discussion on market integration of agricultural products in theory, method, and empirical findings.

Fig. 4 The development of government biofuel R&D-based knowledge stocks for 24 OECD countries constructed with a 6 years lag, 2000–2016 (million USD, 2017 prices and exchange rates). Source: IEA Data Services (2020)

to fossil fuels has led to a causal price relationship where fossil fuel prices influence the arable crop prices, even though not all fossil fuel price shocks will transmit to the agricultural sector (Duc Hong et al. 2019; Taghizadeh-Hesary et al. 2018). For the above reasons, we do not expect domestic variations in end-use petrol prices to influence domestic ethanol production. The main reason for including domestic petrol prices is to account for national (e.g., carbon) taxes, which overall constitute around 50–60% of the consumer petrol price. By accounting for such influences, we reduce the risk for endogeneity caused by omitted variable bias following the presence of country-specific time-varying policy change.¹¹

In the empirical part, we employ data on domestic petrol prices to create the variable PETROL, and an interaction variable PETROL_BLEND_D. The PETROL variable is the household end-user price per liter of petrol (constant 2015 USD using PPP), i.e., the petrol price (including taxes) at the pump. The petrol can contain up to 10% ethanol. The data have been drawn from the database OECD.stat (2020).¹² The BLEND_D component in the new interaction variable is a dummy variable that

¹¹ Clearly, the time-invariant effects are already accounted for with the inclusion of country-specific fixed effects (see further Sect. 4).

¹² The OECD.stat (2020) dataset is originally from the *World Energy Prices in Transport* dataset provided by the International Energy Agency, and it can be accessed at EIA (2020b). The PETROL variable is calculated as the arithmetic average of the household end-user price for the unleaded premium 95, unleaded premium 98, and unleaded regular petrol (OECD documentation 2017).

takes the value of one (1) in case the country has introduced a blending mandate (and zero (0) otherwise).

Tariffs on imports are classical industrial policy measures aimed at supporting infant domestic industries. Information about tariffs specifically targeting biofuels is, however, not available,¹³ and we have only been able to explore the consequences of an average measure of import tariffs for all agricultural raw materials. For our purposes, the variable *TARIFF* is a simple average (%) of so-called AHS, which stands for ‘effectively applied’, and measures the lowest available tariff. These data are drawn from the World Bank through their database the *World Integrated Trade Solution* (WITS, 2020).

The tariff variable has missing data for South Korea and New Zealand, and a few missing observations for Turkey, Slovakia, and Czech Republic (in total 42 observations). Since the missing observations are relatively few (10% of the total observations, see also Table 5 in the Appendix), and the variable is not central to the analysis, we explore the outcome of the variable while keeping in mind its limitations. Still, while it makes sense to incorporate this variable for robustness reasons, the role of trade tariffs is anticipated to be limited due to the significant presence of EU countries, which do not put tariffs on other Member States, in the data sample.

There may be concerns about measurement errors with respect to the tariff variable (Nicita and Olarreaga 2007). However, the most common sources of such errors can primarily be attributed to developing countries where smaller agreements and product origins are not always known or reported due to weak government authorities (e.g., Shaar 2019). Moreover, disruptions of imported-weighted averages are also mostly a concern in the case of developing countries. Our focus on OECD countries over a relatively recent time period, and on a manufacturing sector for which there tend to be few specific duties, should, therefore, imply few concerns for profound measurement errors. Of course, this does not suggest that measurement errors necessarily are non-existent; in Sect. 4.2, we, therefore, also briefly discuss how our estimator affects the risk for endogeneity following measurement errors.

Finally, we also tested to include a number of additional independent variables, including GDP per capita, GDP, arable land (ha), cereal yield (per ha), agricultural employment (% out of total workforce), the value of the oil rent (as share of GDP), and financial support to the agricultural sector. However, none of these variables were found to have a statistically significant effect on the ethanol production share, and their inclusion did not alter any of the results reported below (specific estimation results are available from the authors on request).

¹³ Attempts were pursued to address the role of farm subsidies and tariffs on imported ethanol, this based on data from WITS, OECD, World Bank, and FAO. Still, for data availability reasons, we could not address this.

4 Model estimation and econometric issues

4.1 Model specification

In all model specifications, the dependent variable equals the domestic ethanol production as a share of total fuel use in the transport sector, i.e., the ethanol production share (EPS). In the base model specification, we assume that EPS will be affected by: (a) demand-pull instruments in the form of blending mandates (BLEND); (b) technology-push instruments in the form of government R&D support to biofuel development (R&Dstock); and (c) fixed effects. We have:

$$\text{EPS}_{it} = \beta_1 \text{BLEND}_{it} + \beta_2 \text{R\&Dstock}_{it} + \rho_i + \eta_t + \varepsilon_{it}, \quad (2)$$

where i indexes country ($i = 1, \dots, N$) and t indexes time ($t = 1, \dots, T$). In this model specification, ρ_i represents the country-specific fixed effects, η_t represents the time-specific fixed effects, while all residual variation is captured by the additive idiosyncratic error term, ε_{it} .

By decomposing the error term into a country-specific, time-specific and idiosyncratic part, any biases arising from unobserved time-invariant effects and year-specific effects, are reduced. In this way, therefore, we account for comparative advantages that are relatively stable over time (infrastructure, land area, length of farming season, institutions).¹⁴ These represent unobserved effects that are likely to correlate with our independent variables. The time-specific fixed effects account for, for instance, movements in the global crude oil price, natural hazards affecting the international supply of feedstock, geopolitical events and other global macro-economic shocks. This is important given the fact that there exist global markets for many of the feedstocks used in the production of ethanol.

Building on the discussion in Sect. 2, we also test for the presence of an interaction effect between government biofuel R&D, i.e., R&Dstock, and the stringency of the biofuel blending obligations, BLEND. Specifically, we test the null hypothesis that a marginal increase in R&Dstock will have the same impact on EPS regardless of the stringency of the biofuel blending mandates, BLEND (and vice versa).¹⁵ Thus, this alternative specification can be expressed as:

$$\text{EPS}_{it} = \beta_1 \text{BLEND}_{it} + \beta_2 \text{R\&Dstock}_{it} + \beta_3 \text{R\&D_BLEND}_{it} + \rho_i + \eta_t + \varepsilon_{it}. \quad (3)$$

As noted above, the sign of the β_3 coefficient is a priori ambiguous; it will depend on the extent to which there are positive feedback loops between technology

¹⁴ First-generation biofuels produced from arable crops are widely available worldwide, and the access to arable land gives some countries a comparative advantage in such production. While this notion is addressed in our use of country-specific effects, we instead tested the hypothesis that a blending mandate will have a stronger impact on the ethanol production share (EPS) if the country possesses large arable land areas. However, this test resulted in statistically insignificant results.

¹⁵ It is to add a note on cautiousness when interpreting the presence of statistically insignificant interaction variables as the underlying effect may be under-detected. For a more in-depth discussion about variable power and sample size considerations in relation to detecting interaction variables, see Shieh (2009, 2010) and Durand (2013).

diffusion and R&D but also on whether blending mandates promote biofuel production based on the same technologies as those supported by government R&D. We also test another interaction variable, $R\&D_BLEND_D$, in which the latter part simply describes whether there is a blending mandate in place or not.

In two additional model specifications, we investigate the role of domestic petrol prices. The variable $PETROL$ (USD per liter in 2015 prices) is added, and in another model specification, we incorporate the interaction variable $PETROL_BLEND_D$. We have:

$$EPS_{it} = \beta_1 BLEND_{it} + \beta_2 R\&Dstock_{it} + \beta_3 PETROL_{it} + \rho_i + \eta_t + \varepsilon_{it}, \quad (4)$$

$$EPS_{it} = \beta_1 BLEND_{it} + \beta_2 R\&Dstock_{it} + \beta_3 PETROL_BLEND_D_{it} + \rho_i + \eta_t + \varepsilon_{it}. \quad (5)$$

We also estimate a model in which both $PETROL$ and $PETROL_BLEND$ are included. As noted above, we do not expect these variables to have profound influences on the ethanol production share. Still, including them also provides an opportunity to test the robustness of the estimated policy impacts. Finally, as noted above, the robustness of the results is also investigated by including tariffs on imports ($TARIFF$), as a single addition, and in addition to $PETROL$, and the two interaction variables. As noted above, some additional variables were also tested, but all of these generated statistically insignificant estimates while the remaining results were robust.

4.2 Econometric issues

4.2.1 The PPML estimator

The nature of our dependent variable requires an estimator that can generate unbiased estimates in the presence of truncated data, in our case involving several zeros, as well as country- and year-specific fixed effects. Specifically, the dependent variable EPS contains 143 zeroes, which represent 35% of all the observations. In this respect, the Poisson pseudo-maximum-likelihood (PPML) estimator is an interesting candidate.

PPML is a member of the GLM (generalized linear models) family. It will generate unbiased and consistent estimates in the case of a dependent variable containing non-integers, many zeros, and fixed effects (Santos Silva and Tenreiro 2011). Unlike most estimators, the PPML does not build on strong parametric assumptions, such as normality or a specific distribution of the dependent variable—except for a positive conditional mean (Artuc 2013; Santos Silva and Tenreiro 2011, 2006). This means that the data does not have to be Poisson, and more importantly in our case— y_{it} does not have to be an integer. Furthermore, the data do not have to follow other

standard Poisson properties such as $V[y_{it}|x] = E[y_{it}|x]$ to generate correct inferences. This was noted by Gourieroux et al. (1984) for Pseudo Maximum Likelihood Poisson Models; and later stated by Santos Silva and Tenreyro (2006) and Correia et al. (2019b) in the process of coding the estimator into a statistical package. The PPML estimator generates standard errors that are robust even in the case of under- or over-dispersion and heteroskedasticity, this since inference is based on the so-called Eicker–White (Eicker 1963; White 1980) robust covariance matrix estimator (Santos Silva and Tenreyro 2006) rather than on statistical properties.

Other estimators will also produce unbiased and consistent parameter estimates in the case of a non-negative, non-integer dependent variable with many zeros. Specification tests exist, which can be used to discriminate between the various estimators.¹⁶ Still, for the purpose of this paper, the modeling choice is limited. Other estimators that are able to handle non-normality (many zeros), e.g., the Zero-inflated Poisson (ZIP) estimator and the Negative Binomial regression, both of which are similar to the PPLM, have, however, been developed for count data and would therefore generate biased estimates for our data sample. As noted above, although the PPML is a Poisson estimator, i.e., also developed for count data, it permits applications on continuous data (Santos Silva and Tenreyro 2011).

The PPML estimator has gained popularity in trade gravity modeling, this since trade flows are often zero, something that has introduced bias using the classic OLS estimator (e.g., Brodzicki and Uminski 2018; Bianco et al. 2016; Sun and Reed 2010). A simulation study assessing the performance of different estimators used in trade gravity modeling confirmed that the PPML will be less affected by heteroskedasticity than alternative estimators (Martínez-Zarzoso 2011). There is also simulation evidence suggesting that the PPML estimator involves less bias in the presence of many zeros in the dependent variable (Martin and Phamb 2020).

Despite the above advantages, the PPML estimator is fairly new in the context of policy impact analyses. Groba (2014) bridges this gap by using the PPML estimator to assess the impact of renewable energy policy on trade flows. Moreover, Zhaoa et al. (2013) use a panel data set to estimate the impacts of various policies on renewable energy generation while accounting for year and country fixed effects. They also estimate the models with OLS for comparison, and find that the PPML estimator is superior to the (biased and inconsistent) OLS estimates.

Other models suitable for addressing “corner solutions” including many zeros, such as the Tobit model and the double hurdle model by Cragg (1971), would have been appropriate candidates if it was not for the fact that both these estimators produce biased and inconsistent estimates in the case of a fixed effect approach. These models do not permit a parametric conditional fixed effects model, this since there is no sufficient statistic allowing fixed effects to be conditioned out of the likelihood.

¹⁶ See, for instance, the so-called “hpc” test developed by Santos Silva et al. (2015), which builds on Davidson and MacKinnon (1981).

Even though attempts have been made, such as by Honoré (1992) who developed a semiparametric estimator for fixed-effect Tobit models, the unconditional fixed-effect estimates are still biased. Since the double hurdle models (e.g., the Cragg) include a Tobit model as well as a Probit model—also biased and inconsistent with fixed effects—such models are also inappropriate. The closest to a fixed effects double hurdle model is the two time period panel estimation method presented by Honoré (1992). Our panel, though, has 17 time periods.

For the above reasons, this paper relies on the PPML estimator. Since we have both country- and time-specific fixed effects, we employ a version of the PPML estimator that allows for multiple levels of fixed effects without having to estimate dummy variables, namely the so-called PPMLHDFE.¹⁷ This is also the name of the Stata software package used, first developed by Correia et al. (2019a). The PPML estimator employed is robust to statistical separation and convergence issues, this due to the procedures developed in Correia et al. (2019b, 2020).¹⁸ This estimator drops regressors that may cause the non-existence of the (pseudo) maximum likelihood estimates. If any of the regressors that are dropped is a dummy variable, by default, the standard PPML will drop the observations with the less frequent value of the excluded dummy, something that may not be appropriate (i.e., it is perhaps better then to drop the entire set of dummies). Thus, by using the PPMLHDFE estimator (instead of PPML), which does not estimate dummy variables to capture fixed effects, the risk of dropped variables is reduced.

4.2.2 Functional form, reverse causality, and measurement error

Since the PPML estimator requires very little in terms of assumptions, there are no specific tests associated with the estimator. Santos Silva and Tenreiro (2006), however, suggest that the so-called heteroskedasticity-robust RESET test (Ramsey 1969; Santos Silva and Tenreiro 2006) can shed additional light on the estimated model's adequacy. This is, thus, a test for the correct specification of the conditional expectation, i.e., it tests for functional form. It is performed by checking the statistical significance of an additional regressor constructed as $(x'b)^2$, where b denotes the vector of estimated parameters. We implement the RESET test manually for each regression structure in Stata following Santos Silva and Tenreiro (2006). We start by predicting the fitted values of the regression (including the fixed effects). Then we generate the second power of the fitted values and include these in the regression with clustered standard errors. Finally, we perform a significance test jointly for the

¹⁷ PPMLHDFE stands for “Poisson pseudo-likelihood regression with multiple levels of fixed effects” (Correia et al. 2019a, b).

¹⁸ The PPMLHDFE estimator allows for estimations of high-dimensional fixed effects. That is, even in a situation where the number of groups (dummy variables) is large—the estimation can still be carried out with fixed effects without having to introduce group dummy variables in the model. Moreover, the PPMLHDFE estimator has been developed to converge faster in the presence of several fixed effects. In our case, there is no notable difference in output results between using the PPML or PPMLHDFE, neither in convergence time nor in parameter estimates. Nevertheless, we use the latter since it is specifically developed to deal with more than one fixed effect.

coefficients of the powers. The associated P values of each test are presented along with the other estimations. The more variables that are included in the model, the more likely the RESET is to reject the null. For this reason, we only accept the null hypothesis for P values exceeding the 5% limit.

Our model specifications suggest that an increase in the stringency of blending mandates could lead to higher domestic ethanol production levels, but the presence of a reverse causality cannot be dismissed. In other words, the presence of significant ethanol production in a country could lead to the introduction of a more stringent blending mandate, e.g., as a result of rent-seeking behavior on the part of farmer organizations. One classic approach to deal with reverse causality is the use of lagged explanatory, e.g., policy, variables. The R&D variable is expected to have a lagged effect on EPS, and this is accounted for in the construction of the domestic R&D-based knowledge stocks. As noted above, we also test for different time lags. The BLEND variable is not lagged. The reason for this is that the introduction of the blending mandates has generally been announced well in advance (including also the stringency of obligations over time), and this permits companies to pursue their investment plans well ahead of policy implementation [see Hedeler et al. (2020) for examples]. For this reason, we have not introduced time lags in the BLEND variable.

Two alternative approaches employed to reduce the risk for reverse causality are to estimate a first difference model or include one or more AR terms in the original model. These approaches are appropriate in the presence of so-called path dependency, i.e., if any of the variables are non-stationary, which would make the order of events blurred. Non-stationarity in panel data has traditionally not been a concern, but with an increased use of data sets comprising extended time periods and relatively few cross-section units, a growing concern has emerged that also panel data sets should be subject to non-stationarity examination.

Our use of year-specific fixed effects will take a stochastic trend common to all units of the data into account, but not the country-specific unit-root processes. Still, non-stationarity is less of a concern when the time series (T) is short compared to the cross-section (N). One rule of thumb suggests that if $N > T$, traditional panel data analysis is custom, at least if T is small (30 or less) (Baltagi 2005). In this paper, T equals 17, i.e., clearly lower than 30 as well as larger than the number of countries (N), which equals 24. The unit-root problem is a matter of time dimension, and a 17-year-long period does not necessarily convey the time series features for the variables. For this reason, we do not address non-stationarity any further in this paper, since is not likely to be blurring the order of events.

Although the fixed effects approach and the sample structure provide some protection against reverse causality, it cannot be entirely dismissed. Still, one aspect that supports the assumption of exogenous policy impacts is that our sample is dominated by EU Member States, and these have been subject to supranational legislation leading to the introduction of blending mandates. Specifically, in 2009, the EU passed the Renewable Energy Directive (2009/28/EC), and this stated that all EU Member States had to ensure that at least 10% of their transport fuel use come from

renewable sources by the year 2020. Many EU countries chose to adopt domestic blending mandates from 2009 and onwards (see Figure 3), in part since this was the most straightforward way to comply with the directive. The significance of EU policy implies, we argue, a reduced risk for reverse causality. In fact, even countries with ambitious development in the biofuel sector have been reluctant to implement the requirements in the EU directive (e.g., Hedeler et al. 2020). Furthermore, the competition for the underlying feedstock limits the possibilities for individual interest groups to lobby for policy changes. For instance, in Sweden, the industry organization Swedish Forest Industries has argued against the introduction of more stringent biofuel blending mandates in the country (Beckeman and Larsson 2020).

Our sample includes 16 EU Member States and eight non-EU countries. Due to the suggested exogeneity of EU policy, we test the robustness of the results by also considering a more limited sample consisting only the EU countries. If the results remain overall robust, we argue, there should be little reason to suspect reverse causality in the full sample.¹⁹

Even if we do not perceive measurement errors causing endogeneity issues (e.g., with respect to the tariff variable) as a significant problem in this investigation (see Sect. 3.2), it is useful to briefly comment on our choice of estimator also in this context. In brief, the PPML estimator should not raise concerns about bias resulting from the presence of neither heteroscedasticity (Martin and Phamb 2020) nor measurement errors (Hou 2020). There are potentially more efficient estimators but these are either developed in the context of bilateral trade analyses (Egger and Prusa 2016), or they require the adoption of uncertain assumptions concerning the specific structure of the possible measurement errors (Manning and Mullahy 2001).

5 Results

In this section, we present the results based from the Poisson pseudo-likelihood regression with multiple levels of fixed effects (PPMLHDFE), with two categorical variables to be absorbed (country and yearly fixed effects) along with clustered standard errors stratified by country. For all model specifications, the iteratively reweighted least-squares (IRLS) algorithm converged to a maximum after relatively few iterations; around 10 iterations were required for fitting each model. All model specifications were statistically significant at the 1% level,²⁰ thus rejecting the null hypothesis that all the estimated coefficients equal zero. Overall, we conclude that the PPML estimator and our main model specifications are robust based on the statistically insignificant RESET test result (see associated *P* values of each test presented in Tables 1, 2, 3). These results, thus, overall confirm the adequacy of our

¹⁹ A structural approach using the same logic would be to perform an instrumental variable (IV) analysis. However, this approach comes with its own challenges where the lack of strong instruments is a key one. EU membership is a binary variable and does not involve enough variation to perform a nonlinear IV estimation. As no other suitable instruments could be identified, a proper IV estimation could not be carried out.

²⁰ The Wald Chi-square statistic ranged between 0.0066 and 0.0096, which corresponds to $P < 0.01$.

models. The only exceptions, though, are the models including the petrol price variable (see comments on this case below).

Table 1 shows the model estimation results when we include the policy variables BLEND and the R&Dstock variable calculated with different time lag lengths, i.e., 2, 4, 6, and 8 years. The corresponding marginal effects have been employed to predict the ethanol production shares that follow from introducing blending mandates in the 1–10% range (see Fig. 5 in the Appendix).²¹ For instance, an increase in the blending mandate from 2% (the sample mean) to a 3% share would on average increase the ethanol production share from (roughly) 2.1–2.3%, which is an increase in this share of close to 10%. This corresponds to an increase in the sample mean ethanol production level of 210 barrels per day (from 2094 to 2304), i.e., 76,000 barrels per year (assuming a perfectly own-price inelastic total demand for fuels). Such an increase in ethanol production is in turn roughly equivalent to almost half the capacity of a modern ethanol plant in the EU.

This finding is overall not sensitive to the inclusion of R&D knowledge stocks based on more extended time lags. However, the results display no statistically significant relationship between R&Dstock (regardless of time lag) and the ethanol production share.²² In other words, countries that invest a lot in government biofuel R&D do not necessarily produce more ethanol.

Table 2 shows the estimated coefficients from five alternative model specifications, here adopting the R&Dstock variable with a 6-year time lag as the base model. The first and second column results (models 2a and 2b) illustrate a negative and statistically significant interaction effect between biofuel blending obligations and the R&D-based knowledge stock. Specifically, the results in model 2a suggest that a given increase in R&Dstock will have a lower impact on the ethanol production share if a blending mandate is in place (compared to if such a demand-pull instrument is absent). Moreover, the corresponding result in model 2b is consistent with the notion that a given increase in the stringency of the blending mandates will, *ceteris paribus*, have a more modest impact on the ethanol production share when a biofuel blending mandate is accompanied by high investments in government biofuel R&D (and vice versa). The resulting coefficients, however, are only statistically significant at the 5% level ($P < 0.05$). The individual coefficients for BLEND and R&Dstock, respectively, are robust to the inclusion of both these interaction variables.

The remaining results presented in Table 2, i.e., models 3–5, display the impacts of introducing the domestic petrol price (PETROL) in the regressions. Models 3 and 4 indicate that the isolated effect of this price on the ethanol production share is negative and statistically significant at the 10% level ($P < 0.10$). This negative effect is unexpected but, as illustrated below, it is not robust to the use of alternative model

²¹ The predicted effect of BLEND on EPS represent average effects for the whole sample period. The effect of the mandate increases somewhat over time (see Fig. 5 in the Appendix).

²² It should be noted that overall, there are no high correlation rates between the BLEND and R&Dstock variables. The country-specific pair-wise correlation rates are above 0.70 only in four cases (Austria, Canada, Japan and Mexico). For the remaining countries they are low, and in a few cases (Latvia and Turkey), even slightly negative.

Table 1 Model estimation results: green industrial policy variables

	Model 1a	Model 1b	Model 1c	Model 1d
BLEND	0.068*** (0.02)	0.074*** (0.03)	0.076*** (0.03)	0.078*** (0.03)
R&Dstock (2y lag)	– 0.002 (0.00)			
R&Dstock (4y lag)		– 0.001 (0.00)		
R&Dstock (6y lag)			– 8e–05 (0.00)	
R&Dstock (8y lag)				0.001 (0.00)
Constant	– 2.767*** (0.17)	– 2.883*** (0.15)	– 2.964*** (0.16)	– 3.039*** (0.17)
<i>N</i>	408	408	408	408
RESET test <i>P</i> values	0.2724	0.0967	0.2176	0.0121
Log pseudo-likelihood	– 28.469	– 28.475	– 28.482	– 28.480
Prob > Wald chi2	0.006***	0.001***	0.000***	0.000***
Pseudo <i>R</i> -square	0.238	0.238	0.238	0.238

Statistical significance levels: * stands for $P < 0.10$, ** for $P < 0.05$, and *** for $P < 0.01$. Clustered standard errors stratified by country in parentheses. Stars indicating significance levels starts at P value < 5% for the RESET tests (see Sect. 4.2).

Table 2 Model estimation results: green industrial policy variables, petrol prices and interaction effects

	Model 2a	Model 2b	Model 3	Model 4	Model 5
BLEND	0.113*** (0.03)	0.119*** (0.03)	0.072*** (0.02)	0.077 (0.05)	0.070 (0.05)
R&Dstock (6y lag)	0.002 (0.00)	0.002 (0.00)	0.001 (0.00)	0.001 (0.00)	– 3e–04 (0.00)
R&D(6y)_BLEND_D	– 0.003** (0.00)				
R&D(6y)_BLEND		– 0.001** (0.00)			
PETROL			– 1.155* (0.59)	– 1.160* (0.60)	
PETROL_BLEND_D				– 0.013 (0.09)	0.018 (0.09)
cons	– 3.053*** (0.17)	– 3.079*** (0.18)	– 0.419 (1.24)	– 0.404 (1.27)	– 2.950*** (0.17)
<i>N</i>	408	408	403	403	403
RESET test <i>P</i> values	0.299	0.215	0.021**	0.006***	0.158
Log pseudo-likelihood	– 28.457	– 28.455	– 28.279	– 28.279	– 28.337
Prob > Wald chi2	0.000***	0.000***	0.000***	0.000***	0.000***
Pseudo <i>R</i> -square	0.2384	0.239	0.239	0.239	0.238

Statistical significance levels: * stands for $P < 0.10$, ** for $P < 0.05$, and *** for $P < 0.01$. Clustered standard errors stratified by country in parentheses. Stars indicating significance levels starts at P value < 5% for the RESET tests (see Sect. 4.2).

Table 3 Model estimation results: green industrial policy variables, petrol prices and interaction effects

	Model 6	Model 7	Model 8	Model 9	Model 10
BLEND	0.084*** (0.02)	0.081*** (0.02)	0.078*** (0.02)	0.103** (0.05)	0.124*** (0.03)
R&Dstock (6y lag)	– 2e–04 (0.00)		0.001 (0.00)	– 3e–04 (0.00)	0.002 (0.00)
R&Dstock (4y lag)		0.083 (0.25)			
TARIFF	0.163 (0.22)	– 0.002 (0.00)	0.241 (0.20)	0.258 (0.20)	– 0.002 (0.20)
PETROL			– 0.933 (0.66)	– 0.966 (0.68)	– 0.891 (0.66)
PETROL_ BLEND_D				– 0.065 (0.12)	
R&D(8y)_ BLEND					– 0.001** (0.00)
_cons	– 3.469*** (0.68)	– 3.158*** (0.79)	– 1.726 (1.18)	– 1.661 (1.24)	– 1.338 (1.14)
<i>N</i>	321	321	316	316	316
RESET test <i>P</i> values	0.289	0.086	0.037**	0.023**	0.025**
Log pseudo- likelihood	– 22.594	– 22.590	– 22.427	– 22.425	– 22.405
Prob> Wald chi2	0.000***	0.000***	0.000***	0.000***	0.000***
Pseudo <i>R</i> -square	0.224	0.224	0.225	0.225	0.225

Statistical significance levels: * stands for $P < 0.10$, ** for $P < 0.05$, and *** for $P < 0.01$. Clustered standard errors stratified by country in parentheses. Stars indicating significance levels starts at P value $< 5\%$ for the RESET tests (see Sect. 4.2)

specifications. Moreover, when PETROL is added to the model, two things happens: the P value of the RESET test becomes statistically significant (1–5% significance level), thus suggesting that the model can be improved, and BLEND becomes statistically insignificant in Models 4 and 5. The results also show no statistically significant interaction effect for PETROL and having a blending mandate in place. The above suggests that PETROL is not a robust variable, and its meaning should, therefore, be sparsely interpreted. One possible reason for this is that the various components (global crude oil price, domestic taxes, and local time-varying factors) of this variable could in different periods co-vary and then cancel out in other periods.

Table 3 explores the effect of import tariffs for all agricultural raw materials (TARIFF) on EPS, along with blending mandates, government biofuel R&D, petrol prices, and a few interaction variables. Overall, TARIFF is shown to have a statistically insignificant impact on EPS. It is important to note, though, that the results for both our policy variables appear robust in all of these alternative model specifications, i.e., positive and statistically significant estimates in the case of BLEND and insignificant results for R&Dstock (also when the 6-year lag is replaced by a 4-year lag). The result suggesting a negative interaction between

R&D support and the stringency of the blending mandate is also robust. However, as mentioned above, the negative—and statistically significant—result for PETROL cannot be detected in these alternative model specifications (see models 8–10). This confirms previous observation—that the PETROL variable is not robust, and the inclusion of this variable affects the overall model performance negatively (again, a statistically significant RESET *P* value).

As noted above, we also re-estimated four of the models above employing a more limited data sample consisting of only the 16 EU Member States, this in order to discern the risk of reverse causality. The results from these model estimations are reported in Table 6 in the Appendix; these show that the estimates with respect to blending mandates and government R&D remain robust.

In brief, our results suggest that whereas blending mandates are positively correlated with EPS, government biofuel R&D is not. Moreover, there is a negative and robust interaction between government R&D and blending mandates. We find, though, that neither petrol prices nor import tariffs have any statistically significant impacts on ethanol production shares. As noted above, this also goes for a set of additional independent variables that were tested (e.g., oil rents, GDP, arable land, etc.). One reason for these statistically insignificant results is that many of the added variables are relatively constant over time (for a given country), and the corresponding effects are, therefore, picked up in the country-specific fixed effects. Another reason could be that the variables are not precise enough—the different components of the variables can capture other effects, which can cancel out the true effect (always or at times).

6 Discussion

While previous studies have assessed the impacts of demand-pull policies (Palage et al. 2019a; Freitas and Kaneko 2012) and technology-push policies (e.g., Arnold et al. 2019) on biofuel innovation, we find robust evidence that such policies, not least demand-pull policies in the form of biofuel blending mandates, may also influence the domestic industrialization process. In this section, we provide a discussion of our results in the light of previous studies. The section is divided into four separate parts: (a) demand-pull policy in the form of blending mandates; (b) technology-push policy in the form of government R&D support; (c) the interaction between demand-pull and technology-push policies; and (d) political economy aspects.

6.1 The link between biofuel blending mandates and domestic ethanol production

Blending mandates, the main demand-pull instrument employed to stimulate the establishment of biofuels markets, regulate the ratio of biofuels to total fuel volumes sold at the pump. These mandates do not specify where the ethanol can be produced, and demand-pull policies will often lead to inter-country spill-over effects (e.g., Hoppmann et al. 2013; Peters et al. 2012; Palage et al. 2019a). Thus, even though

the blending mandates guarantee a market share for biofuels, they do not guarantee an increase in domestic ethanol production. The results reported in this paper show robust evidence for the notion that more stringent blending mandates are associated with increases in domestic ethanol production; this is in spite of the fact that most countries in our sample are not competitive ethanol producers. Below, we discuss two possible reasons for this finding: (a) factors holding back market integration and that, thus, prevent behavioral change following relative price movements; and (b) how a domestic demand for ethanol may stimulate biofuel production but not necessarily innovation.

First, international trade patterns do not always (fully) respond to changes in relative prices. The presence of trade barriers and underlying (national) preferences may hold back the level of market integration (Nelson and Hertel, 2011). Olper and Raimondi (2008) analyze agricultural market integration among the OECD countries; to overcome the issue of deficient data on trade tariffs, they use an indirect estimation approach and find that crossing a national border within the OECD induces an average trade-reduction effect of a factor 13. While part of this effect can be explained by the presence of trade tariffs, not all of it can. Even in the absence of any tariffs (as is the case among the EU Member States), other factors will contribute to reduced trade volumes. These include non-tariff trade barriers such as various regulations (import licensing and rules of origin) (WTO 2020), but also national preferences in the form of ‘home bias’.

Even though international comparisons show that the OECD area has relatively few non-tariff trade barriers (e.g., Ing et al. 2018), home bias is likely present. The latter stems from the strong political will in some countries to pursue green industrial policy ambitions, and thus develop a domestic bio-economy (Ebadian et al. 2020). Previous literature has found strong evidence for home biases in global trade, in technology development (Bacchiocchi and Montobbio 2010), for agricultural products (Morey 2016), and in the OECD area (Wei 1996; Olper and Raimondi 2008). Nelson and Hertel (2011) reject the null hypothesis of global market integration for biofuels and conclude that geography matters due to product differentiation by place of origin. This also contributes to the interpretation of our finding of a positive relationship between the biofuel blending mandates and domestic production of ethanol.

Second, as noted above, creating a stable demand through blending mandates is expected to encourage investments even though the biofuel market is not yet mature. Though previous studies typically do not find strong evidence for blending mandates leading to innovations (i.e., patenting) in the biofuel sector (e.g., Palage et al. 2019a), our study shows a positive impact on domestic biofuel production. This is in line with the notion of the first-generation biofuels dominating the global biofuel market, and with previous research suggesting that blending mandates primarily tend to favor mature technologies (Costantini et al. 2015; Ebadian et al. 2020;

Hoppmann et al. 2013). In other words, blending mandates will likely help expand the biofuel sector also in the case of a non-competitive supply chain. Over time, this sector will benefit from cluster formation, labor pooling, and input–output linkages, which will make it more productive, though not necessarily induce a switch to the advanced biofuel technologies.

6.2 The link between government R&D and domestic ethanol production

Our results show that government R&D support to biofuel development has not tended to be correlated with higher ethanol production shares in the OECD area. Even if R&D historically has played a key role in developing the first-generation biofuels, government R&D during the last two decades has mainly focused on advanced biofuel technologies. The advanced biofuels are still not commercial, and most biofuel production occurs in pilot and demonstration plants (Bacovsky et al. 2013).

Our results should, therefore, not be interpreted as suggesting that government R&D plays no role in overall biofuel development. For instance, the results presented by Palage et al. (2019a) and Costantini et al. (2015) suggest that government co-funding of key experimental pilot and demonstration plants²³ has had clear positive impacts on advanced biofuel patenting in Europe, and this may help promote increased production of advanced biofuels in the future. During the last two decades, however, government support for biofuel R&D and blending mandates have largely targeted different categories of biofuels, i.e., first-generation versus advanced biofuels, respectively. This notion is, in part, also reflected in the results for the interaction effect between these two policy instruments.

6.3 The interaction between blending mandates and government R&D

Our results show a negative and (weakly) statistically significant interaction between blending mandates and government R&D. Since both basic knowledge generation as well as various learning process, which help improve the performance of the technology through increased production and use, are deemed necessary for enabling the growth of novel biofuel value chains, this result is somewhat unexpected. Still, as noted above, a negative or statistically insignificant interaction effect could well be consistent with the notion that government R&D and the biofuel blending mandates tend to target different technological fields, i.e., advanced technology versus commercial first-generation technologies. In such a situation, more stringent biofuel blending requirements will not necessarily generate significant feedback loops to R&D, and vice versa. Indeed, the adoption of blending mandates could even lead

²³ Experimental pilot and demonstration plants aim at testing the viability of new technologies, i.e., by providing opportunities for the technology to be optimized, fine-tuned, and permit progressing towards an optimal design (Karlström and Sandén 2004). This is in contrast to the so-called *exemplary* pilot and demonstration plants, which instead aim to demonstrate the value of the new technology to potential adopters, thus creating awareness and legitimacy (see also Palage et al. 2019a).

to less interest in advanced biofuel R&D if existing policy targets can be met using first-generation biofuels. Palage et al. (2019a) argue along similar lines, and report a corresponding negative interaction effect in their study on advanced biofuel patenting outcomes.

Furusjö and Lundgren (2017) present results that partly support this conclusion in the context of the Swedish blending requirement (reduction quota). During the first years, the quota has been met primarily through imports of less advanced biofuels (e.g., HVO); marginal increases in the quota are not likely to change this pattern. Still, the country's R&D efforts in advanced biofuel technology have been significant, but these have instead focused on making use of side-streams from the forest industries (Hellsmark et al. 2016b). This has, therefore, provided meager scope for positive feedback loops unless the blending requirements become considerably more stringent and/or targeted towards specific (advanced) biofuels.

In other words, stringent blending mandates may primarily increase the demand for biofuels that are cost-effective from a short-term perspective, e.g., imported first-generation biofuels (see also Hansson et al. 2018). This could in turn lead to decreased interest in developing advanced biofuels with high long-run potentials, since stringent blending mandates make it easier to comply with existing national targets relating to biofuel use in the transport sector. A few scholars have also argued that the production and use of first-generation ethanol will not likely bridge the conversion to advanced biofuels (Eggert and Greaker 2014).

6.4 The political economy of green industrial policies

Our results show that green industrial policies, not least in the form of demand-pull instruments, may induce the emergence of domestic industrial production. The findings also point to the importance of implementing demand-pull and technology-push instruments that reinforce each other rather than encouraging a competition between different technological fields. Ebadian et al. (2020) reach a similar conclusion and argue that countries with a mix of demand-pull and technology-push policy instruments have been most successful in developing domestic biofuel sectors (see also Hellsmark and Söderholm 2017). Still, even if green industrial policies may be effective, designing and implementing these in practice is likely to be difficult.

Oliveiraa et al. (2017) shed light on this complexity in the biofuel sector; domestic production could be the result of lobbying and corporate interests maximizing profits at the expense of environmental goals, energy security, and food security (see also Deppermann et al. 2016). It is often argued that domestic biofuel production has advanced furthest in countries where major corporate sectors such as agroindustry and petroleum, have aligned with each other (Oliveiraa et al. 2017). As noted above, policies targeting specific sectors and/or technologies are prone to regulatory capture by interest groups (Lerner 2009; Aalbers et al. 2013), and this could lead to

inefficient outcomes, thus neglecting broader societal values. For instance, it is well known that blending mandates primarily create incentives for mature technologies, but first-generation biofuels come with negative side-effects such as land use change implying reduced biodiversity (Langpap and Wu 2011) and increasing food prices (Chakravorty et al. 2009). Moreover, green industrial policies supporting biofuel development risk “locking-in” inefficient first-generation biofuels, and thus forestall the transition to more advanced biofuels (Berti and Levidow 2013; Oberling et al. 2012; Klitkou et al. 2015; Oliveiraa et al. 2017).

Still, the negative impacts following rent-seeking behavior should not be exaggerated. Previous work shows that advanced biofuels can be integrated into first-generation biofuel processes [see Bamidele Ayodelea et al. (2020) for a recent literature review]. Thus, the lock-in effect could be mitigated, and first-generation biofuels can constitute a stepping-stone towards the advanced biofuels. This requires, though, a well-aligned mix of technology-push and demand-pull policy instruments.²⁴ It is also important to recognize that in the biofuel industry, the scope for rent-seeking behavior could be limited due to the competition among various interests. In his seminal study, Becker (1983) points out that as a result of interest group competition, governments may avoid inefficient redistribution policies. In the biofuel industry, there is often competition for the underlying feedstock, in turn implying that some groups lobby for more stringent blending mandates while others argue for the opposite (e.g., Beckeman and Larsson 2020).

7 Concluding remarks and avenues for future research

This paper investigated the role of green industrial policies—and their interaction—on domestic industrialization processes in the context of biofuel production among OECD countries. The results show that blending mandates are positively correlated with domestic ethanol production, but this is not the case for government biofuel R&D support. These findings are robust across the various model specifications, and thus suggest that a more stringent blending mandate does not only increase the domestic use of ethanol, but also domestic production (as a share of total fuel use). Nevertheless, the blending mandates tend to primarily favor commercialized first-generation biofuels. Our results even suggest a negative interaction effect between government R&D and blending mandates, thus implying that these two policies target different technological fields, i.e., advanced biofuel technology versus

²⁴ Recent research has emphasized that this policy mix also needs to involve so-called systemic instruments, e.g., including activities deliberately implemented to influence the structure and the substance of actor networks and the collaborative processes taking place in these networks (Rogge and Reichardt 2016; Söderholm et al. 2019).

commercial first-generation technologies. In such case, there is little scope for positive feedback loops between the technology-push and demand-pull instruments.

For future assessments of green industrial policies in the biofuel sector, we encourage further research on the role of demand-pull and technology-push policies, and their interaction, in the biofuel sector. Our inability to fully resolve these issues illustrates the importance of collecting (not yet available) disaggregated data by feedstock and technology. In addition, future work should also recognize that a few countries (e.g., USA, Austria, Denmark and the Netherlands) have—or will quite soon—adopt blending mandates targeting advanced biofuels, this in order to promote the transition towards more sustainable biofuels (Babcock et al. 2011; Ebadian et al. 2020). Future research should monitor and evaluate these novel demand-pull initiatives to generate more knowledge on how green industrial policies in the biofuel sector affect domestic industrialization, and interact with other policies.

Appendix

See Tables 4, 5, 6 and Fig. 5.

Table 4 Countries included in the data sample used in this paper (24 in total)

Austria	Germany	Mexico	Spain
Belgium	Hungary	The Netherlands	Sweden
Canada	Ireland	New Zealand	Switzerland
Czech Republic	Italy	Poland	Turkey
Denmark	Japan	Slovakia	UK
Finland	Latvia	South Korea	Slovakia

Table 5 Descriptive statistics. The sample period is 2000–2016 (yearly data) and includes 24 OECD countries, which form a panel with a maximum of 408 observations per variable

Variable	Description and units	N	Mean	Std. Dev	Min	Max
Dependent variable						
EPS	Domestic ethanol production as a percentage share of total fuel use ^a (both measured in average daily production in thousands of barrels over 1 year)	408	2.10	3.89	0.00	23.78
Independent variables						
BLEND	Blending mandate (lowest percentage share of biofuel in fuels sold at the pump) ^b	408	0.52	1.46	0.00	7.00
R&Dstock	Government R&D knowledge stock, 6-year lag (million USD, 2019 prices and exch. rates ^d)	408	63.52	91.38	0.00	357.46
R&D_BLEND	Interaction variable between BLEND and R&Dstock	408	42.13	251.95	0.00	1520.40
R&D_BLEND_D	Interaction variable between BLEND > 0 and R&Dstock	408	13.68	50.77	0.00	357.56
PETROL	Domestic end-use petrol price incl. taxes (US dollars per liter, 2015 prices)	403	1.95	0.97	0.77	6.27
PETROL_BLEND_D	Interaction variable between PETROL and a binary variable taking the value of one (1) if a blending mandate is in place (and zero otherwise)	401	0.17	0.52	0.00	3.91
TARIFF	Import tariffs (AHS ^c Simple Average (%) for Agricultural Raw Materials)	321	3.21	2.00	2.09	18.32

^aFuel use refers to petrol sold at the pump (often a mix of petrol and ethanol)

^bFor countries that have separate blending mandates for ethanol and biodiesel, we use their ethanol blending mandate. For countries where the mandate is not specified to type of biofuel, we have used that biofuel mandate available

^cAHS stands for “Effectively Applied” and is defined as the lowest available tariff by The World bank

^dThe exchange rate is calculated as an annual average based on monthly averages (local currency units relative to the US dollar). Note that the exchange rate is the same for EURO member states.

Table 6 Model estimation results: green industrial policy variables, tariffs, petrol prices, and interaction effects using the sample of 16 EU Member States

	EU: model 1a	EU: model 2a	EU: model 3	EU: model 8
BLEND	0.081*** (0.02)	0.109*** (0.03)	0.077*** (0.02)	0.076*** (0.02)
R&Dstock(6y)	0.002 (0.00)	0.002 (0.00)	0.003 (0.00)	0.001 (0.00)
R&D(6y)_BLEND	(0.00)	− 0.003 (0.00)		
PETROL			− 1.720** (0.84)	− 1.627 (1.13)
TARIFF				omitted (.)
cons	− 2.946*** (0.21)	− 2.967*** (0.22)	0.874 (1.78)	0.428 (2.22)
<i>N</i>	241	241	240	198
RESET test <i>P</i> values	0.066	0.143	0.040**	0.031**
Log pseudo-likelihood	− 25.416	− 25.403	− 25.205	− 19.666
Prob > Wald chi2	0.000***	0.000***	0.000***	0.000***
Pseudo <i>R</i> -square	0.180	0.181	0.184	0.184

Statistical significance levels: * stands for $P < 0.10$, ** for $P < 0.05$, and *** for $P < 0.01$. Clustered standard errors stratified by country in parentheses. Stars indicating significance levels starts at P value < 5% for the RESET tests (see Sect. 4.2)

Fig. 5 Predicted effect of BLEND (for 1–10% blending mandate) on EPS for the full sample (2000–2016), illustrated with a 95% confidence interval. R&Dstock is not added to the prediction since it is statistically insignificant. The predicted mean of EPS is presented in shares; multiply by 100 for percentage share of domestic production of consumption

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