Driving Innovation?
Carbon Tax Effects in the Swedish Transport Sector*

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Abstract: This paper examines the impact of a carbon tax on innovation in clean technologies in the transport sector. Rapid advances in clean technologies are critical to reaching the ambitious sector climate targets. We contribute to the understanding of the link between carbon pricing and clean innovation by providing the first empirical estimate in the transport sector using patent data and applying the synthetic control method (SCM). We estimate the local effect on clean innovation of the Swedish tax reform in 1990/91 which introduced a carbon tax and expanded the VAT on the sale of motor fuels. Across various specifications and multiple robustness checks, we consistently find positive and economically significant effects of the tax reform on the invention of clean transport technologies between 1990 and 1999. By disentangling the two components of the tax reform package, we provide indicative evidence that the salience of the carbon price in terms of innovation effects is larger than that of the pure fuel price, and thereby find that the carbon tax induced the majority of the overall effect. These results suggest that a salient carbon price can be an effective instrument to foster the transition to a decarbonized transport sector by inducing clean innovation. In particular, a carbon tax may be more effective in regard to its innovation effects than previous estimates using fuel price elasticities have suggested.

Keywords: carbon tax; clean innovation; technological change; synthetic control; salience
JEL Classification: H23, L91, Q54, Q55, Q58

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1 Introduction

In view of the Paris Agreement on climate change (UNFCCC, 2015), an ever-increasing number of firms and countries are pledging to achieve carbon neutrality by approximately mid-century, with the tendency to set more and more ambitious targets. However, the proclamation of precise dates for carbon neutrality stands in stark contrast to most countries' still deficient strategies and plans for the decarbonization of their economies. The challenge now that the targets are set is to introduce policies that are suitable for achieving them, in particular by providing incentives for the development and large-scale deployment of low-emission technologies. The dominant policy approach is a *green growth strategy*, as manifested most prominently in the European Union's Green Deal (European Commission, 2019), i.e. the goal of decoupling economic growth and greenhouse gas emissions through technological innovation and CO_2-free energy production and industrial processes. Internalizing negative environmental externalities by putting a price on greenhouse gas emissions such as carbon dioxide (CO_2), by implementing either a carbon tax or a cap on emissions within a permit trading system, is widely regarded as the least expensive and most efficient way to avert the risk of unchecked climate change and should thus constitute the cornerstone of climate policies at every level (see e.g., Stiglitz and Stern, 2017 and Howard and Sylvan, 2015). In recent years, in a remarkable convergence between science-based recommendations and policy practice, the number of implemented carbon pricing policies and their respective levels of ambition have increased significantly (World Bank, 2019).

From a sectoral perspective, transport is perceived as posing particularly great decarbonization challenges. In recent years, rather than declining, CO_2 emissions from road transportation have tended to increase globally and in most European countries (International Energy Agency, 2020b; European Environment Agency, 2021). To turn this trend, more and more countries have recently implemented carbon pricing policies in the transport sector or are currently considering to do so. Most notably, in July 2021, the European Commission proposed in its "Fit for 55" legislative package an emission trading system for the European transport sector which would constitute the world's largest

carbon pricing system for this sector to date (European Commission, 2021).

From a theoretical perspective, carbon pricing is considered to be cost-effective in reducing emissions (see e.g., Baumol and Oates, 1988). Empirical studies support this hypothesis by finding that pricing carbon is effective in reducing CO_2 emissions (Andersson, 2019; Elgie and McClay, 2013; Rivers and Schaufele, 2015). Besides being effective in reducing emissions, an essential feature of carbon pricing is its potential ability to incentivize innovations that foster the transition to a low-carbon economy. Consequently, market-based policies such as carbon prices are considered to be one of the main policy levers for clean innovation (Hepburn *et al.*, 2018; Stavins, 2007).

Carbon pricing can influence clean innovation via two complementary channels: a price channel on the one hand and a credible policy commitment channel on the other. The price based effect is underpinned by the induced innovation hypothesis dating back to Hicks (1932).[1] According to the induced innovation hypothesis, an increasing relative price of one factor of production incentivizes innovations that reduce the use of that factor. Applying the hypothesis to the road transport sector, making fuel relatively more expensive through a carbon price establishes demand to reduce its relative usage thus spurring demand for innovation in clean technologies which reduce fuel consumption. These technologies include innovations that improve the fuel efficiency of vehicles or enable alternative (i.e. less environmentally harmful) energy sources for road transportation. Importantly, in the case of the transport sector, the demand for these technologies is not coming directly from the producers but is passed upstream from the consumers who bear the burden of the carbon pricing. The fuel saving incentive for the consumers translates into the opportunity for an increased market share of cleaner vehicles and thereby holds out the prospect for the producers of higher returns to investment in clean innovations (Aghion *et al.*, 2016).

The second channel relates to the perceived strength of public policy commitments. Since climate policy influences the critical expectations of future returns on investment on

[1] More recently, Porter (1991) and Porter and van der Linde (1995) have started the research agenda on the effects of environmental regulation on technological change. Acemoglu *et al.* (2012) added directed technical change in the climate change mitigation context to the discussion.

the part of companies, climate policy uncertainty can lead to sub-optimal investment behavior in clean technologies (International Energy Agency, 2007). Accordingly, increasing policy certainty due to consistent introduction of policies and credible commitments reduces the risk for firms which results in higher investments (International Energy Agency, 2007). Consequently, the growth in the knowledge stock is pushed into the direction that best matches the pay-off structure that is established by credible policies (North, 1993). Overall, if the climate policy commitment is strong and credible, firm's investments in low-carbon technologies are affected positively (Brunner *et al.*, 2012; International Energy Agency, 2007).

There is an extensive strand of the literature that evaluates the impact of market-based environmental policies on innovation. After the seminal empirical studies on induced innovation of Newell *et al.* (1999) and Popp (2002), several studies investigated the case of carbon prices.[2] The effect of carbon prices on innovation has been analyzed in particular for the industry and energy sectors. Earlier studies used qualitative interviews (Christiansen, 2001; Gulbrandsen and Stenqvist, 2013; Hoffmann, 2007; Rogge and Hoffmann, 2010; Rogge *et al.*, 2011b,a) while the more recent ones use quantitative methods aimed at causality (Calel and Dechezleprêtre, 2016; Calel, 2020; Kim *et al.*, 2017; Schmidt *et al.*, 2012; Zhang *et al.*, 2019).

These studies generally find positive effects of carbon prices on clean innovation (Calel, 2020; Calel and Dechezleprêtre, 2016; Christiansen, 2001; Hoffmann, 2007; Gulbrandsen and Stenqvist, 2013; Rogge and Hoffmann, 2010; Rogge *et al.*, 2011b; Schmidt *et al.*, 2012; Zhang *et al.*, 2019), but also some insignificant results (Rogge *et al.*, 2011a; Kim *et al.*, 2017; Schmidt *et al.*, 2012). However, many look at carbon prices with arguably low stringency such as the phases 1 and 2 of the EU ETS which were characterized by relatively low carbon prices and broad free allocation of permits (Calel, 2020; Calel and Dechezleprêtre, 2016; Gulbrandsen and Stenqvist, 2013; Hoffmann, 2007; Rogge and

[2]For reviews of the empirical studies on the impact of environmental policies on clean innovation, see e.g., Popp *et al.* (2010), Popp (2019) and Grubb *et al.* (2021). In a recent review focusing on carbon pricing, Lilliestam *et al.* (2021) conclude that there is no empirical evidence for the effectiveness of carbon pricing in promoting technological change needed for full decarbonization. However, this paper has been criticized on methodological grounds by van den Bergh and Savin (2021).

Hoffmann, 2010; Rogge *et al.*, 2011a,b; Schmidt *et al.*, 2012).

In the transport sector, however, existing empirical studies have only analyzed the innovation effects of tax-inclusive (Aghion *et al.*, 2016; Barbieri, 2015, 2016; Crabb and Johnson, 2010; Fredriksson and Sauquet, 2017; Hascic *et al.*, 2009) or tax-exclusive fuel prices (Crabb and Johnson, 2010; Kim, 2014). These studies find that higher fuel prices increase innovation in clean technologies. Furthermore, higher prices direct innovation away from dirty to clean technologies (Aghion *et al.*, 2016; Barbieri, 2016; Crabb and Johnson, 2010).

Fuel prices can be a proxy for carbon prices due to their inherent relation and therefore, the respective literature provides the first estimates for the potential effect of carbon taxes. However, to the best of our knowledge no study examines the effect of a carbon price on clean innovation in this sector specifically. This is particularly relevant since recent studies show that carbon taxes in Canada and Sweden in the transport sector are more salient than fuel prices (Andersson, 2019; Rivers and Schaufele, 2015). In other words, emissions decline more strongly in response to a carbon tax increase than to an equivalent fuel price increase. If consumers are more responsive to carbon prices, we may also see a stronger increase in the demand for clean innovation than established when using fuel prices as a proxy.

Against this backdrop, we aim to fill this knowledge gap by answering the following research question: What is the impact of a carbon tax on clean innovation in the transport sector? To that end, we empirically analyze the impact of the Swedish tax reform 1990/91 which inter alia introduced a carbon tax on clean innovation in the transport sector.

Studying the tax reform in Sweden is relevant given its early and stringent introduction of a (high) carbon tax with full coverage of the road transport sector. Most existing studies examining the impact of carbon pricing policies on innovation do not use quasi-experimental approaches since they usually lack a convincing counterfactual due to their country- or region-level wide introduction.[3] Recent methodological advances in form of the synthetic control method have made quantitative comparative case studies at such ag-

[3]Exceptions are studies exploiting the plant-level inclusion criterion of the EU ETS (Calel and Dechezleprêtre, 2016; Calel, 2020)

gregated level possible and popular. The synthetic control method was first introduced by Abadie and Gardeazabal (2003) and further developed by Abadie *et al.* (2010) and Abadie *et al.* (2015). It allows the construction of an optimal weighted-average counterfactual based on a set of comparison units. This "synthetic control unit" then provides a pathway that the treated unit would have followed in absence of the treatment and thus serves to identify the impact of the treatment. The synthetic control method is thus a powerful generalization of the difference-in-difference estimation (Cunningham, 2021). Recently, several studies applied the synthetic control method to analyze the Nordic carbon taxes for which convincing counterfactuals are otherwise difficult to obtain (Andersson, 2019; Mideksa, 2021; Runst and Thonipara, 2020).

Given those considerations, we apply the synthetic control method to estimate the impact of the Swedish green tax reform in 1990/91 on clean innovations in the transport sector. Our synthetic unit consists of a weighted average of Spain, France, Belgium, and the United States, and closely resembles Sweden in key predictors of clean innovation. We find that the green tax reform increased the number of clean transport patents by 71 percent between 1990 and 1999. Applying various robustness checks, we consistently find positive albeit smaller treatment effects. Disentangling the carbon tax effect from the fuel price effect, we find that the estimated coefficient of the carbon tax is substantially larger. In line with the literature, we thus argue that these findings provide evidence for a stronger salience of the carbon tax. A simulation based on the estimated coefficients shows that the carbon tax contributed the majority of the effect of the 1990/91 tax reform on clean innovation. Furthermore, we contextualize the result and explore potential reasons for the magnitude of the effect in Sweden.

The remainder of the paper is organized as follows. Section 2 presents the context of the green tax reform in Sweden in 1990/91, and some insights into the Swedish transport sector and its innovation environment. Section 3 explains the data and empirical strategy. Section 4 presents the results and discusses the robustness of the findings. Moreover, we disentangle the carbon tax effect from the general tax reform in Sweden. Finally, Section 5 discusses the findings and Section 6 concludes.

2 Background and context

Sweden has long been regarded as a pioneer in climate policy (Sarasini, 2009). It has a long history of taxing energy sources (petrol since 1924 and diesel since 1937), initially intending to raise fiscal revenues. Amidst rising environmental concerns in the 1980s and climate policy becoming increasingly important to political parties, Social Democrats first proposed a carbon tax in 1988 (Andersson, 2019). Sweden implemented the carbon tax in 1991 thus being one of the first countries to do so (Brännlund *et al.*, 2014). Since its introduction, the carbon tax has increased in relevance and remains a cornerstone of Swedish climate policy, contributing to a broad range of environmental objectives (Ministry of Finance, 2021).

The introduction of the carbon tax was part of a major tax reform (with the catchy slogan "tax reform of the century" (Agell *et al.*, 1996)) with the aim of broadening the tax base while simplifying the tax structure and dramatically reducing the marginal income tax (Agell *et al.*, 1996). The tax reform affected all sectors, reduced and simplified labor taxes, lowered direct taxes while increasing indirect taxation, and introduced a tax on sulfur and carbon dioxide (CO_2) while cutting the energy tax (based on energy content) by half (Brännlund *et al.*, 2014; Sterner, 2020). One year prior to the introduction of the carbon tax, the Swedish government increased and extended the scope of its existing value-added tax (VAT) to also cover the sale of transport fuels. Ever since, the VAT rate of 25 percent is uniformly levied on all components of the retail price (Andersson, 2019). Given the increase of environmental taxes and the simultaneous decrease of other types of taxes, the 1990/91 tax reform has been described as an early example of a green tax shift reform (Hammar and Åkerfeldt, 2011).

Figure 1 depicts the historical development of carbon tax rates in Sweden. The tax rate was initially introduced at SEK 250 per ton of CO_2.[4] All sectors that produced energy-related emissions outside the electricity sector were initially covered by an equal tax rate, amongst others industry, residential, and road transport sectors.

Concerns regarding competitiveness and carbon leakage, i.e., the concern that domes-

[4]SEK 1 is equivalent to US$0.12 in 1991, resulting in a converted carbon tax of US$30 per ton CO_2.

tic industry might move abroad to countries where it is cheaper to emit CO_2, resulted in exemptions of the energy tax and and a reduction of the carbon tax to only 25 percent of the statutory tax level for manufacturing firms in 1993 (Brännlund *et al.*, 2014). The industry tax rate was increased to 50 percent of the statutory tax rate in 1997 and further adjusted in 2001 when it became independent of the statutory tax rate (Brännlund *et al.*, 2014). Between 2001 and 2014, the industry tax rate was between 21 and 50 percent of the statutory tax rate. With the introduction of the European emissions trading system (EU ETS), the tax has been gradually phased out for firms included under the EU ETS legislation (Brännlund *et al.*, 2014). Industry tax rates have experienced a steep increase since 2015 and the ending of tax exemptions in 2017 resulted in a uniform carbon tax rate for all sectors since 2018.

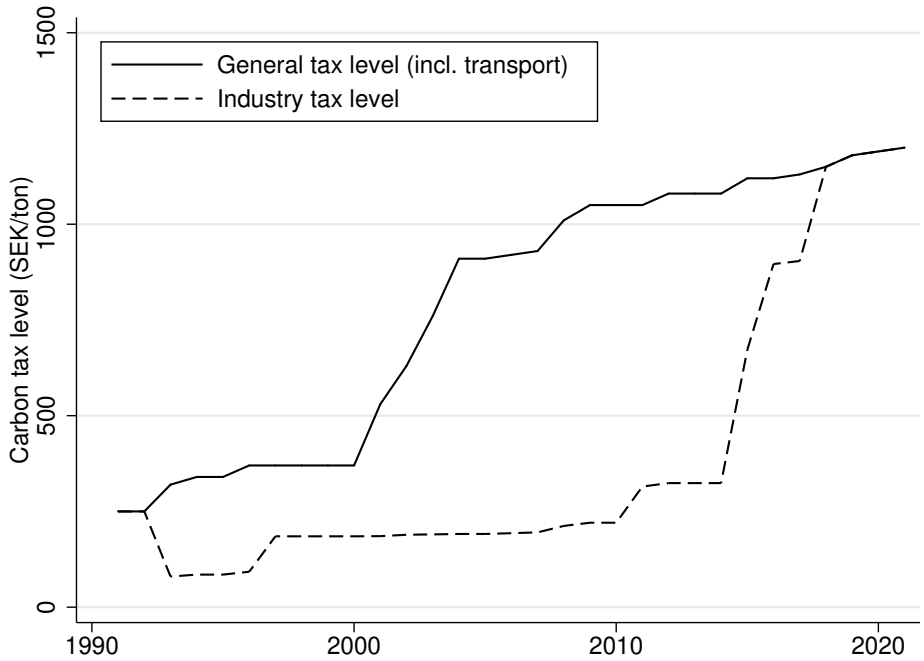
Between 2001 and 2006, environmental taxes increased substantially. However, the steep increases in the carbon tax were accompanied by reductions in the energy tax, which resulted in a less steeply increasing overall tax burden while its carbon price component increased significantly over time (Hammar and Åkerfeldt, 2011).[5] Since 2007, the carbon tax rate has been steadily increasing to today's rate of SEK 1200 per ton of CO_2, which constitutes the highest carbon tax rate in the world (Sterner, 2020; World Bank, 2019).

The carbon tax has generated yearly revenues of around 0.5 to 1 percent of Swedish GDP between 2000 and 2015 (Hammar and Åkerfeldt, 2011). Moreover, the Swedish carbon tax entailed only low additional administrative costs because, first, it relied on the established structures of the energy tax[6] and second, it did not tax actual emissions but was levied upon the average carbon content of fossil fuels. The Swedish government determined the average carbon content per unit for different fossil fuels (e.g., coal, natural gas, petrol). According to this definition, the combustion of one liter of petrol releases 2.323 kg of CO_2. Applying the carbon tax rate of SEK 0.25 per kg of CO_2 in 1991 resulted in additional costs of SEK 0.58 per liter for consumers.

[5]For example, the overall tax burden on one liter of unleaded petrol was raised from SEK 4.47 in 2000 to SEK 4.79 in 2004 (an increase of 7.2 percent), while the carbon tax component increased from 19 percent to 44 percent of the total tax (Hammar and Åkerfeldt, 2011).

[6]The administrative burden is estimated to be 0.1 percent of the revenues generated by the carbon and energy tax (Hammar and Åkerfeldt, 2011).

Figure 1: Swedish carbon tax rates, 1991 - 2021



Source: Tax and Customs Department, Division for Tax Policy Analysis, Swedish Government

Following Andersson (2019), the retail price of petrol can be disentangled into the price without taxes p_t, the energy tax $\tau_{t,energy}$, the carbon tax τ_{t,CO_2} and the value-added tax:

$$p_t^* = (p_t + \tau_{t,energy} + \tau_{t,CO_2})VAT_t \tag{1}$$

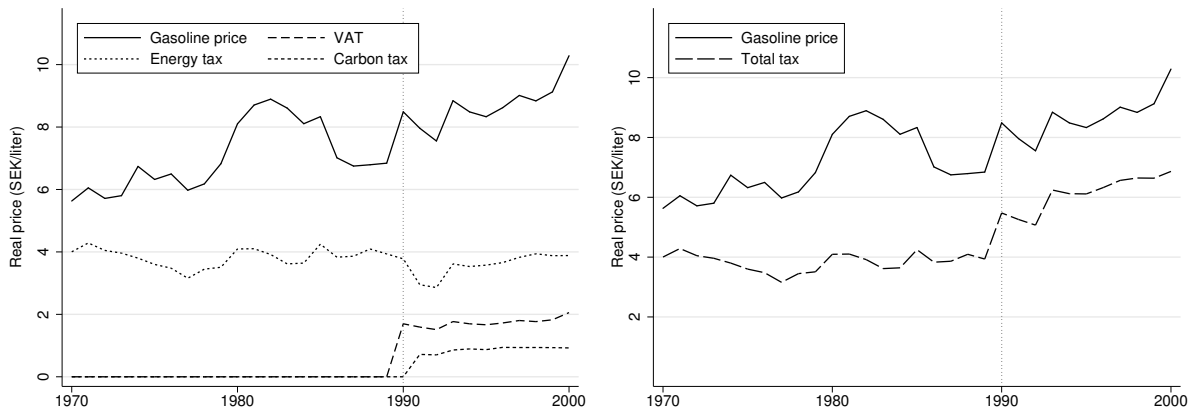
Figure 2, panel A, graphically displays the decomposition of tax components into real (inflation-adjusted) prices. Panel B displays the total tax levied on the consumption of gasoline. The total tax rate increased by 39 percent from 1989 to 1990[7] and by 69 percent from 1989 to 1999,[8] after which the total tax rate increased further.

For the hypothesized price channel to be effective, it is of major importance that the policies affect consumers through changes in the gasoline price. Fortunately, Andersson (2019) finds that adjustments to the Swedish energy and carbon tax are fully passed through to consumers.

Taking the exemptions mentioned above into account, the Swedish carbon tax cur-

[7] 3.94 SEK/liter in 1989 to 5.47 SEK/liter in 1990.
[8] 3.94 SEK/liter in 1989 to 6.64 SEK/liter in 1999.

Figure 2: Gasoline Price Components in Sweden 1970-2000



(a) Panel A: Tax components **(b)** Panel B: Total tax

Source: Adopted from Andersson (2019), based on SPBI (2016), Statistics Sweden (2015) and Swedish Tax Agency (2018).

rently covers approximately 40 percent of Sweden's greenhouse gases (World Bank, 2021). The transport sector is – except for domestic aviation – fully covered. Emitting close to 40 percent of CO_2 emissions in the 1990s, it constitutes Sweden's largest CO_2 emitting sector (Ministry of the Environment and Energy, 2009; European Environment Agency, 2021). The importance of the transport sector is further highlighted by the fact that 95 percent of current carbon tax revenues stem from the sale of motor fuels (Ministry of Finance, 2021).

Sweden is a suitable test-bed for the innovation effects of carbon carbon taxation in the transport sector due to the great importance of its domestic automotive industry inter alia as an engine of growth and a large employer. From an international perspective, it is unique that a small country in terms of population is home to two leading truck manufacturers (AB Volvo and Scania CV AB) and two large car manufacturers (Volvo Car and Saab Automobile) being complemented by a large and heterogeneous network of component suppliers.

Accordingly, the automotive industry plays an important role in terms of employment, export revenues, and research: first, Sweden is one of the countries most dependent on its automotive sector, which has the highest employment of all industries in absolute

terms Norgren *et al.* (2007).[9] Second, the Swedish automotive industry is internationally integrated and export-intensive with the automotive industry being Sweden's largest export sector in 2000. Lastly, the automotive industry was responsible for 31 percent of total industrial R&D expenditure and accounted for 29 percent of the employment in industrial R&D operations (Hepner, 2010).

All large vehicle manufacturers have comprehensive research and development capacities[10], with "environment and energy" being identified as a key area of their expertise by VINNOVA, the Swedish innovation agency Norgren *et al.* (2007). Corroborating this characterization, a recent study finds that Sweden's green technological specialization and patenting activity is particularly strong in the transport sector (compared to other Nordics and other sectors within Sweden) (Tanner *et al.*, 2019).

From an overarching perspective, it is noticeable that, in the 1990s, Sweden's R&D intensity was higher than in most other OECD countries (Mathieu and Van Pottelsberghe de la Potterie, 2010), with its private sector contributing on average 68.5 percent of R&D expenditure in the 1990s.[11] The Swedish innovation system is characterized by highly integrated public and private sector research structures as well as by extensive regional and international technological co-operations. The tasks of setting priorities and initiating projects is mainly done through the work of intermediary agencies like the Swedish Innovation Agency (VINNOVA) that also conduct technology foresight studies which aim to identify technological trends at a very early stage and to influence research policy formulation (Meissner, 2007). The private sector is involved in the formulation of research priorities and needs, particularly through consultations, workshops, and hearings (Meissner, 2007). Having identified the challenges and needs of industrial relevance, VINNOVA then seeks to match the identified technology areas with funding priorities to enable needs-based and problem-oriented research and development. Furthermore,

[9] In 2000, the automotive industry employed more than 650.000 people, of which just above half were employed by large manufacturers.

[10] According to (Norgren *et al.*, 2007), as a result of the complete takeover by GM in 2000, SAAB Automobile now only has lead development activities for some special technology fields within the GM Group.

[11] Calculation based on the MSTI database by OECD Statistics (2021a).

research programs made up of industry, university and public actors are another area where the private sector is (financially) involved, further strengthening the industrial relevance of knowledge creation (Norgren *et al.*, 2007). In synthesis, the private sector involvement in the formulation of the Swedish (sectoral) innovation policy is perceived as conducive and key to the competitiveness of the Swedish industrial sectors (Meissner, 2007).

The involvement of the private sector in the determination of research needs of industrial relevance and, more generally, in the configuration of innovation structures is particularly pronounced in the automotive sector. For example, a clear structure for automotive research in form of a Council for Vehicle Research (PFF) was established in 1994 as a response to the automotive industry's wish for a stronger research environment and recruitment base (Norgren *et al.*, 2007). In the early 2000s, several sectorial industry R&D programs were created and administered by the PFF, among others a jointly financed public-private automotive engineering research program, the Swedish Green Car Initiative 1 (GB1) as well as the Emissions Research program (EMFO) (Norgren *et al.*, 2007). The 'Swedish Green Car Initiative 1' which started in 2000 is a large automotive R&D program where a direct link to our outcome clean innovation is likely. It had a volume of around SEK 230 million per year of which the government contributed around 30 percent. According to VINNOVA, the government financially supported automotive-related R&D programs in the 2000s with more than 600 million SEK per year. The funding increased further (volume of around SEK 1 billion per year) with the start of the strategic vehicle research and innovation program (FFI) in 2008, one objective being to reduce the environmental impact of road transport (FFI, 2015). In contrast, the government spending on automotive R&D programs was comparatively small before the year 2000 and organized almost exclusively around competence centers for combustion processes. Given the potential interference of the larger R&D programs with our research design, we decide to limit the post-treatment period to the years 1990 to 1999.

3 Empirical strategy

3.1 Main Data

To measure innovation, we use patent data from the Worldwide Patent Statistical Database (PATSTAT) of the European Patent Office (2020). The advantages and disadvantages of patent data are well documented in the literature.[12] The main limitations of patent data are the differing value of patents and that not every innovation is patented. First, only some patents have a large commercial impact while many patents are only of incremental value. We address this issue in the later part of this section. Second, patents do not portray the entirety of innovation activity. Some research is not successful and some inventions are not patented but, for example, kept secret. We can only capture patented outcomes of the innovation processes. However, it has been shown that patents, dated by their first application (since the timing is closely related to the innovation process), are a good measure of innovation activity. Furthermore, they correlate strongly with R&D expenditures which are a measure of the input into the research process (see e.g., the review of Griliches, 1990).

Following many other empirical innovation studies, we use patent data primarily to identify and distinguish patented technologies at a very detailed level. This allows us to measure specifically the part of innovation that is in theory affected by the policy intervention. Furthermore, the measure is available and comparable across countries. In contrast, currently available R&D expenditure data sets do not possess those features.

The distinction of technologies is made possible by the fact that each patented invention is classified according to its type. Often the technologies of interest fall into many different classification codes and it takes expertise in patent classification systems to, in a given case, identify all relevant categories. For example, one invention for a "method and arrangement for starting a four-stroke injection engine" which improves inter alia energy efficiency when the engine is started[13] has six different Cooperative Patent Classification

[12] For a detailed discussion of the characteristics and limitations of patent data, see OECD (2009).
[13] The invention's first (priority) filing in 1997 has the application number SE9702633A.

(CPC) codes.[14]

In this respect, one major advantage of our approach is that we are able to exploit the Y02 classification system. It was initiated by the European Patent Office, the United Nations Environmental Program (UNEP), and the International Centre on Trade and Sustainable Development (ICTSD). Patent examiners and external experts developed a strategy to specifically classify climate change mitigation technologies with the aim to facilitate future empirical research and, ultimately, to better inform the political and public debate on climate change mitigation. The resulting classification system tries to minimize wrong classifications and to improve on the conventional ways to identify the relevant technological innovations in this area (Veefkind *et al.*, 2012).

Given those considerations, we use the PATSTAT 2020 Autumn edition (European Patent Office, 2020) and extract all patents falling into the category Y02T which denotes all technologies related to climate change mitigation in transportation. We include all patents with their earliest filing year between 1978 and 1999 and their respective family.[15] We exclude the categories related to air, rail, and water transportation, to only focus on technologies for road traffic vehicles. The remaining categories include for example technologies for improved efficiency of the internal combustion engine (Y02T 10/12), use of alternative fuels (Y02T 10/30), hybrid vehicles (Y02T 10/62), and energy storage systems for electromobility, e.g. batteries (Y02T 10/70). We include a complete overview of the ultimately included technological categories and their frequency in our data in Appendix H, Table H.1.

We count patent families since we are interested in the number of technologies that are invented in Sweden and not in the number of underlying patent applications. Additionally, families allow us to use an established procedure to address the problem that inventions are of different value. One approach in the literature is to control for the value

[14]The exact codes are F02D41/009, F02D41/40, F02D2041/389, F02M59/42, F02D41/062 and Y02T10/40. To an untrained eye, only the code Y02T10/40 clearly shows that the technology is "clean" while the other codes only state to which function and process the technology relates (e.g., F02D41/009 stands for using means for generating position or synchronization signals in electrical control of supply of combustible mixture or its constituents in electrical control of combustion engines).

[15]A patent family is a set of patent applications that protect the same or closely related technologies. For example, a patent family can consist of three patent applications for the same technology, one giving protection in France, one in Germany, and one in the United Kingdom.

by only including inventions that were filed in specific jurisdictions. Only inventions of relatively high value will be filed in many[16] and major patent offices. There are fees for patent applications to patent offices which tend to be higher in larger offices than in smaller national patent offices. Therefore, the system discourages applications to many and large patent offices for inventions with low expected commercial value (Dernis and Khan, 2004).

Therefore, applications that are designated to multiple countries at once using for example the European Patent Office (EPO) and Patent Cooperation Treaty (PCT)[17] applications characterize families of relatively high value. Additionally, looking at these transnational applications controls for home bias, which could be a problem when choosing families according to specific national offices. That is, inventors are more likely to patent at their domestic patent offices and might have different preferences towards different patent offices. Therefore, to control for value and get a measure that is comparable across countries, we follow the proposal of Frietsch and Schmoch (2010) and only include families with at least one transnational filing (EPO or PCT).[18,19] Since both the EPO and the PCT were introduced in 1978, this year naturally marks the start of the time frame we analyse.

One invention can have multiple inventors who jointly invented the technology. Since we are interested in the number of technologies invented in Sweden, we take inventors' country locations and weigh them within each family which is common practice in the literature. For example, our example-invention around the priority application number

[16] It has been shown that the size of a patent family can function as a measure of the value of the respective invention (Harhoff *et al.*, 2003; Lanjouw *et al.*, 1998).

[17] These types of patents give protection in multiple countries. For example, a European patent application is filed and approved first centrally by the EPO and the applicant decides in which countries belonging to the EPO, they seek intellectual property protection. A PCT application works similarly as a transnational application, but also to most countries that are not EPO countries.

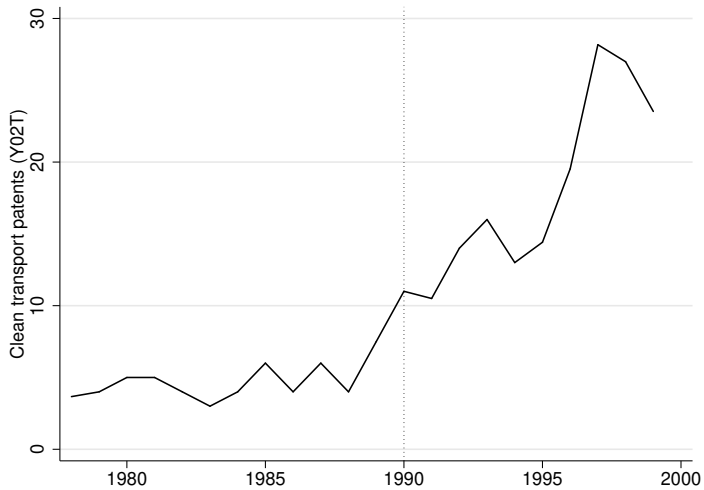
[18] We use the INPADOC family definition (Martinez, 2010) following for example Aghion *et al.* (2016).

[19] We tried alternative family types to control for the value of patents. One type of family that is used and discussed in the literature are triadic families (Dernis and Khan, 2004; Frietsch and Schmoch, 2010). These are families with applications to the three major patent offices – the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), and the Japan Patent Office (JPO). Respective results are presented in Appendix G.1 and did not alter our main findings. However, since the triadic family definition is very restrictive our yearly counts are reduced substantially and thereby the problem of potentially matching noise is exacerbated (further discussed in the later part of this section). Therefore, we opt for the still restrictive, but less strict transnational family type in our main analysis.

SE9702633A has two inventors in its patent family, one of which is from Sweden and one from the US. Therefore, we count 1/2 of the invention for Sweden and 1/2 for the US.[20]

We count these families according to the earliest filing year of the underlying applications. Figure 3 presents the trend of the resulting set of patent families which were invented in Sweden in our analyzed period (1978-1999). The number of annual clean patents has been relatively low between 1978 and 1988 and then started to generally rise with a maximum of 28.17 patents in 1997. The average increase in patents seems to get stronger after the general tax changes and the 1990/91 tax change. However, we cannot conclude any causality from this figure without an appropriate counterfactual, especially since the increase already starts shortly before the treatment. We will explain the construction of this counterfactual in the next section.

Figure 3: Annual count of clean inventions by Swedish inventors, 1978-1999



The simple inventor-weighted patent count also shows large year-to-year fluctuations. These erratic fluctuations are caused by the nature of patent data (Griliches, 1990). Innovation is a process with an inherently uncertain outcome. There can be years with many successful outcomes followed by years with many failures. Combined with the low level of annual patents, due to the fact that we look at a very specific type of innovation in

[20]We only look at inventor and not at applicant locations. For example, in our example-invention around the priority application number SE9702633A, the stored information on the Applicant is "Scania CV AB", while the registered information on the Inventors is "Neidenstroem, Bo; Westman Bjoern".

only one sector, this inevitably leads to relatively large year-to-year fluctuations. Clemens and Rogers (2020) also have to deal with this challenge. They analyze relatively low levels of yearly patent data with the synthetic control method and argue that due to this data characteristic, matching on trends would lead to matching noise. Therefore, they opt for matching levels and using a four-year moving average of patents as their outcome. This approach is corroborated by Abadie (2021) who provides an in-depth discussion of the potential advantages when matching on levels. In the following analysis, we thus decide to match our outcome on levels.[21]

3.2 The Synthetic Control Method

The synthetic control method (SCM) was introduced by Abadie and Gardeazabal in 2003. Since then, the method has gained a lot of traction which prompted Athey and Imbens (2017) to state that it was "arguably the most important innovation in the policy evaluation literature in the last 15 years" (p.3). Moreover, the authors regard the synthetic control method as one of the most important additions to quantitative comparative case studies (Athey and Imbens, 2017). The synthetic control method represents one possible answer to the great policy evaluation question, which asks how the outcome of interest would have evolved in absence of the treatment. In short, it represents a possibility to construct a counterfactual with which the effect of the intervention can be estimated. To this end, the synthetic control method assigns a set of weights to comparison units in a donor pool to optimally estimate the counterfactual to the treated unit. The evolution of the counterfactual then depicts what would have happened with the treated unit in absence of the treatment.

The synthetic control method is particularly powerful when there are only few units measured at an aggregate level (e.g., states, countries, etc.) since in these contexts it is usually difficult to find a suitable control unit with similar characteristics to the treated unit. The approach of using a weighted average of units in the donor pool to construct the counterfactual is based on the observation that a combination of various

[21] We do not use moving averages in our main specification, but Appendix F.1 presents results using a three year moving average. Results stay qualitatively the same.

units is usually more successful in resembling characteristics than only one individual comparison unit (Cunningham, 2021). In short, the synthetic control unit is a weighted average of comparison units that best resembles the characteristics of the treated unit in the pre-treatment period. Its development in the post-treatment period represents the path that the treated unit would have followed in absence of the treatment.

According to Abadie (2021), the synthetic control method has many advantages over regression-based methods. First, he argues that the method makes the contribution of each comparison unit to the counterfactual explicit by presenting weights while they are hidden in regression-based methods. Second, the method avoids extrapolation and instead relies on interpolation. In other words, the causal effect is the difference between the treated unit and its synthetic counterpart, whereas the latter is composed of a convex hull of comparison countries and thus based on real data points.

We follow Abadie (2021) in our application of the synthetic control method. In our case $J+1$ denotes the number of OECD countries in our sample with $j = 1$ denoting Sweden. The donor pool, a collection of untreated units which are not affected by the Swedish carbon tax, is denoted by $j = 2; ...; J+1$. Suppose that we can observe our units for the time periods $t = 1, 2, ..., T$ with sufficient pre-intervention periods $1, ..., T_0$ as well as sufficient post-intervention periods $T_0+1, T_0+2, ..., T$. This will allow us to construct a synthetic Sweden on the one hand (using pre-intervention data), and to evaluate the impacts of the carbon tax on clean patents in the transport sector on the other hand (using post-intervention data).

We observe our outcome of interest Y_{jt} (clean patents in the transport sector) for each country (j) and year (t). Let Y_{it}^I be the observed outcome of unit i at time t exposed to the intervention and Y_{it}^N the outcome that would be observed for unit i at time t in absence of the intervention. We aim to estimate the effect of the intervention on the treated unit, thus $\tau_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N$ for $t > T_0$.

The synthetic control unit ("Synthetic Sweden") is defined as a weighted average of the control countries in the donor pool which can be formally represented by a $Jx1$ vector

of weights $W = (w_2, ..., w_{J+1})'$ with $0 \leq w_j \leq 1$ and $w_2, ..., w_{J+1} = 1$. Each value of W represents a set of weights which characterize a potential synthetic control. Further, let X_1 be a $(kx1)$ vector of pre-treatment predictors of the outcome variable (Y02T patents) of Sweden. Similarly, let X_0 be a (kxJ) matrix containing the same predictors for all units in the donor pool. Abadie and Gardeazabal (2003) and Abadie *et al.* (2010) propose to choose W such that the constructed synthetic control best resembles Sweden's pre-intervention values of key predictors of the outcome variable. We chose the vector $W^* = (w_2^*, ..., w_{J+1}^*)'$ such that $||X_1 - X_0 W||$ is minimized and subject to the previously mentioned weight constraints. In other words, the synthetic control $W(V)$ is chosen to minimize the difference to Sweden with respect to a number of key predictors of our outcome variable.

The selected predictors are assigned weights reflecting the relative importance of the predictors being closely matched. There are various methods available to choose the predictor matrix V, for example, by assigning weights based on empirical studies or out-of-sample validation methods (Abadie *et al.*, 2015). We follow Abadie and Gardeazabal (2003) and Abadie *et al.* (2010) and choose V such that the resulting set of country weights $W(V)$ minimizes the mean squared prediction error (MSPE) of the outcome variable over the pre-treatment period.[22] Having determined W and V, the estimated treatment effect for Sweden in period t is $\hat{\tau}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} W_j^* Y_{jt}$.

To finalize our set-up, we discuss the time frame, donor pool and key predictors. First, our sample period is 1978 to 1999, limited at the start by data availability of our innovation measure as dependent variable (introduction of the EPO and PCT systems) and at the end by the start of the large R&D subsidy programs in Sweden (e.g., the 'Swedish Green Car Initiative 1') which may affect our outcome variable and hence confound the effect of the carbon tax. In sum, we have 12 years of pre-treatment data to construct the counterfactual and 10 years of post-treatment data to evaluate the impact of the tax change.

Second, our initial sample consists of all OECD member states in 1990. We then

[22] We use the Stata package *synth_runner* by Galiani and Quistorff (2017) to determine W and V.

proceed to exclude all countries which had similar policy shocks in our sample period. Therefore, we exclude Finland, Norway, and the Netherlands since they introduced a carbon tax in the transport sector. Germany, Italy, and the United Kingdom are excluded since they made large changes to fuel taxes.[23] Furthermore, we exclude Island and Ireland since they have no clean patents in our pre-treatment period and are therefore too dissimilar to serve as a donor. This leaves us with 15 potential donor countries, namely Australia, Austria, Belgium, Canada, Denmark, France, Greece, Japan, Luxembourg, New Zealand, Portugal, Spain, Switzerland, Turkey, and the United States.

Turning to the selection of predictors, Table 1 lists the selected predictors of clean patents in the transport sector and their data sources. We use the accumulated patent stock in clean technologies[24], the total triadic patents by inventors in the country,[25] a measure of the total patents related to manufacturing of motor vehicles,[26] and the mean of these patents in the pre-sample period between 1970 and 1977.[27]

Table 1: Key predictors of clean patents in the transport sector

Predictor	**Source**
Patent stock	PATSTAT
Total patents (triadic)	OECD.Stat
NACE2 29.1 patents [Manufacture of motor vehicles]	PATSTAT
Pre-sample mean NACE2 29.1 patents ('70-'77)	PATSTAT
Y02T patents pre-treatment average	PATSTAT

Notes: List of key predictors and respective data source.

[23]See Andersson (2019) for more details.

[24]This variable is calculated using the perpetual inventory method and a depreciation rate of 15%, which is commonly assumed in the literature, according to the equation $K_{it} = P_{it} + (1 - \delta)K_{it-1}$. P is the number of patents in clean technologies per country (i) and year (t), δ is the yearly depreciation rate which reflects the fact that existing knowledge becomes less important and outdated over time, and K is the patent stock. The initial patent stock is assumed to be zero because of the low number of clean patents in the early years of the sample period.

[25]Triadic patents are another way to control for the value of patents and make the data more comparable across countries. They are similarly defined as our transnational patents, by only including inventions which are filed at the three largest patent offices, i.e. the EPO, the United States Patent and Trademark Office (USPTO), and the Japan Patent Office (JPO) (Dernis and Khan, 2004).

[26]We identified relevant patents using the fact that International Patent Classification (IPC) codes have been matched to the European NACE2 industry classifications in PATSTAT. We use the specific code NACE2 29.1 (Manufacture of motor vehicles) code and include all transnational families which contain at least one patent in this category and count them analogously to our outcome variable.

[27]For the pre-sample measure we include all families with at least one granted application and not just families with a transnational filing since both the EPO and the PCT system entered into force around the start of 1978.

Patent stocks and the pre-sample average of patents related to the manufacture of motor vehicles measure accumulated technology-specific knowledge in a country and the country's automobile industry respectively. These variables tend to be important predictors of clean innovation because innovation is path dependent (e.g., Aghion *et al.* (2016), Acemoglu *et al.* (2012) and Popp (2002)). That is, accumulated knowledge in some type of technology positively affects future innovation in that same type of technology because it makes it easier or less costly. The former variable measures the knowledge in clean technologies accumulating in the period before intervention. The latter measures whether a country has a long history of innovation in the automobile industry already before our period of interest as a foundation for future research. As for the other predictors, the two total patent variables represent the size of the innovation system and the innovative capacity of a country or the country's automobile industry in the pre-intervention period respectively. All predictors are averaged over the entire pre-treatment period.

Lastly, we add the average (1978-1990) of the pre-intervention outcome. There is a vivid debate on the correct inclusion of pre-treatment outcomes in the estimation of the synthetic control unit. The lack of guidance regarding the inclusion of the outcome variable has resulted in a wide array of specifications applying the synthetic control method.[28] However, Kaul *et al.* (2021) demonstrate theoretically and empirically that using all pre-intervention outcomes as predictors renders all other covariates irrelevant. The authors find that using the average pre-treatment outcome in addition to other economic covariates yields the best results in their selection procedure.

Given those considerations, not having to choose somewhat arbitrary pre-intervention outcome years to be included as covariates and the fact that including the average pre-treatment outcome as a predictor is well established in the literature (see e.g., Abadie and Gardeazabal, 2003, Abadie *et al.*, 2015), we decide to include the latter in our main synthetic control estimation.[29]

[28]For example, Abadie and Gardeazabal (2003), Abadie *et al.* (2015) and Kleven *et al.* (2013) use the pre-treatment average and other covariates as economic predictors; Billmeier and Nannicini (2013) and others use all pre-treatment outcomes as predictors; Abadie *et al.* (2015) and Smith (2015) select a (arguably arbitrary) number of pre-treatment outcomes while Montalvo (2011) uses only the last two pre-intervention outcomes. For more details please see Ferman *et al.* (2020).

[29]Please see Appendix C for robustness checks which encompass different outcome lag choices and the

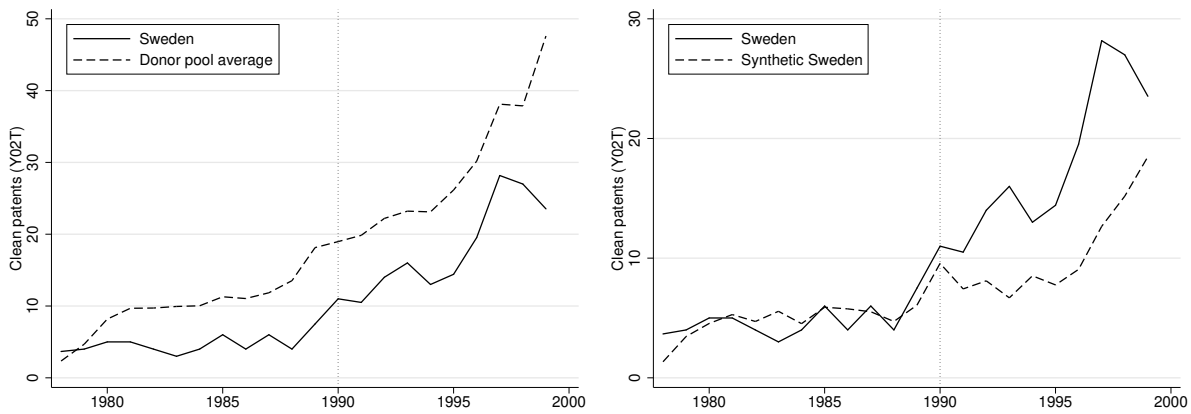
4 Results

In this section, we first present the findings of the synthetic control method estimating the impact of the 1990/91 green tax reform on clean innovation in the transport sector. Second, we proceed with disentangling the impact of the carbon tax from the effect of the VAT tax change (while comparing our main results with a basic OLS estimate).

4.1 Synthetic Sweden

Figure 4, Panel A displays the development of clean patents in Sweden and the average of the 15 OECD countries in the donor pool from 1978 to 1999. It indicates that while the number of clean patents follows a similar direction, the identifying assumption of a parallel time trend of the difference-in-differences estimator (DiD) would be violated, and standard DiD results thus biased. Meanwhile, Panel B depicts the path of clean patents in the pre- and post-treatment period for Sweden and its synthetic control unit. Here, the synthetic counterpart tracks the trajectory of clean patents of Sweden in the pre-treatment period closely and much better than the OECD average, with an average (absolute) difference of 0.10 clean patents.

Figure 4: Counterfactual Comparison: OECD average vs. Synthetic Sweden



(a) Panel A **(b)** Panel B

Notes: Comparison of annual clean patents (1978-1999) in Sweden compared to a simple donor pool average (Panel A) and the synthetic control unit (Panel B).

robustness section of this paper for further specifications following Ferman *et al.* (2020).

Remember that if the synthetic control method is able to closely match the outcome variable in the pre-treatment period and comes close to the values of key predictors, the identifying assumption that the synthetic control unit depicts the path of clean patents in absence of the carbon tax is supported. Regarding the first and having in mind the previously discussed volatile and erratic nature of patents, the pre-treatment fit can be considered good.[30]

Concerning the second point, Table 2 compares the average of the key predictors in the pre-treatment period for Sweden, its synthetic counterpart as well as the average of the 15 OECD countries in the donor pool. Generally, the predictor means of Sweden and its synthetic counterpart are fairly similar and much closer to each other than the OECD average except for the pre-sample average of patents that is related to the manufacturing of automobile vehicles. This result is particularly evident for the patent stock as well as for the average of the Y02T patents in the pre-treatment period.

Table 2: Clean transport patent predictor means prior to tax reform

Predictor	**Sweden**	**Synthetic**	**OECD Sample**
Patent stock	17.54	17.94	34.93
Total patents (triadic)	418.40	452.87	1326.02
NACE2 29.1 patents	58.56	50.91	80.45
Pre-sample average NACE2 29.1 patents	57.11	46.37	48.27
Y02T patents pre-treatment average	5.17	5.15	10.72

Notes: The columns report the predictor averages in the pre-treatment period (1978-1989) of Sweden (X_1), synthetic Sweden (X_0W^*) and average of the 15 OECD countries in the donor pool.

The key reason behind this finding is displayed in Table 3 which highlights the predictor weights V. The patent stock and the average number of clean patents in the pre-treatment period receive the largest weights, while the number of total patents in the economy as well as the number of patents related to the manufacture of motor vehicles each receive a relatively small weight.

[30]See Appendix Figure F.1 for a smoothed specification using a three-year moving average.

Table 3: Predictor weights V

Predictor	**Predictor weight** v
Patent stock	0.430
Total patents (triadic)	0.063
NACE2 29.1 patents [Manufacture of motor vehicles]	0.030
Pre-sample average NACE2 29.1 patents ('70-'77)	0.029
Y02T patents pre-treatment average	0.448

Notes: Weights of the predictors. Weights sum up to one by definition.

This distribution of weights highlights two points: first, predictors that measure characteristics of the innovation system of a country as a whole or even just of the respective automobile industry are of relatively little importance in predicting the outcome compared to those predictors which are specific to the technologies of interest. This observation highlights that clean innovation is difficult to predict with unspecific aggregate measures.[31] Second, the relative weights assigned to the predictors explain the diverging balance of predictors between Sweden and synthetic Sweden.

Table 4: Country weights W

Country j	**Weight** w_j^*	**Country** j	**Weight** w_j^*
Australia	0	Luxembourg	0
Austria	0	New Zealand	0
Belgium	0.099	Portugal	0
Canada	0	Spain	0.743
Denmark	0	Switzerland	0
France	0.141	Turkey	0
Greece	0	United States	0.017
Japan	0		

Notes: Weights of the donor countries which make up the synthetic control unit. Weights sum up to one by definition.

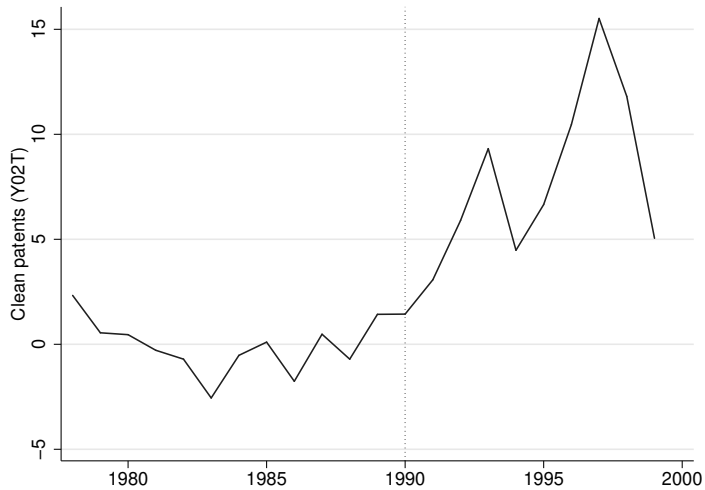
Lastly, Table 4 depicts the country weights W which are determined by the synthetic control method and which show that the synthetic counterpart is a weighted average made up of Spain, France, Belgium, and the United States (weights decreasing in this order, with Spain receiving by far the largest weight). As we will show later, the results do not depend qualitatively on any of those countries receiving a weight greater than

[31] When including even less specific predictors such as GDP, these predictors also tend to get a weight close to zero (see Appendix D).

zero. The distribution of weights is sparse with most of the countries in the donor pool receiving a weight of 0. This is in line with Abadie (2021) who notes that the distribution of weights across the donor pool is typically sparse with only a small number of units in the donor pool contributing to the estimation of the counterfactual.

Figure 5 illustrates the gap in clean patents between Sweden and its synthetic counterpart. As can be seen in Figure 5 and in Figure 4, Panel B, a gap starts opening up after the 1990/91 green tax reform. The increase in patents between 1990 and 1999 is on average 7.37 clean patents per year which corresponds to an average increase of around 71 percent compared to the synthetic control unit. In other words, our benchmark result suggests that in absence of the 1990/91 tax reform, the yearly number of clean patents in Sweden would have been much smaller.

Figure 5: Gap of Y02T patents between Sweden and Synthetic Sweden

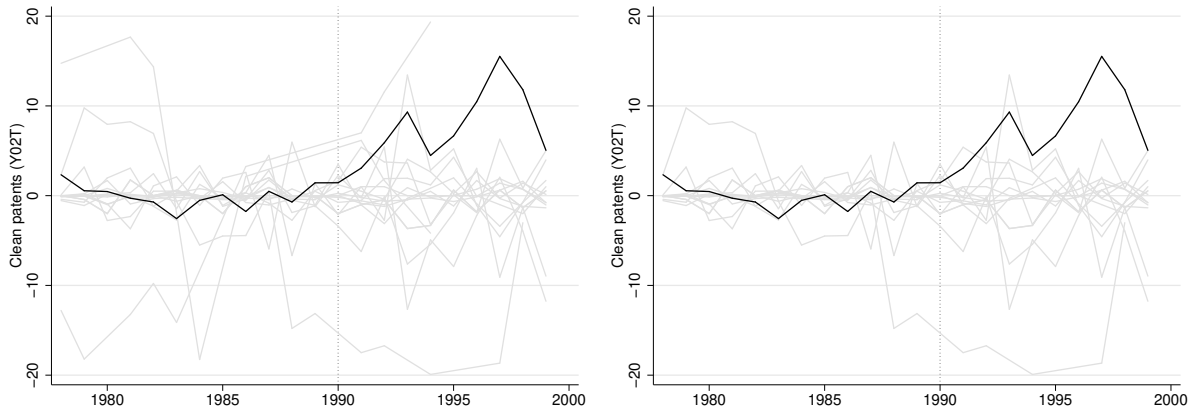


4.2 Placebo tests

To determine if a result obtained via the synthetic control framework might have been produced by chance, Abadie *et al.* (2010) propose a mode of inference that is based on permutation methods. The permutation distribution is obtained by iterative reassigning the treatment to units in the donor pool and estimating the "placebo effects" of each iteration. The presence of large "placebo effects" would indicate that the method might

produce effects by chance since the units in the donor pool received no actual treatment. In other words, the method tests whether our baseline results could be driven by chance. Applied to our case, the effect of the carbon tax on clean transport patents in Sweden is deemed to be significant when its magnitude is large relative to the placebo effects.

Figure 6: Permutation test (placebo study in space): Y02T patent gap in Sweden and placebo gaps for the comparison countries



(a) Panel A **(b)** Panel B

Notes: Panel A shows the Y02T patent gap for Sweden and placebo gaps for all 15 OECD comparison countries in the donor pool. In Panel B countries with a pre-treatment RMSPE 20 times larger than Sweden's are excluded (13 countries, USA and Japan excluded).

First, we iteratively assign the treatment (tax reform 1990/91) to the units in the donor pool, while Sweden itself moves to the donor pool. The iterative procedure provides us with a distribution of computed estimated effects which received no treatment. Figure 6 displays the result of the placebo test. While the light lines represent the gaps in Y02T patents of each state in the donor pool and its synthetic version, the black line denotes the gap estimated for Sweden. Panel A indicates that the applied synthetic control method is unable to replicate the path of Y02T patents for some countries in the pre-treatment period (1978-1989) by a convex combination of the Y02T patents of the other states. This is especially the case for the United States and Japan, which is unsurprising since those two states have the largest pre-treatment average of Y02T patents (56.3 and 62.2, respectively) and are always at the top of countries with the most Y02T patents by year. Therefore, following Abadie *et al.* (2015), we exclude countries with a pre-treatment

root mean squared prediction error (RMSPE) at least 20 times larger than Sweden's pre-treatment RMSPE (the United States and Japan) which is presented in Panel B. Overall, Figure 6 shows that the effect in Sweden is substantially larger than any effect which is created simply by chance in the placebo estimates.

A similar, and arguably less arbitrary, inferential method consists of first carrying out the same permutation-based placebo analyses and then comparing the ratio of post-treatment RMSPE to pre-treatment RMSPE for each "treated" country (Abadie *et al.*, 2010). The underlying assumption is that a large ratio indicates a causal effect from treatment. The RMSPE measures the gap in the outcome variable (Y02T patents) between each country and its respective synthetic control unit. However, since a large post-treatment RMSPE does not necessarily identify a large treatment effect if the pre-treatment RMSPE is also large, the ratio helps to evaluate the effect at hand. According to Andersson (2019), using the ratio is advantageous since it does not require to discard countries based on rather arbitrary cutoffs.

Figure 7: Ratio test: Ratios of post-treatment RMSPE to pre-treatment RMSPE for Sweden and 15 OECD control countries

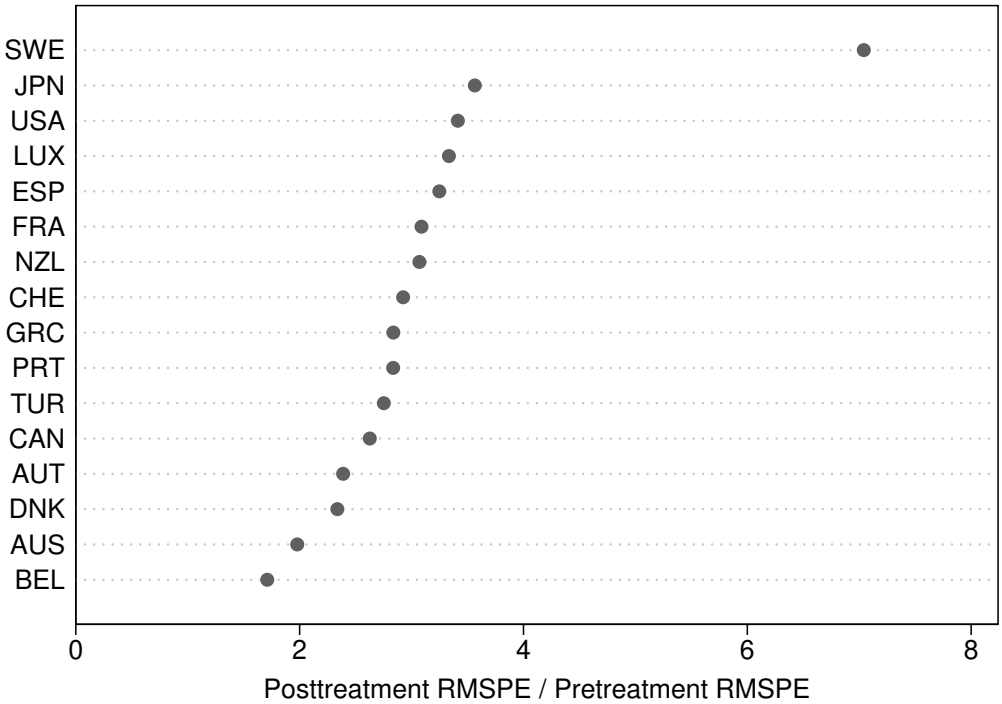


Figure 7 reports the ratios of the post-1990 RMSPE over the pre-1990 RMSPE for Sweden and all countries in the donor pool. Of all the countries in the sample, Sweden clearly has the highest ratio by a wide margin. Its post-tax reform gap is roughly seven times larger than the pre-tax reform gap. If we wanted to transfer this finding into a standard statistical significance measure, we would look at the chance of obtaining a ratio at the top of the distribution when one would assign the treatment at random. This chance would be $1/16 \approx 0.0625$ and thus we obtain the smallest possible p-value with our sample (see Abadie *et al.*, 2015).

4.3 Robustness checks

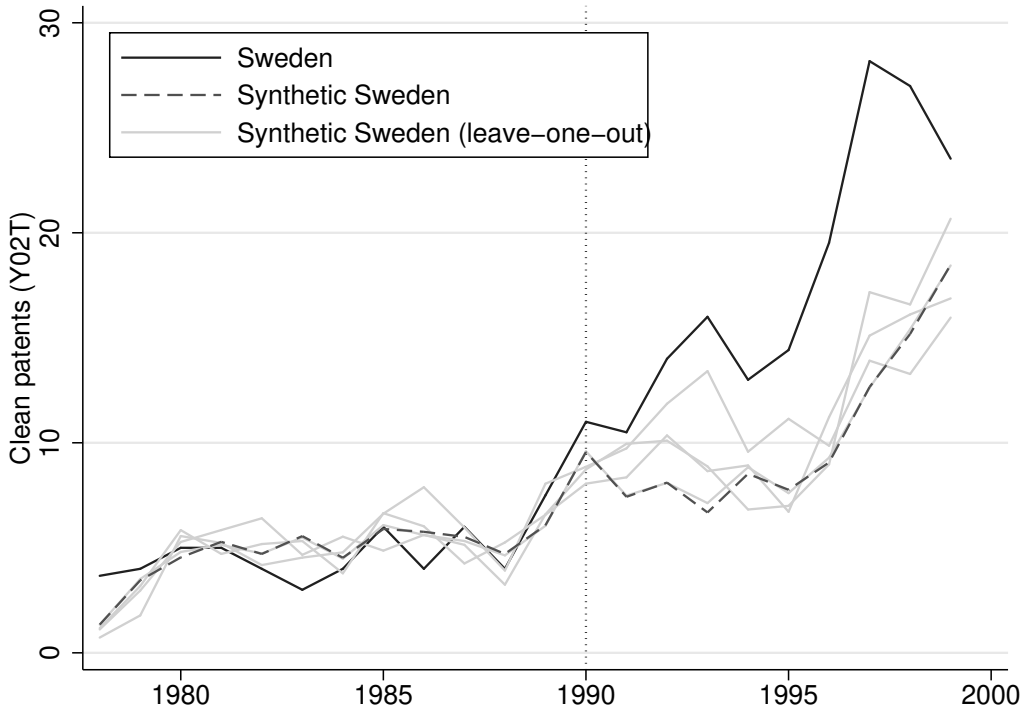
In this section, we run robustness checks to determine whether our results are sensitive to any choices in the setup of the synthetic control method. First, we check whether our estimate is robust to changes in the the choice of the donor countries. Second, we provide different specifications altering the choice of key predictors, in particular the outcome lag.

First, we investigate the country weights W^*. Recall from Table 4 that synthetic Sweden is estimated using a weighted average of Spain, France, Belgium, and the United States. As a robustness check we re-estimate our initial synthetic control model to construct a synthetic Sweden but then iteratively omit one of the countries which have received a positive weight in Table 4 (Abadie *et al.*, 2015). While the procedure inevitably sacrifices some goodness of fit, this sensitivity check allows us to gauge whether the results are driven by one donor countries.

Figure 8 displays both the initial lines from Panel B of Figure 4 as well as the leave-one-out estimates in grey. The figure shows that while the results of the previous analysis are qualitatively fairly robust to the exclusion of one particular donor pool country, the effect size now tends to be smaller.

The leave-one-out robustness check provides us with a range of estimates: the exclusion of Belgium renders an average increase in clean patents of 69.5 percent in the post-treatment period while the most conservative estimate of 50.6 percent is the result

Figure 8: Leave-One-Out Test: Distribution of synthetic control units when excluding donor countries

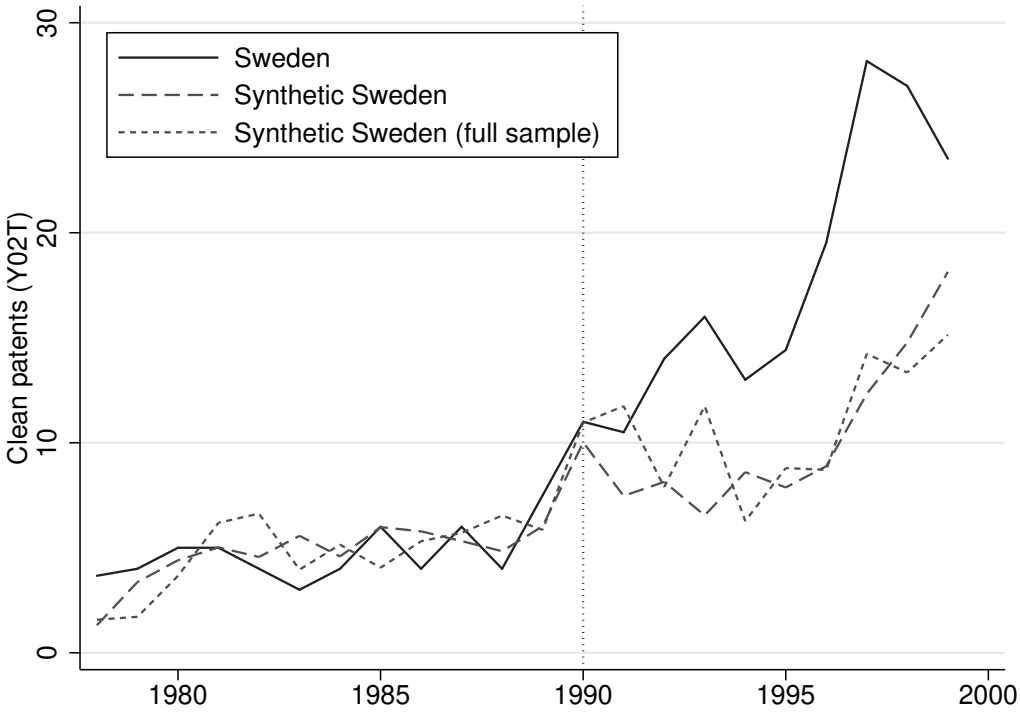


of omitting France. Leaving the United States or Spain out of the estimation, we get an average increase in clean patents of 54.2 and 60.5 percent, respectively. The average of the effects from the leave-one-out robustness check is 58.7 percent.

Summing up, while the effects differ in magnitude, we consistently estimate a positive and large, albeit smaller, impact of the 1990/91 tax change on clean innovation. This finding is further corroborated by the ratio test (post-treatment RMSPE/pre-treatment RMSPE) reported in Figure A.1 in Appendix A. It shows that even when dropping iteratively countries that receive a positive weight, Sweden consistently depicts the largest ratio.

For a second robustness check, we use the full sample of 24 OECD countries as the donor pool to ascertain whether our exclusion of certain potential donor countries due to policy changes or large dissimilarity drove the benchmark results. Figure 9 presents the path of clean patents for Sweden and for its synthetic counterpart both from our main specification and from the robustness exercise without prior exclusion of potential donors (full sample). The effect size changes to 70.2 percent and, thus, stays qualitatively similar.

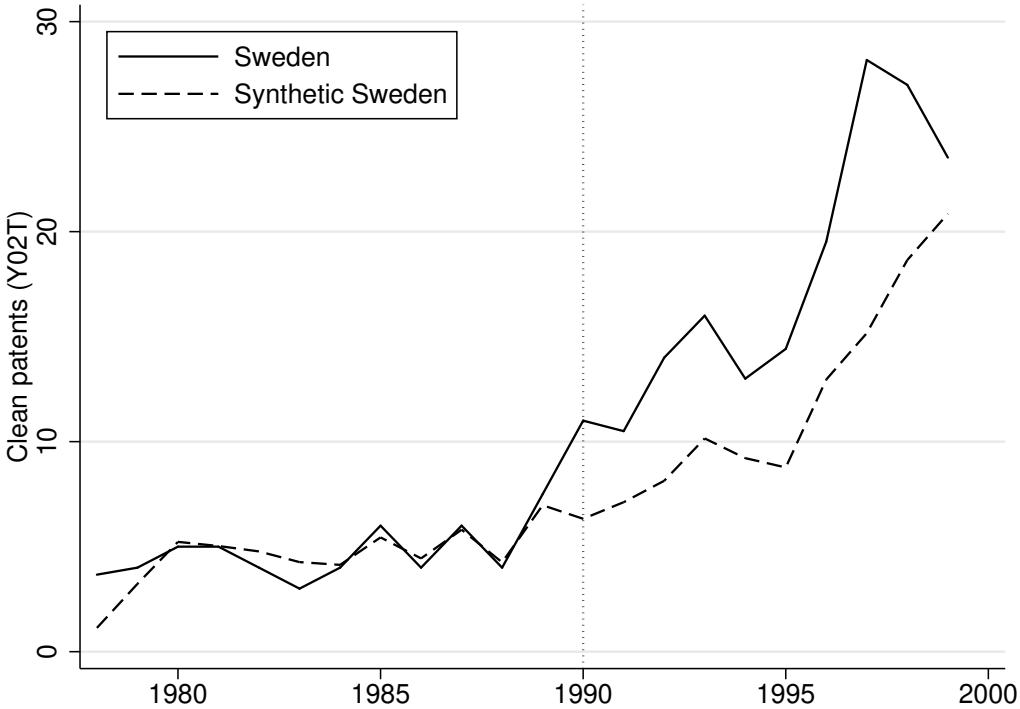
Figure 9: Path and Gap Plot of Y02T patents: Main Results versus Full Sample



As a third robustness check, we follow the recommendation by Ferman *et al.* (2020) and present a specification that includes only pre-treatment outcome values as predictors. The authors argue that the lack of guidance on how to choose the matching variables creates room for specification search and recommend to present also a baseline specification that contains only pre-treatment outcome lags as predictors (see Figure 10). The results stay qualitatively the same. Figure A.2 in Appendix A presents the ratio test of this specification in which the effect again stays statistically significant.

We follow the approach of Ferman *et al.* (2020) further and also show specifications in which the pre-treatment average of the outcome variable has been replaced by alternative pre-treatment outcome lag choices. Figure 11 presents the results when using the choices that Ferman *et al.* (2020) propose, namely the first three-fourths of the pre-treatment outcomes, the first half, all odd or even pre-treatment outcomes, the pre-treatment mean (our main specification), and the first, middle and last pre-treatment outcome. The effect stays qualitatively similar across all specifications.

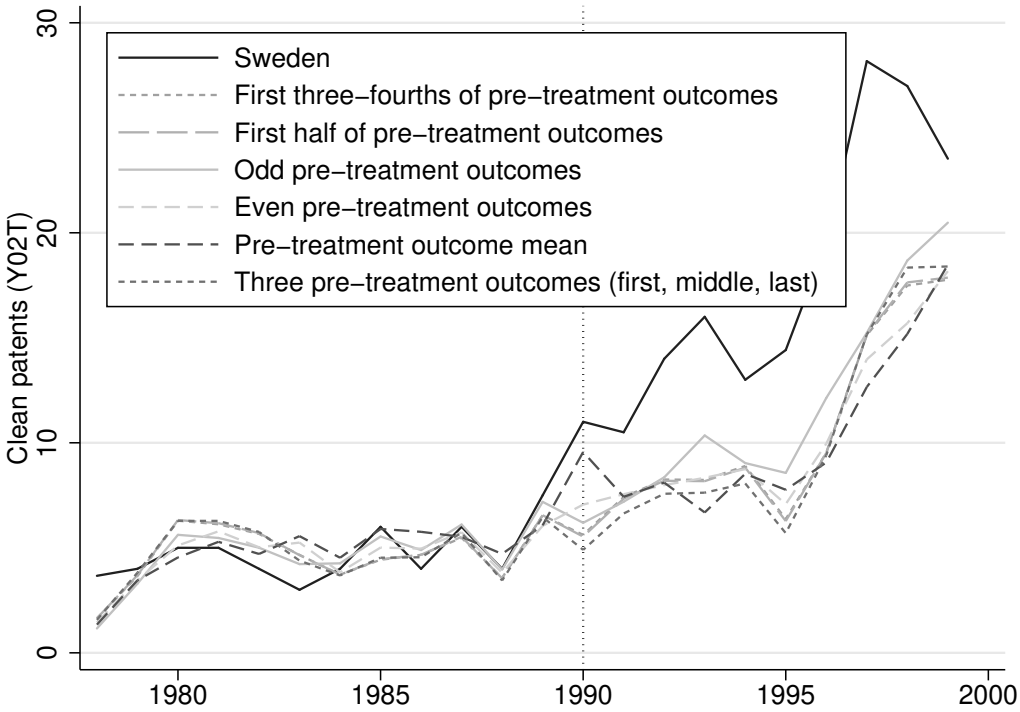
Figure 10: Specification with only pre-treatment outcome values



Following Ferman *et al.* (2020), who in turn base their approach on Cohen-Cole *et al.* (2009) and Christensen and Miguel (2018), we take the simple average of the treatment effects across all these 7 specifications in Figure 11 to account for model-uncertainty. The average effect across these specifications is 65.2 percent with our main specification being the second largest individual effect. Appendix B presents the respective ratio tests in which Sweden always stays on top.

To further verify that our results do not depend on the selection of the outcome lag(s), Appendix C provides different specifications in which all economic predictors are kept unchanged and only the outcome lag selection is varied. We plot the results using a) one outcome lag in the middle of the pre-treatment period (1984), b) the last pre-treatment outcome lag (1989) as proposed by Kaul *et al.* (2021), c) three outcome lags (1979, 1984 and 1989) following Andersson (2019) and Abadie *et al.* (2010), and d) all pre-treatment outcome lags as done by e.g., Billmeier and Nannicini (2013). We find that the results of the different specifications are qualitatively similar and that our findings are not driven by the outcome lag selection and are thus robust to different alternatives.

Figure 11: Specifications with different choices of outcome lags as proposed by Ferman *et al.* (2020)



In Figure C.1 we provide the ratio tests for those specifications and show that Sweden remains on top for all specifications.

To check whether our results are robust to further changes to the set of included key predictors, Appendix D presents the results that were obtained from specifications with additional predictors. Adding GDP, GDP per capita, the amount of R&D subsidies and the number of B60 patents as predictors (Figure D.1), and additionally the value-added share of the industry related to "Motor vehicles trailers and semi-trailers" (C34) (Figure D.2) does not change the results qualitatively and the effect stays significant according to the ratio tests. Furthermore, this specification corroborates our observation that broad factors are relatively unimportant as predictors compared to technology specific factors since the new predictors receive weights that are relatively close to zero (Table D.1 and Table D.2).

Lastly, we conduct a test which follows the logic of the leave-one-out test for the donor pool, but where we now iteratively exclude one of our key predictors (Appendix E). The results again stay qualitatively the same.

Summing up, the innovation effect of the tax reform remains economically meaningful across a large set of different specifications. While it is difficult to settle on a single point estimate given this procedure, we feel that the extensive reporting of different specifications and variations increases the robustness of the identified causal effect. Moreover, when reporting a variety of specifications, the decision rule to reject the null if any of the specifications is insignificant is very conservative (**?**). The finding that Sweden dominates the ratio tests no matter the chosen specification is therefore overall a strong indicator that the effect is statistically significant.

4.4 Disentangling the carbon tax impact on clean innovation

Finally, we try to disentangle the effect of the carbon tax from the effect of the general 1990/91 tax change. This has the additional benefit that we can compare our main results with a basic OLS estimate. To this end, we follow the approach of Andersson (2019) and regress the outcome on the different fuel price components while controlling for confounding factors.[32] The components are a carbon-exclusive component p_t^v and the carbon tax component τ_{t,CO_2}^v (both including a multiplier for the VAT (v)).[33] The log-linear model has the following equation:

$$ln(P_t) = \beta_0 + \beta_1 p_t^v + \beta_2 \tau_{t,CO_2}^v + \beta_3 D_{t,CO_2} + \beta_4 X_{t-1} + \epsilon$$

Our outcome is the natural logarithm of P which denotes the number of clean patents in Sweden per year (t). D_{t,CO_2} is a dummy that is equal to one from the introduction of the carbon tax in 1991 onwards. X_{t-1} is a vector of control variables lagged by one year to allow the impact on patents to be sluggish. We control for patentstock, GDP per capita measured as expenditure-side real GDP at chained PPPs (in mil. 2017 US$) taken from Penn World Table 10.0 (see Feenstra *et al.*, 2015), and a time trend. Finally, we control for R&D subsidies for energy efficiency in transport by taking the countries RD&D budget (million USD in 2019 prices and PPP) in this area from the IEA's Energy

[32] See Table 2 for descripitives and sources of these components.

[33] For a more detailed explanation of the disentangling of the fuel price into these components, see Andersson (2019).

Technology and R&D database (International Energy Agency, 2020a).[34] This enables us to expand our time frame to 2005 for the regressions and thus our small sample size since we are able to control for the larger R&D subsidy programs that started in 2000. Furthermore, this gives us more variation in the height of the carbon tax.

Table 5: Disentangling Results

	(1)	(2)	(3)	(4)
Fuel price with VAT_t	0.0964	0.118**	0.118	0.138**
	(0.0594)	(0.0454)	(0.0788)	(0.0623)
Carbon tax with VAT_t	0.198	0.237	0.238***	0.273***
	(0.126)	(0.151)	(0.0819)	(0.0685)
Carbon tax dummy_t	0.366***	0.294***	0.293	0.449
	(0.0807)	(0.0602)	(0.214)	(0.291)
Trend_t	0.0661***	0.0739***	0.0740*	0.0501
	(0.0169)	(0.0170)	(0.0368)	(0.0499)
R&D subsidies_{t-1}		-0.00760**	-0.00760***	-0.00882***
		(0.00300)	(0.00234)	(0.00296)
Patent stock_{t-1}			-2.50e-05	-0.00356
			(0.00489)	(0.00304)
GDP per capita_{t-1}				0.00818
				(0.00583)
Constant	0.379	0.191	0.189	-1.431*
	(0.553)	(0.478)	(0.808)	(0.726)
Observations	28	27	27	27
R^2	0.94	0.95	0.95	0.95

Notes: Newey-West autocorrelation and heteroscedasticity robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Standard errors are calculated using 15 lags. Lag-length was determined using the method of Newey and West (1994).

Table 5 presents the results of this regression when adding the control variables systematically. The coefficient of the carbon tax is consistently approximately twice as large as the coefficient of the carbon tax-exclusive price. In our preferred specification (Col-

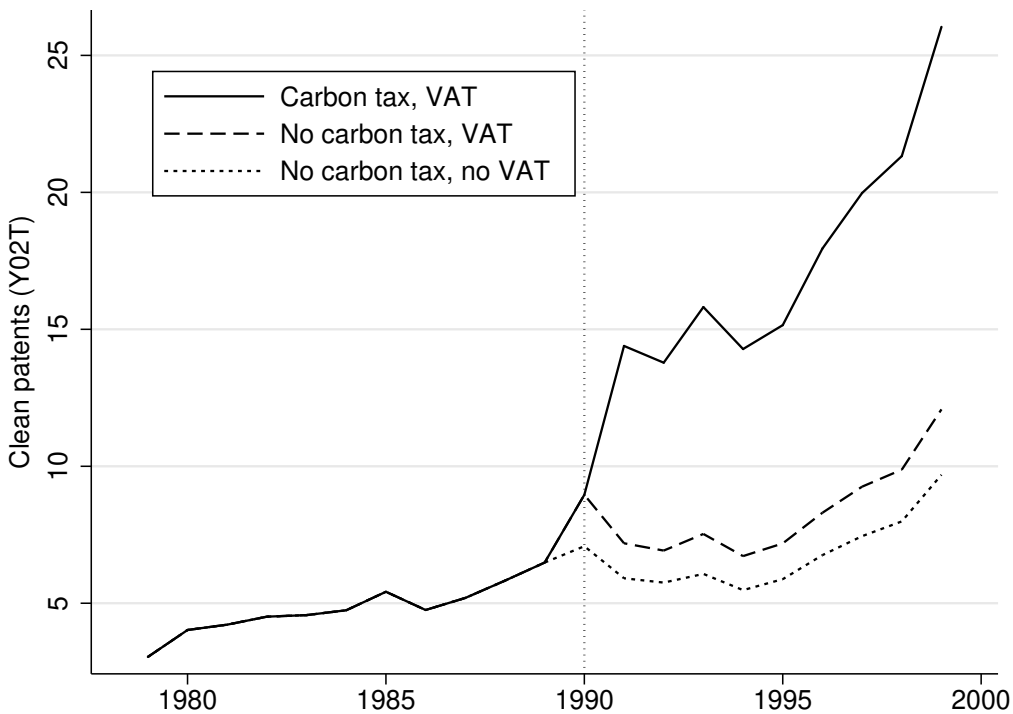
[34] We take the expenditures in the category "13 Transport" which relates to energy efficiency in transport with subcategories such as "Advanced power electronics, motors, EV/HEV/FCV systems", "Advanced combustion engines" and "Vehicle batteries/storage technologies". We take the total RD&D measure. Notably, this category does not contain expenditures for hydrogen-electric related technologies, however this data is not well available for our time frame (see, Aghion *et al.*, 2016 for the same reasoning). We expect this not to be a major drawback since, in our time frame, fuel cell technologies only play a minor role for transportation (H.1).

umn 4) the tax-exclusive fuel price and carbon tax coefficients are statistically significant at the 5 percent and 1 percent level, respectively. That is, a one-unit increase in the carbon tax-exclusive fuel price or the carbon price is on average associated with a, ceteris paribus, increase in clean patents of 13.8 percent and 27.3 percent, respectively.

In elasticities, this result converts to a tax-exclusive fuel price elasticity and carbon tax elasticity of 1.17 and 2.31, respectively.[35] This indicates that the carbon tax is more salient than the fuel price for the innovation response, which is in line with the literature finding this salience distinction in the fuel consumption response (Andersson, 2019; Rivers and Schaufele, 2015).

It should be noted that the results are not robust to the lag structure of the variables. The magnitude of the elasticities should thus not be generalized. We only use them in the following to get a better feeling for the importance of the different price components and to further test our main results from the synthetic control method against a basic estimation.

Figure 12: Disentangling the Tax Components

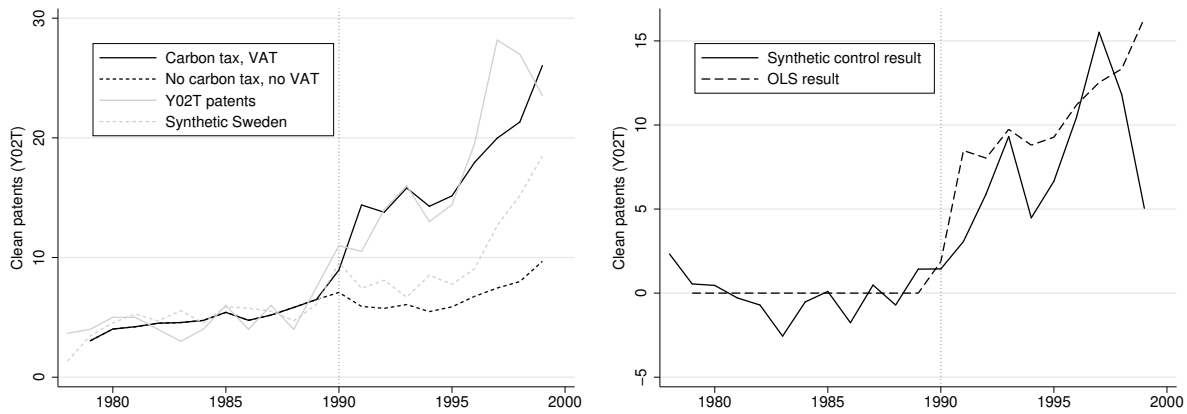


[35]To get the elasticities we multiply the coefficients with the sample mean of the real price of gasoline which is 8.47.

Following Andersson (2019), we use the estimated coefficients to visualize the disentangling of the tax changes by simulating how the trajectory of clean innovation would have evolved in scenarios with only certain components of the fuel price in place. Figure 12 depicts the trend of yearly clean innovation in Sweden without any tax change, with the introduction of the VAT only and with the introduction of the VAT and the carbon tax. According to our estimation, the carbon tax contributes the majority of the tax change effect in the treatment period.

The average effect of the combined carbon tax and VAT using this method (the difference between the solid and the dotted line) is 10.0 patents per year (compared to 7.4 in our main estimation using the synthetic control method). To put this into perspective, Figure 13 compares the effect with our main synthetic control estimate. Panel A compares the simulated treated and untreated outcome paths to the observed and synthetic outcomes from Section 4. Panel B contrasts the effect (gap between solid and dotted line in Figure 12) of the 1990/91 tax reform (VAT and carbon tax) using our OLS estimates and the effect from our synthetic control estimation. The effects are of approximately similar magnitudes and follow similar paths which further corroborates our results.

Figure 13: Disentangling: Comparison of the Aggregate Impact of the Tax Reform to Main Estimate



(a) Panel A **(b)** Panel B

Notes: Panel A shows the yearly annual clean patents in the simulated treated and untreated case from the disentangling. It also shows the observed outcome and the outcome in synthetic Sweden. Panel B plots the gaps from both the simulation and the synthetic control method.

5 Discussion

We find economically large effects of the 1990/91 Swedish tax reform on clean innovation with the carbon tax accounting for the larger part of it. While we find smaller effects in our robustness checks (see Section 4), they are still consistently positive and quite large in economic terms.

It would be interesting to compare our results with estimates of other carbon pricing policies to see if the magnitude of our effect is in line with these studies. However, since we are, to our best knowledge, the first to estimate the innovation effect of a carbon tax in the transport sector, the comparison to other estimates is complicated. As mentioned, the literature that analyzes the impact of carbon prices on innovation either focuses on other sectors or uses fuel prices as a proxy for carbon prices.

Nonetheless, when comparing our effect to other empirical estimates in other sectors, it seems to be relatively large. For example, Calel and Dechezleprêtre (2016) and Calel (2020) evaluate the introduction of the EU ETS and both find an impact on clean innovation of regulated firms of about 10 percent. Even when accounting for the fact that the Swedish tax reform also incorporated an increase of the VAT, our estimated effect seems relatively large. Especially since we provide indicative evidence that the carbon tax contributes the majority of the effect.

However, several factors complicate this comparison to findings in other sectors. First, the incentive channel through which the carbon price influences innovation may differ in other sectors. For example, in the industry sector, firms are priced directly and are incentivized to innovate to reduce the costs from their emissions. Consequently, the demand for clean technologies does not originate from consumers as it is the case in the transport sector. Moreover, innovation intensities (Pavitt, 1982), the patenting intensity of innovation (Pavitt, 1982; Cohen *et al.*, 2000), the state of technological transition, or innovation characteristics such as industrial structure and innovation focus (Pavitt, 1984) may also differ substantially across sectors. Furthermore, carbon pricing policies may include free permit allocations and can differ substantially in their price level compared to the Swedish carbon tax.

In short, while we cannot compare our estimates directly to related estimates in the literature, our effect seems relatively large, which motivates a careful investigation and contextualization of the results. In the following, we aim to highlight some points which may help to explain and contextualize why the tax reform could unfold such a strong impact in Sweden.

First, Sweden is traditionally considered to be a country with an environmentally very conscious population (Nature, 1969). Hence, the carbon tax might unfold such a strong effect since the Swedes may react more strongly to environmental policy (see Section 1 for the channel). Moreover, not only households but also Swedish firms tend to have general environmental concerns (Ministry of Finance, 2021).

Second, as we discussed in Section 1, the carbon policy may not only work through the price-based channel, but the credibility of the political commitment which is perceived by innovating firms might also play a crucial role. Brunner *et al.* (2012) argue that government reputation is key for this channel to work. More specifically, the reputation is build through a history of compliance in repeated political transactions.[36] We argue that this condition was fulfilled when the Swedish government introduced the carbon tax in 1991.

First, the general government reputation is good as high level levels of political trust in Sweden in the 1990s demonstrate (Holmberg, 1999). Second, the public support for climate and environmental policies at the time of the introduction of the carbon tax was high (Raab, 2017). Public support may have been strengthened and supported due to the step-wise implementation of the carbon tax which gave consumers the time to adapt and increased the political feasibility of the policy (Sterner, 2020). In addition, the introduction of the carbon tax as well as future increases were accompanied by broad tax cuts which dampened the direct carbon tax impact. The resulting public support might reduce expectations of a change in policy and therefore increase credibility of commitment.

What's more, cross-party climate policy consensus (Hammar and Åkerfeldt, 2011)

[36] If the reputation is strong enough, no additional measures such as binding commitment devices are needed (Brunner *et al.*, 2012).

resulted in low political volatility which may have undermined the policy credibility (Brunner *et al.*, 2012). Furthermore, firm resistance to the carbon tax may have been low due to industry exemptions and step-wise carbon tax implementation which gave firms the time to adapt. Lastly, Sweden has presented itself internationally as a climate policy "pioneer" with the aspiration to lead by example (Lundquist, 1997).

All those reasons may have contributed to a credible climate policy setting with little policy uncertainty. In short, the high credibility of the political commitment to climate policy could have contributed to the magnitude of the effect which the carbon tax has had on clean innovation since firms expectations of future profits with clean technologies were affected positively.

Given those considerations, the external validity of our estimate may be limited. Future studies estimating the effect of carbon taxes on clean innovation in the transport sector are needed to put our estimates into perspective. Furthermore, it will be interesting to see if the following patterns of differences to other estimates hold up: first, it would be fruitful to investigate whether the higher innovation effect of carbon pricing in the transport sector compared to other sectors is corroborated and to identify potential reasons for the discrepancies. Second, one should analyze whether the higher salience of carbon prices (compared to fuel prices) and its implications for innovation impacts is robust. This would change the predicted innovation effect of carbon pricing in the transport sector substantially and may lead to different policy recommendations. Third, it would be valuable to specifically estimate the impact of credible policy commitment to the innovation impact of climate policies to better understand what part the perception of a credible government commitment played in the Swedish experience.

6 Conclusion

Carbon pricing is on the cusp to become the leading policy instrument in the fight against climate change. More regions will implement it in one of the least decarbonized sectors to date – transportation. However, even though important in theory, the impact of carbon

taxes on innovation in environmentally friendly technologies has not yet been quantified in the transport sector. Therefore, we set out to identify the impact by looking at one of the oldest and most ambitious carbon pricing policies covering this sector, namely the Swedish carbon tax.

We use the synthetic control method to construct a counterfactual for Sweden in absence of the 1990/1991 tax reform. We consistently find positive and economically large effects of the tax reform on clean innovation in an average year between 1990 and 1999. Using simple OLS estimation to decompose the tax reform, we find that the coefficient of the carbon price component is about twice the size of the one for the fuel price component. This finding provides indicative evidence that also with respect to the innovation effect, carbon prices are more salient than fuel prices. In a simulation, we show that the carbon price contributed the larger part of the effect of the 1990/1991 tax reform on innovation.

Our estimates suggest that a carbon price can be effective not only in reducing emissions (see e.g., Andersson, 2019) but also in fostering innovation in clean technologies. However, the carbon tax might have had an especially strong impact in Sweden due to government commitment with respect to climate policy that was widely perceived to be credible.

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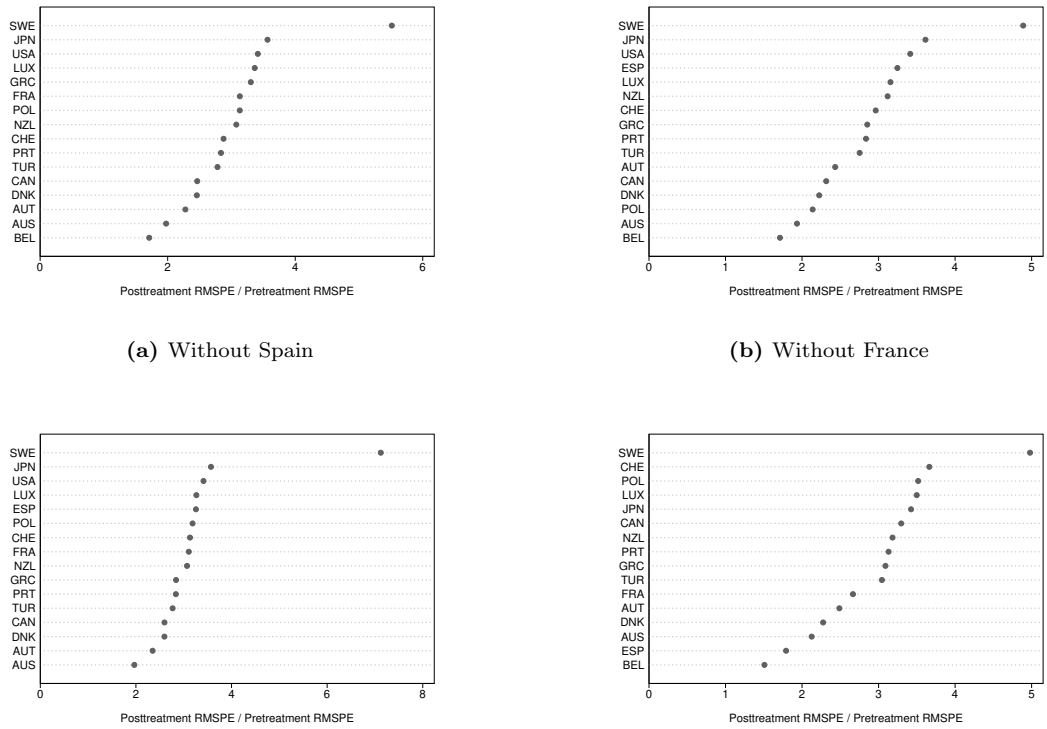
Appendix

A Ratio Tests for Robustness Checks

Figure A.1: Ratio Test for Leave-One-Out Robustness Checks



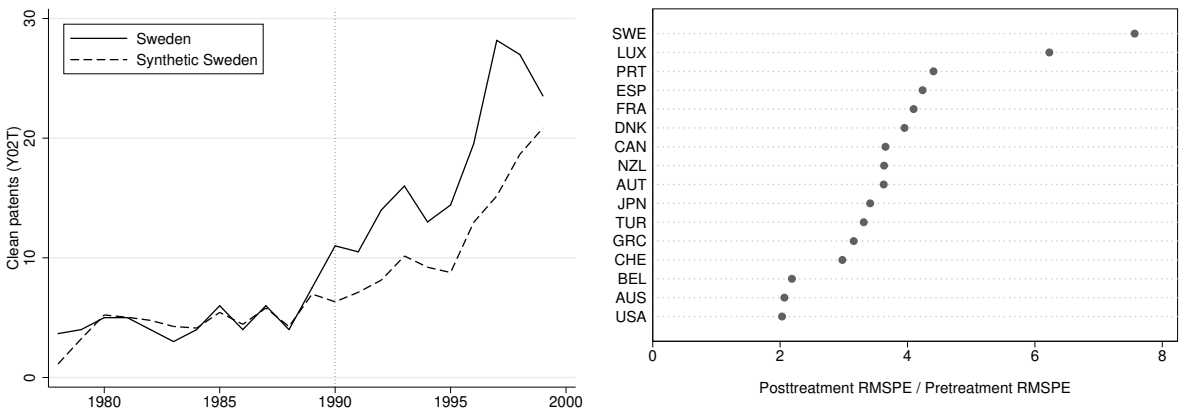
(a) Without Spain

(b) Without France

(c) Without Belgium

(d) Without USA

Figure A.2: Specification with outcome lags only



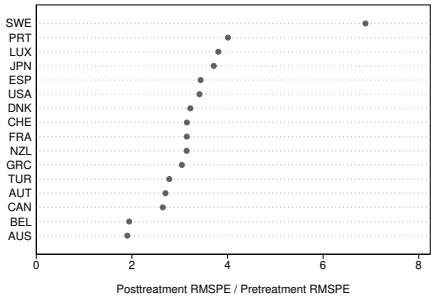
(a) Panel A

(b) Panel B

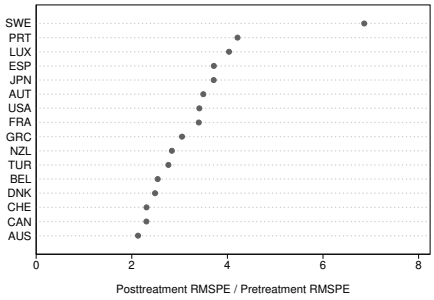
Notes: Here, we follow Ferman *et al.* (2020) and include only the lagged outcome values as a benchmark specification.

B Specifications with choices of outcome lags proposed by Ferman *et al.* (2020)

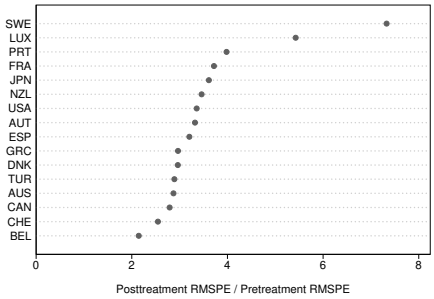
Figure B.1: Specifications as proposed by Ferman *et al.* (2020)



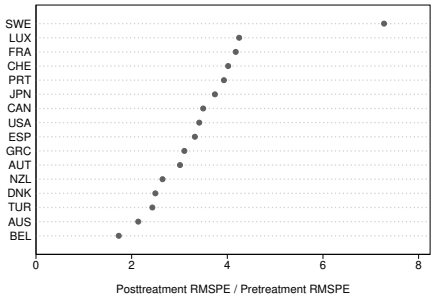
(a) First three-fourths of pre-treatment outcomes



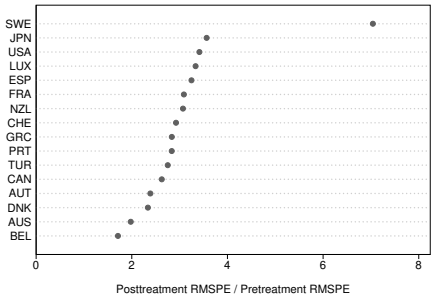
(b) First half of pre-treatment outcomes



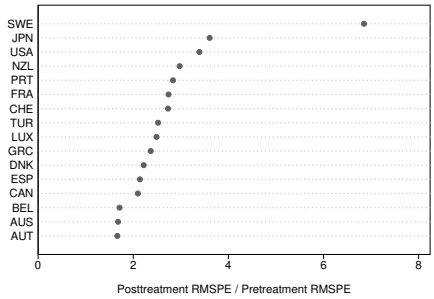
(c) Odd pre-treatment outcomes



(d) Even pre-treatment outcomes



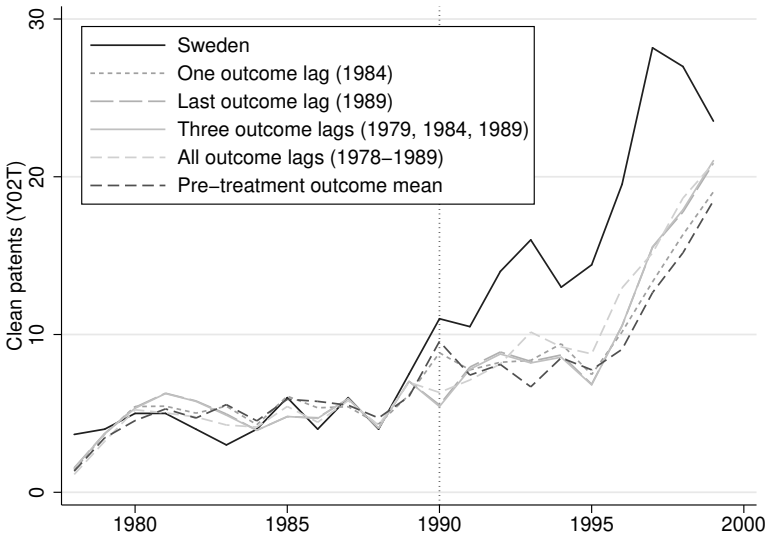
(e) pre-treatment outcome mean

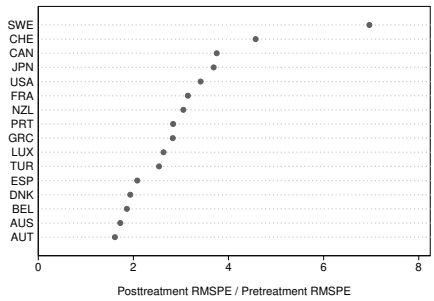


(f) Three pre-treatment outcomes (first, middle, last)

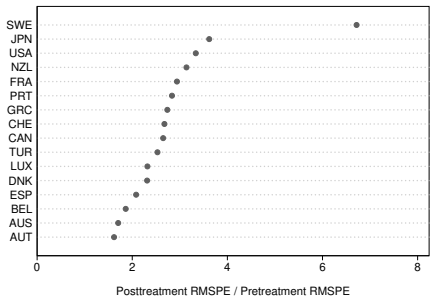
C Specifications with different outcome lags

Figure C.1: Specification with different pre-treatment outcome values

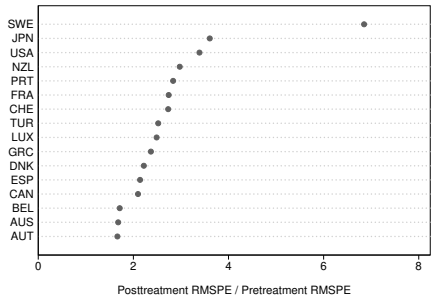




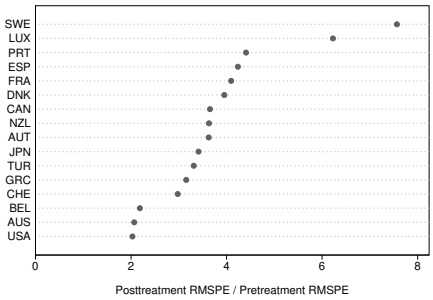
(a) One outcome lag as predictor (1984)



(b) Last pre-treatment outcome lag as predictor (1989)



(c) Three outcome lags as predictors (1979, 1984, 1989)

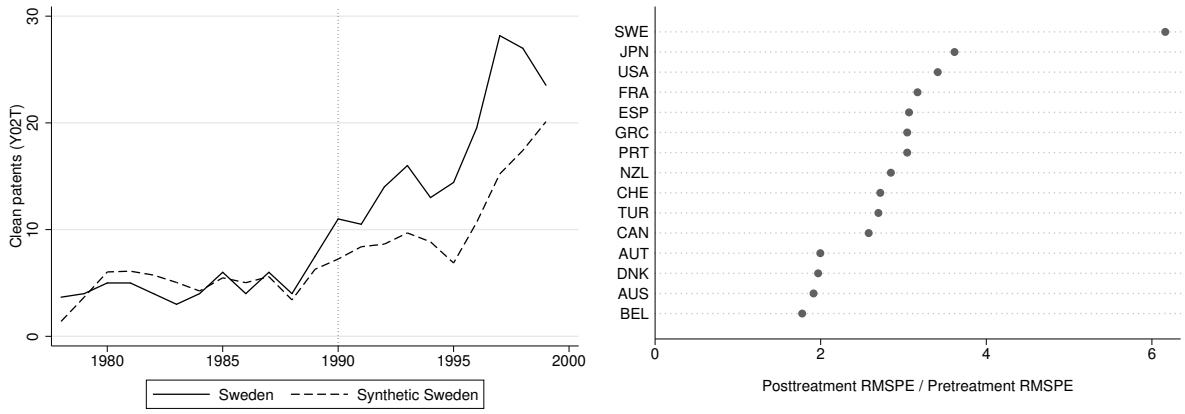


(d) All outcome lags as predictor (1978 - 1989)

Notes: In Panel a) we choose a random outcome lag (1984) in addition to our economic predictors and instead of the average of all pre-treatment outcome lags, while in Panel b) we follow the recommendation of Kaul *et al.* (2021) and include the last pre-treatment outcome lag (1989) as predictor in addition to our economic predictors. In Panel c) we follow Andersson (2019) and Abadie *et al.* (2010) and choose three outcome lags (1979, 1984 and 1989) in addition to our economic predictors. Lastly, in Panel d) we follow e.g., Billmeier and Nannicini (2013) and include all outcome lags (1978-1989) in addition to our economic predictors.

D More (broader) predictors

Figure D.1: Synthetic control – Extended predictors)



(a) Panel A **(b)** Panel B

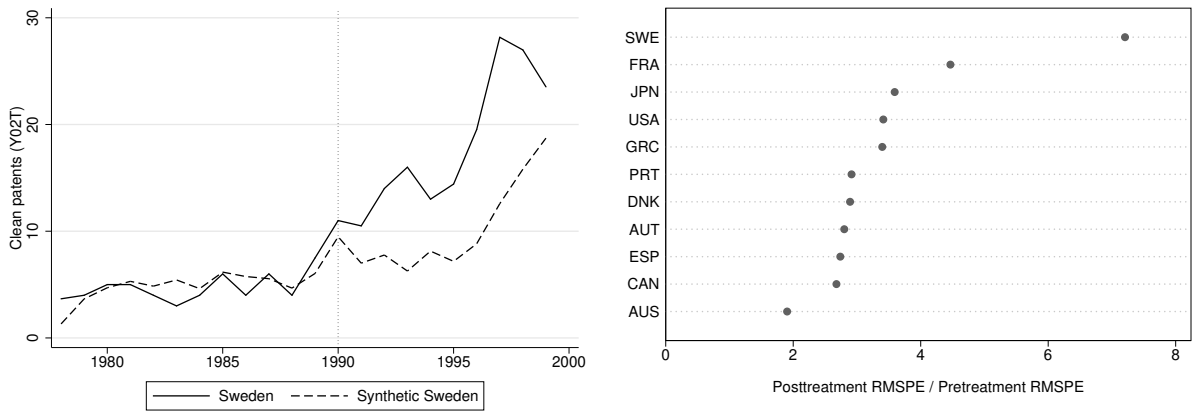
Notes: Synthetic control results when additionally using GDP, GDP per capita, R&D subsidies and B60 patents as predictors. We exclude Luxembourg since information on R&D subsidies is missing in all pre-treatment years. Panel A shows the annual clean patents of Sweden and the synthetic control unit. Panel B presents the result of the ratio test.

Table D.1: Predictor weights and means

Predictor	Weight	Sweden	Synthetic
Patent stock	0.383	17.54	18.72
Total patents (triadic)	0.125	418.40	484.41
NACE2 29.1 patents	0.099	58.56	54.17
Pre-sample average NACE2 29.1 patents	0.069	57.11	45.02
Y02T patents pre-treatment average	0.252	5.17	5.02
GDP	0.001	213602.6	587674.6
GDP per capita	0.000	25521.36	24097.47
R&D subsidies	0.007	7.67	6.94
B60 patents	0.064	12.06	11.63

Notes: Weights of the predictors and the predictor's pre-treatment average in Sweden and synthetic Sweden. GDP and GDP per capita are measured as expenditure-side real GDP at chained PPPs (in mil. 2017US$) and taken from Penn World Table 10.0 (see Feenstra *et al.* (2015). R&D subsidies (government RD&D expenditures related to energy efficiency in transport) are measured in million USD (2019 prices and PPP) and taken from the IEA's Energy Technology and R&D database (International Energy Agency, 2020a). IPC B60 ("Vehicles in general") patents are measured as triadic families and taken from OECD Statistics (2021b).

Figure D.2: Synthetic control – Extended predictors + value-added share of relevant industry



(a) Panel A **(b)** Panel B

Notes: Synthetic control results when additionally to the extended set of predictors also using the value-added share of industry related to "Motor vehicles trailers and semi-trailers" (C34) (OECD Statistics, 2021c). We additionally exclude Belgium, Switzerland, New Zealand and Turkey since information on C34 value-added share is missing in all pre-treatment years. Panel A shows the annual clean patents of Sweden and the synthetic control unit. Panel B presents the result of the ratio test.

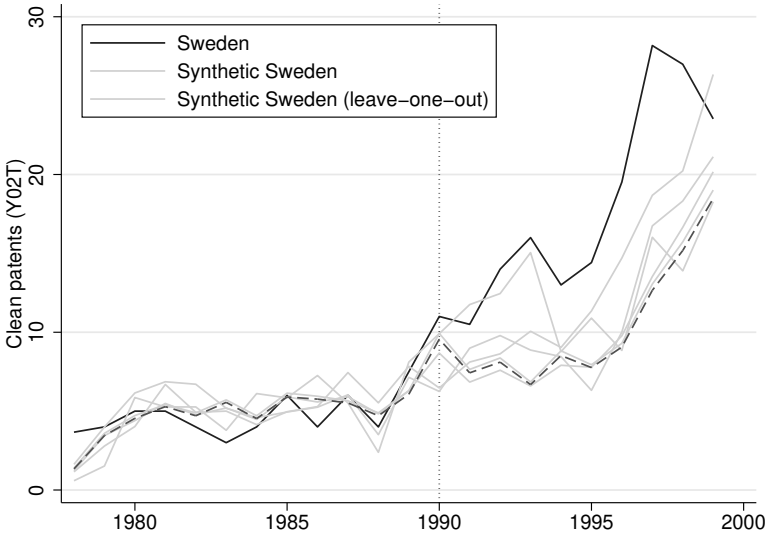
Table D.2: Predictor weights and means

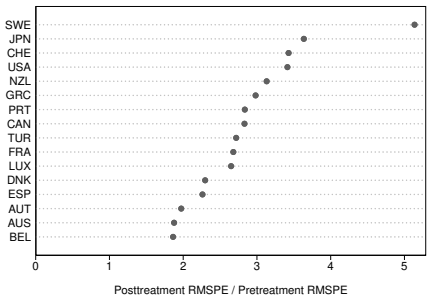
Predictor	**Weight**	**Sweden**	**Synthetic**
Patent stock	0.535	17.54	18.22
Total patents (triadic)	0.42	418.40	387.72
NACE2 29.1 patents	0.086	58.56	52.84
Pre-sample average NACE2 29.1 patents	0.023	57.11	37.55
Y02T patents pre-treatment average	0.279	5.17	5.20
GDP	0.002	213602.6	75.1080.8
GDP per capita	0.000	25521.36	17202.66
R&D subsidies	0.002	7.67	3.64
B60 patents	0.031	12.06	11.08
value-added share of C34	0.000	2.05	1.38

Notes: Weights of the predictors and the predictor's pre-treatment average in Sweden and synthetic Sweden. Value-added share of C34 ("Motor vehicles trailers and semi-trailers") relative to the total economy from OECD Statistics (2021c).

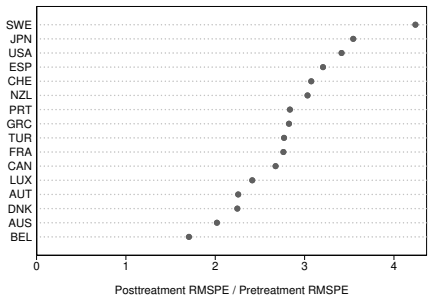
E Predictor Leave-One-Out Test

Figure E.1: Predictor Leave-One-Out Test: Distribution of synthetic Sweden and ratio tests

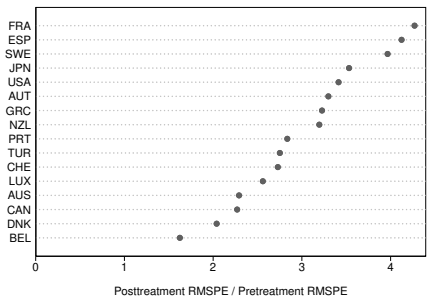




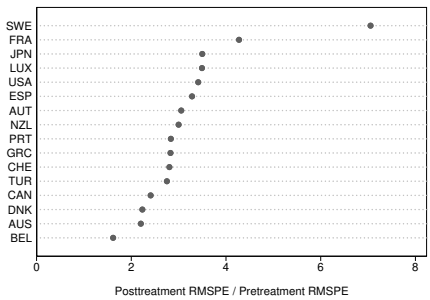
(a) Without Patentstock



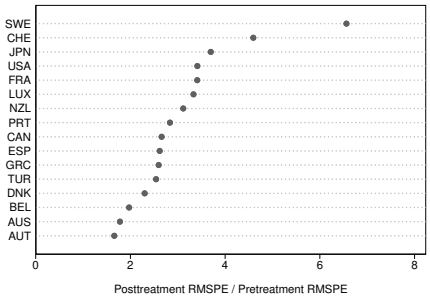
(b) Without NACE2 29.1 patents



(c) Without Total patents (triadic)



(d) Without pre-sample average NACE2 29.1 patentes

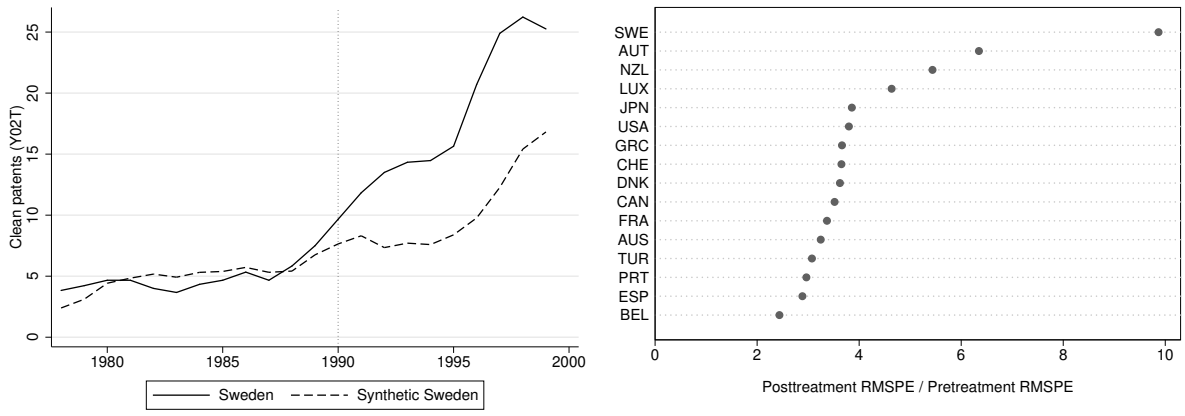


(e) Without Y02T patents pre-treatment average

Notes: Distribution of synthetic Sweden's outcomes and respective ratio tests when iteratively excluding one predictor.

F Smoothed synthetic control

Figure F.1: Synthetic control – smoothed outcome (moving average of three years)

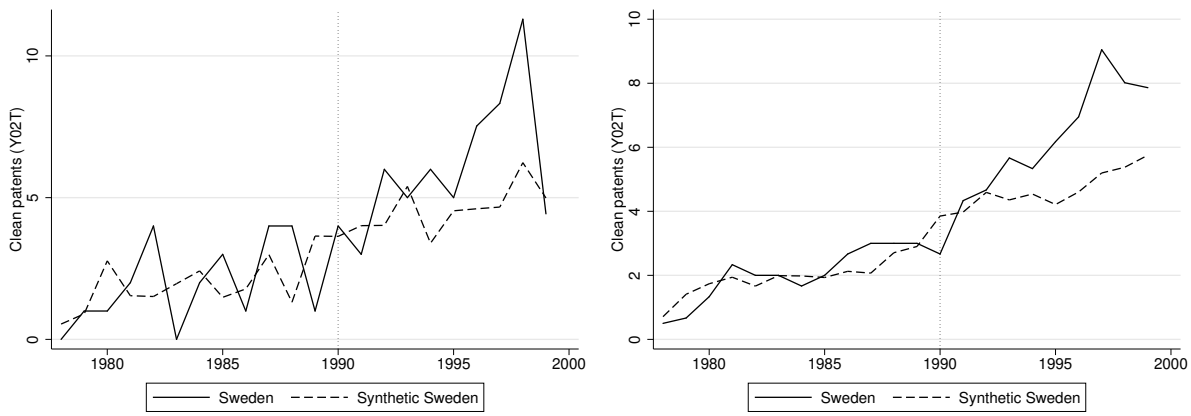


(a) Panel A **(b)** Panel B

Notes: We follow Clemens and Rogers (2020) and smooth our patent data. We apply a three-year moving average. Panel A shows the annual clean patents of Sweden and the synthetic control unit. Panel B presents the result of the ratio test.

G Triadic families

Figure G.1: Synthetic control – triadic families



(a) Panel A **(b)** Panel B

Notes: Panel A displays the synthetic control estimation using the triadic patent family definition (see Section 3). Evidently, the erratic nature of patents is exacerbated in this definition. In Panel B, we follow Clemens and Rogers (2020) and apply a three-year moving average.

H Relevant technology categories

Table H.1: Relevant technology categories of patents with participation of Swedish inventor between 1978 and 1999

CPC code	Description	Freq.	Percent
Y02T 10/12	Improving ICE efficiencies	196	58.86
Y02T 10/30	Use of alternative fuels, e.g. biofuels	12	3.60
Y02T 10/40	Engine management systems	32	9.61
Y02T 10/62	Hybrid vehicles	16	4.80
Y02T 10/64	Electric machine technologies in electromobility	8	2.40
Y02T 10/70	Energy storage systems for electromobility, e.g. batteries	22	6.61
Y02T 10/7072	Electromobility specific charging systems or methods for batteries, ultracapacitors, supercapacitors or double-layer capacitors	13	3.90
Y02T 10/72	Electric energy management in electromobility	10	3.00
Y02T 10/82	Elements for improving aerodynamics	1	0.30
Y02T 10/84	Data processing systems or methods, management, administration	3	0.90
Y02T 10/86	Optimisation of rolling resistance, e.g. weight reduction	1	0.30
Y02T 10/88	Optimized components or subsystems, e.g. lighting, actively controlled glasses	5	1.50
Y02T 10/92	Energy efficient charging or discharging systems for batteries, ultracapacitors, supercapacitors or double-layer capacitors specially adapted for vehicles	1	0.30
Y02T 90/12	Electric charging stations	3	0.90
Y02T 90/14	Plug-in electric vehicles	2	0.60
Y02T 90/16	Information or communication technologies improving the operation of electric vehicles	3	0.90
Y02T 90/167	Systems integrating technologies related to power network operation and communication or information technologies for supporting the interoperability of electric or hybrid vehicles, i.e. smart grids as interface for battery charging of electric vehicles [EV] or hybrid vehicles [HEV]	2	0.60
Y02T 90/40	Application of hydrogen technology to transportation, e.g. using fuel cells	3	0.90
Total		333	100.00

Notes: Relevant clean technology categories (CPC codes) of patents with participation of Swedish inventor between 1978 and 1999. Descriptions are taken from the USPTO. The full list of relevant categories that we would include is larger (namely all of Y02T 10/00 "Road transport of goods or passengers" and Y02T 90/00 "Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation"), but some categories have not been filed with Swedish participation in our period. One invention can have multiple relevant codes.