Policy-induced innovation in clean technologies: Evidence from the car market

Policy-Induced Innovation in Clean Technologies: Evidence from the Car Market

Rik Rozendaal, Herman Vollebergh

Abstract: This article analyzes the effects of fuel economy and greenhouse gas emission standards on the direction of innovation. We develop an intuitive measure of standard stringency that captures the policy's most important attributes for the incentive to innovate. To test the role of standards, prices, and taxes for the innovation decision, we construct a firm-level panel of patents in clean and dirty automotive technologies for the years 2000–2016. Our results indicate that standards are a robust driver inducing zero emission technologies in the car market, while taxes also play a role. The effect of standards is driven by patenting for electric vehicle and hydrogen fuel cell technologies. We find no evidence that these policies negatively impact dirty innovation.

JEL Codes: O3, Q55, Q58

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RECENT YEARS HAVE SEEN rapid changes in the car market in many countries around the world. Hybrid vehicles have become a common sight, and even more radical innovations, such as vehicles powered by electricity, are also quickly penetrating

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the car market. The global fleet of electric passenger vehicles has exploded from about 17,000 in 2010 to over 40 million in 2023 (IEA 2024). Moreover, in its recent Fit for 55 proposal, the European Union aims to cut greenhouse gas (GHG) emissions from newly sold passenger vehicles completely by 2035.

What explains this remarkable shift toward alternative technologies? It has already been demonstrated that climate policies in the EU and the United States stimulated the adoption of new automotive technologies (e.g., Klier and Linn 2016; Reynaert 2021). A different question, however, is what spurs new inventions. This study examines the effects of two main climate policies in the car market—fuel taxes and standards for fuel economy or GHG emissions—on clean and dirty innovation.

A common view in the economic literature on technological change is that innovation and its direction are the result of research investments, which are driven by relative prices. A large body of work tests this prediction in the context of the environment, distinguishing between clean and dirty inventions, typically using patents to measure innovation. The focus in most of this literature is on prices or market-based instruments like taxes and cap-and-trade schemes. For instance, Popp (2002) shows that energy prices positively impact energy-efficient innovations, Aghion et al. (2016) show that fuel prices (which include taxes) steer technological change in a clean direction, and Calel and Dechezleprêtre (2016) study the innovation effects of the EU Emission Trading System.

However, though market-based policies are clearly important, nonmarket instruments have accounted for a larger and growing share of Organisation for Economic Co-operation and Development (OECD) countries' environmental policy stringency over the past three decades (Kruse et al. 2022). Standards are particularly important in the car market, where some externalities are difficult to regulate (Jacobsen et al. 2023). Yet, the literature that studies the innovation effects of nonmarket instruments empirically is limited, especially in contexts where both market and nonmarket instruments are present. This study aims to fill that gap by examining the innovation effects of a market-based policy—fuel taxes—and a nonmarket policy—fuel economy and GHG emission standards. We find that proper identification of the potential impact of environmental policy instruments reveals a prominent role of standards in innovation inducement, in particular in zero emission technologies.

Innovation is a dynamic process. Decisions to innovate, in particular investments in the market for ideas, are typically forward-looking and costly, which means that expectations about (future) prices, market developments, taxes, regulation, and subsidies are all relevant to a firm's decision whether or not, and in which technologies, to innovate. Research in radically new technologies is particularly costly and risky and will only be undertaken if it is expected to pay off in the future. These expectations are typically conditional on the characteristics of the regulatory menu of instruments used by the government, such as their regulatory base and stringency level.

Our focus is on the effect of different regulatory instruments to reduce CO_2 emissions from car use on the direction of innovation using patent data, in particular fuel taxes and standards, while controlling for other drivers such as the fuel price. To identify the potential differential effect of taxes and standards we first separate excise taxes from tax-exclusive fuel prices, as is in line with the recent literature on tax incentives. For instance, Davis and Kilian (2011) and Li et al. (2014) show that taxes affect car use more strongly than prices. Second, we account for the effect of fuel economy and GHG emission standards in a novel way. Car standards are usually pool-based targets announced years in advance. We develop an intuitive measure that captures both this time dimension between the announcement of new targets and the year from which they are enforced, and their strictness by the level of the target relative to current average performance. We define stringency as the amount of CO_2 per kilometer that the average car manufacturer in a country (or the EU) needs to improve per year in the period that remains before the most recently announced target will be enforced. Interaction with a dummy guarantees that we only measure stringency when a standard is binding, that is, mandatory and stricter than current average performance. Accordingly, our measure combines the most important characteristics of this particular instrument in a single dimension and it is comparable across countries.

We test the impact of excise taxes and standards, controlling for R&D subsidies, fuel prices, and knowledge stocks on inventions using patents for automotive technologies as the key indicator. Our patent pool consists of triadic patent families, which are classified as dirty or clean based on their International Patent Classification (IPC) following Aghion et al. (2016).[1] Within the set of clean patents we distinguish between zero emission technologies and hybrid vehicle technologies. Zero emission includes electric vehicles and hydrogen fuel cells. Hybrid vehicles are also clean but not zero emission because they still also rely on the internal combustion engine. Dirty patents are related to the internal combustion engine only and can be split up in gray patents, which aim to increase fuel efficiency, and purely dirty patents.

We compile a firm-level panel for the years 2000–2016 and use data from 1978 to 1999 to construct pre-sample variables and weights. Using our stringency indicator we estimate the effect of tax-exclusive prices, excises, and standards on patenting for different inventions for car technologies at the firm level. We use several empirical models (negative binomial, Poisson, zero-inflated Poisson) for estimation. Pre-sample patenting is used to proxy firm fixed effects in order to control for unobserved differences between firms. We also tackle the potential bias of omitted variables that could affect both policy and innovation.

Our results indicate that both fuel taxes and GHG emission standards have been important in clean technology inducement within our sample period. The effect of

1. Thus, our pool consists only of highly valuable and precisely targeted patents for the different car technologies. A triadic patent family is a group of patents that includes at least one patent at each of the three main patent authorities (those in the EU, United States, and Japan) and that protect a single invention, which is a common way to control for differences in quality between patents. Aghion et al. (2016) select the appropriate patent classes based on earlier research and discussions with patent experts.

standards is particularly strong and robust. These standards strongly stimulated research in zero emission technologies. The search for radically new technologies in our sample period increased due to changes in regulation in the United States and the EU around 2010. We find no evidence for the prediction that regulation shifts resources for invention away from dirty technologies, though we do find that the tax-exclusive fuel price negatively affects dirty innovation.

This study relates to two strands of literature. First, we contribute to the literature on instrument choice for environmental regulation and especially to the debate on the regulation of GHG emissions from road transport. This debate is centered around fuel taxes and several types of standards, though vehicle taxes, feebates, and subsidies are also considered. Bento et al. (2020) analyze the welfare effects of the American Corporate Average Fuel Economy (CAFE) standards, while Leard et al. (2017) study the interaction between standards and fuel prices and show that the effect of fuel prices on the car manufacturers' market share was stronger before 2008 than after that year, though they find little evidence that this was due to more stringent fuel economy standards. Anderson and Sallee (2016) review the incentives that are created by the different instruments. Klier and Linn (2010, 2016) show that both standards and fuel taxes are associated with technology adoption in the United States and Europe. Our contribution to this literature is that we show the impact of these policies on inventions, in particular on decisions to do research on clean technologies that help car manufacturers to comply with stricter regulation. We focus only on the empirical effectiveness of the two policies that are in place and not on a welfare comparison between instruments.

Second, our work contributes to the literature on directed technical change (DTC) and the environment. The theoretical DTC literature poses that relative prices, market sizes, and knowledge stocks determine the direction of innovation, and that environmental regulation can steer technical change to a cleaner path (e.g., Smulders and de Nooij 2003; Acemoglu et al. 2012). The empirical literature tests those predictions, typically by using patent data.[2] Despite their large and growing importance, work on the impact of nonmarket policies is limited. Notable exceptions are Popp (2006), who studies NO_X and SO_2 standards, Lee et al. (2011), who study air quality standards for cars, Noailly (2012), who studies building codes, and Grégoire-Zawilski and Popp (2024), who study interoperability standards for electricity grids.[3]

Most of these studies consider settings where standards are the only relevant policy, while we study standards in a setting where taxes also play an important role. In addition, the representation of standard stringency in much of the literature suffers

2. This literature is recently reviewed by Grubb et al. (2021).

3. Johnstone et al. (2012) also include a dummy variable for a particular category of standards in their analysis of a variety of policies and innovation. Dekker et al. (2012) study the effect of signing international air pollution protocols on innovation.

from limitations that we address. Only two papers have studied the innovation effects of fuel economy or GHG emission standards in the car market in more detail (Crabb and Johnson 2010; Vollebergh 2010). These papers fail to find an effect on green patenting, which is due to two reasons. First, we show that standards were nonbinding for the average firm for most of these studies' sample periods. Second, the standards were represented simply by their current or lagged level rather than by a stringency measure that takes into account anticipation and current performance. Our stringency measure improves on this by accounting for timing and for whether a standard binds or not. Our results indicate that the way in which stringency is measured is important.

This paper continues as follows. Section 1 elaborates on climate regulation in the car market, discussing the innovation incentives that are provided by different policy instruments. This section also explains the importance of carefully identifying regulatory stringency and introduces our measure of standard stringency. Section 2 discusses our data. Section 3 explains our empirical strategy. Section 4 shows our results, and section 5 concludes.

1. REGULATION AND INNOVATION IN THE CAR MARKET

1.1. Innovation Incentives and Abatement Responses

This study examines technologies that contribute to mitigating the climate externality of car use, and, in particular, how inventions of these technologies are influenced by policy instruments that address vehicles' GHG emissions. Both excise taxes on car fuels and standards that regulate either fuel economy or GHG emissions per unit of distance are considered. In theory, these instruments provide the incentive to improve vehicles' climate performance (Parry 2020), but their impact on innovation is likely to differ. The theoretical literature that compares innovation effects of taxes and standards is inconclusive on which policy is more effective (e.g., Magat 1978; Malueg 1989; Montero 2002; Requate 2005). Whether or not a firm innovates, and in which technologies, depends on the characteristics of the incentive.

Fuel tax increases shift demand toward cleaner vehicles (Busse et al. 2013; Allcott and Wozny 2014; Gillingham et al. 2021), incentivizing manufacturers to produce more fuel efficient cars, which can be achieved through technology adoption or innovation. Car manufacturers have a variety of margins along which they can adapt to stricter standards, including innovation (Reynaert 2021; Gillingham 2022). If a fuel economy standard or GHG emission standard applies to a firm's sales-weighted average, a natural solution would be for the firm to adjust its vehicle mix by changing relative prices of high-emission and low-emission vehicles.[4] Firms have also been shown to trade off

4. They can also do so by switching from gasoline vehicles to diesel vehicles, which have better fuel economy, though diesel vehicles face stricter air quality regulation in most countries. They could also shift from large, heavy, high-emission vehicles to smaller and lighter vehicles. The incentive to make cars smaller and lighter is reduced, however, if attribute-based standards

vehicle characteristics (Knittel 2011). For instance, they can reduce a particular model's weight or horsepower to improve its fuel economy. Moreover, firms may adopt new car technologies to comply with more stringent regulations. Klier and Linn (2016) use vehicle-level data and estimate technology frontiers to show that observed changes in vehicle characteristics cannot be explained by trading off vehicle characteristics alone. They interpret this result as evidence that adoption of emission-saving technologies is another important channel to respond to more stringent regulation.[5]

These new technologies require up-front investments in R&D. Car manufacturers are likely to weigh the costs of mix-shifting, manipulating vehicle characteristics, and investing in new research. As long as compliance with a specific tax or a standard is possible by adopting less dirty technologies, car manufacturers and their innovators are unlikely to invest in technologies that are much farther away from the market. Innovation is expensive and will only take place if research is likely to become profitable (or if it is directly subsidized, of course). Hence, only if the policy impulse is strong enough will inventing in zero emission technologies such as electric vehicles or hydrogen fuel cells become part of firms' cost-efficient response and will radical research in this area pay off. Note that innovators in the car market are not necessarily car manufacturing firms. Many inventing firms are technology or component providers to the car manufacturers. An innovator's market is not limited to their country of origin. The potential size of their market is also determined by developments in regulation abroad.

We expect both fuel taxes and climate standards to affect innovation, but their relative impacts depend on the direction and strength of the incentives that they provide. The regulatory signal of a standard differs from that of a tax in several respects, such as strictness and timing, and can lead to differences between the effects of the two policies. Their announcement and implementation are also likely to differ. For standards, a new target is usually announced years before it is enforced. A tax change, on the other hand, can be implemented more quickly. As road transport is heavily regulated through both taxes and standards in most countries, the car market provides an excellent laboratory to test which incentives drive changes in the market for ideas.

1.2. Characterizing Incentive Effects of Regulatory Instruments

More stringent regulation is expected to induce innovation in clean car technologies. Government instruments, however, often vary along multiple dimensions, which makes

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are in place (which is the case in most countries of interest). Using bunching analysis, Ito and Sallee (2018) even show that Japanese firms increased vehicle weight in response to weight-based standards. This, of course, harms overall fuel economy.

5. In addition Reynaert and Sallee (2021) show that car manufacturers in the EU also game policies by making their vehicles perform better in the lab where they are tested than they do on the road.

comparisons difficult (Brunel and Levinson 2016).[6] Our challenge is to capture those features that determine regulatory stringency in a one-dimensional measure or to control for different dimensions separately. We focus on three key design attributes that matter for differences in their potential regulatory impact: (i) the instrument's tax or regulatory base, (ii) its level of strictness in the regulated dimension, and (iii) its timing.

Fuel taxes can be relatively easily compared in these three dimensions. First, fuel taxes have the same tax base over time, that is, fuel use of either gasoline or diesel, which is directly linked to the regulated dimension (either fuel efficiency or GHG emissions). Second, their strictness is defined by the level of the tax rate. In turn, the tax rate can easily be converted to one currency and adjusted for differences in purchasing power between countries and over time. Third, tax changes are usually announced within a relatively short time frame (typically about one year between announcement and implementation). They depend on the political process and are usually persistent and bounded from below.

For climate standards this comparison is more involved. Standards that regulate fuel efficiency or GHG emissions of car manufacturing companies are typically introduced as targets that car producers must meet in a specified year in the future. For instance, standards on GHG emissions specify CO_2 emissions per kilometer driven. Both fuel economy and GHG emission standards typically do not apply to individual cars but to the fleet of cars sold on the market by a manufacturer.[7] Usually they set a minimum (maximum) on a car manufacturer's sales-weighted average fuel economy (GHG emissions per kilometer) and not on an individual car basis. They can be voluntary or mandatory.

Our analysis mainly focuses on the EU, the United States, and Japan, which are the three leaders in the automotive industry, both in terms of R&D and regulation. We summarize the regulation across countries and time in appendix A (apps. A–C are available online). The United States has the longest history of regulating fuel economy, introducing its first CAFE standards for passenger vehicles and light trucks in the 1970s. Japan's Top Runner program, introduced in 1999, sets targets based on the current top performer in the industry. In recent years the EU has been most stringent in its GHG emission regulations. Canada, South Korea, and Mexico also have mandatory standards.

Differences along various dimensions of the instrument across countries and time make comparisons difficult. The first element to characterize the incentive effect is to

6. Brunel and Levinson (2016) also discuss simultaneity, industrial composition, and capital vintage as obstacles. We consider these issues as context dependent whereas we focus on the role of design characteristics of the instruments themselves.

7. When applied to a specific car, a fuel economy (kilometer/liter) and a GHG (grams of CO_2/kilometer) standard are essentially equivalent as kilometers per liter (fuel economy) and CO_2 emissions per kilometer are inversely related through a fixed amount of CO_2 per liter of fuel and because a specific abatement technology for GHG emissions from fossil fuel-based combustion in cars is not available (Anderson et al. 2011).

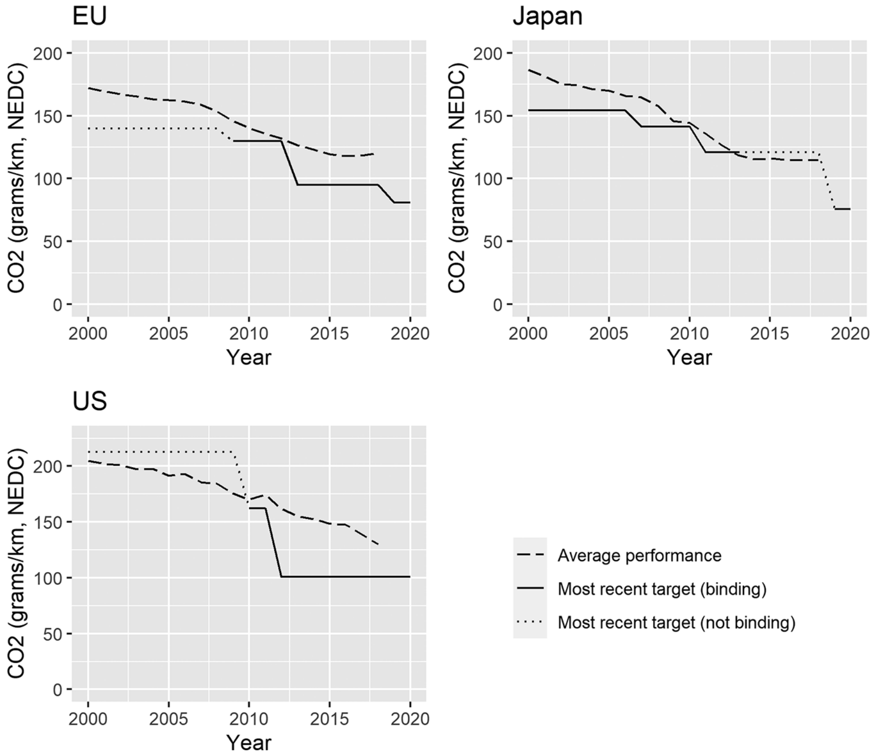

Figure 1. Fuel economy and GHG emission standards and average performance for selected countries. Average performance and targets are converted to CO_2 emissions per kilometer (New European Driving Cycle [NEDC]). Most recent target represents the most recently announced target level for newly sold cars. These are binding if the target (in the future target year) is mandatory and lower than (current) average performance. *Data source*: International Council on Clean Transportation.

translate the different approaches to the same regulatory base of the standard. In order to do so we first convert all standards to the same units and test cycle, namely, grams of CO_2 per kilometer measured using the New European Driving Cycle (NEDC).[8] This also allows us to illustrate the relevance of the other design attributes of the car standards for their stringency more clearly.

Figure 1 shows standards and performance for the EU, Japan, and the United States in this dimension. The dotted or solid line is the most recently announced target. So,

8. NEDC is a procedure to test for vehicle attributes like fuel economy and emissions per kilometer. It is one of the most commonly used test cycles in the world. Test cycles differ in the amount of city/highway driving and average speed. Section 2.3 elaborates on the conversion between test cycles.

the level of the target changes when a new target is announced, not when it becomes enforced. We take the final target as the binding constraint. For example, in 2012 the US government announced a gradual tightening of the CAFE standard with a target of approximately 100 grams per kilometer (converted) to be reached by 2025. No further changes were announced after 2012. The solid line is thus flat at the 2025 target from 2012 until 2020. The dashed line shows average performance of newly sold vehicles, measured at the same scale as the target. Figure C1 (figs. A1, C1–C4 are available online) shows a similar graph for Canada, South Korea, and Mexico.

The other two steps to characterize the incentive effect relate to the level of strictness in the regulated dimension and the timing of the standards. To determine the strictness of a particular announced target or standard, we use two criteria: (i) whether the announced target is voluntary or mandatory; (ii) if it is mandatory, whether the standard is below the contemporaneous average performance level, that is, to what extent it is really binding. The standard line in figure 1 is dotted if the target is nonbinding and solid if binding. For example, the EU had only voluntary targets until 2009, when it announced its first mandatory standards (supported by fines), which were subsequently tightened in 2013 and 2019. Japan has had mandatory standards in place for the entire period, but these were not binding for the average firm between 2013 and 2018. Standards in the United States were mandatory but not binding for the average firm until 2010, when the very stringent targets for 2025 were announced.

Next, we define an index that reflects the different attributes: its level relative to current performance, whether or not it is binding, and its time horizon. In particular, we compute the standard stringency for each country and year as the yearly reduction in CO_2 emissions per kilometer that the average car manufacturer in a country needs to achieve to comply with the most recently announced target. Note that this way of measuring stringency captures and weighs both its credibility and anticipation effect, that is, to what extent the standard is binding relative to current performance and how much time is left for the car manufacturing firms to comply with the new regulation.

Our index is computed as follows for country c in year t.

$$\text{StandardStringency}_{ct} = \text{Binding}_{ct}\frac{\text{Actual}_{ct} - \text{Target}_{ct}}{\text{TargetYear}_{ct} - t}, \tag{1}$$

where Actual is the current actual performance of the average car manufacturer, Target is the level of the most recently announced target, TargetYear is the year in which firms need to comply with the target, and Binding is an indicator that is one if the target is mandatory and more stringent than current performance and zero otherwise. To illustrate this with an example: in 2009 the EU announced its first mandatory target of 130 grams per kilometer in 2015. Average emissions for newly sold cars in 2009 were 145.7 grams per kilometer, so the standard was binding. The required annual decrease is thus 2.62 grams per year (15.7 grams in six years).

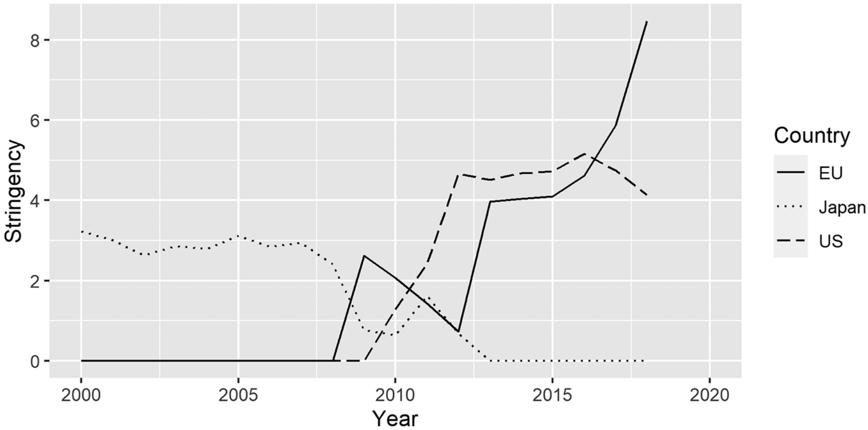

Figure 2. Stringency for selected countries. Stringency for the EU, Japan, and the United States defined as the average required annual reduction in CO_2 emissions per kilometer (New European Driving Cycle) to meet the most recently announced target, computed following equation (1). *Data source*: International Council on Clean Transportation.

Note that we compute stringency at the country (or EU) level and not at the car manufacturer level. We have several reasons to do so. First, most innovating firms are not themselves car manufacturers, but rather suppliers of parts or research firms. Hence, even if we had the emissions data for each manufacturer by country and year, we would still not be able to compute stringency for most firms in our sample. Since parts suppliers and research firms in principle do not care to which manufacturer they sell their product, the average stringency in the market is a reasonable measure of the extent to which the regulation creates an incentive to innovate for these firms. Furthermore, firms in the United States receive tradable credits for overcompliance, and firms in the EU are allowed to pool their fleets under certain circumstances. These features of the instrument go some way at equalizing the marginal costs of compliance with the standard across car manufacturers within a jurisdiction.[9]

Figure 2 shows our stringency indicator for the EU, Japan, and the United States. The difference between the EU and the United States on the one hand and Japan on the other hand is striking. Stringency in Japan was relatively stable and positive until 2008, while standards in the EU and the United States were not yet binding. Japan's stringency then declined due to improved performance and a lack of ambitious targets, whereas the EU and United States started introducing binding targets and gradually increasing their stringency.[10]

9. Appendix A elaborates on how we deal with the attribute-based nature of standards.

10. Figure C2 shows a similar graph for Canada, South Korea, and Mexico. Canada largely followed the United States, Mexico had low stringency even in the brief period in which its

To identify the impact on a dynamic variable like innovation requires accounting for anticipation effects. Defining stringency as the required annual improvement does exactly this. We start counting from the year in which a policy is announced, which is when car manufacturers and their innovators receive the impulse to start innovating. If performance does not improve, the need for a radical innovation becomes stronger as the target year approaches.

2. DATA

2.1. Patents

This study uses patent counts as a measure of innovation, as is common in the empirical economic literature. Despite its drawbacks, this approach is often used, as there are no better alternatives.[11] R&D investment, for instance, is the closest substitute, but it is often not available at the firm level and cannot easily be classified by technology. Concerns about firms' propensity to patent and patent values will be addressed by including a proxy for firm fixed effects and using only a select group of patent families.

Patent data are collected from the October 2020 version of the Patstat database, which is maintained by the European Patent Office (EPO). It is used to establish a panel of counts by firm and year for each category (clean, dirty). Our sample includes 3,646 distinct patent holders and the years 2000 until 2016.[12] Selected patents are classified as clean or dirty based on their International Patent Classification (IPC) code, which categorizes patents by the type of technology they protect. In selecting patents we used the same criteria as Aghion et al. (2016), who base their selection on work by the OECD (e.g., Vollebergh 2010) and conversations with patent experts.[13] Dirty inventions relate to the internal combustion engine. A subgroup of these dirty patents is gray, meaning that they aim to improve the fuel efficiency of the internal combustion engine (making dirty less dirty). The other subgroup is classified as purely dirty. Clean inventions are those

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regulation was binding, and South Korea's stringency drastically increased in recent years as the 2020 target was approaching but performance lagged behind.

11. Drawbacks of the approach include the fact that not all innovations are patented and that the values of patents are highly heterogeneous. Furthermore, patents measure the outcome of the innovation process rather than the inputs, such as R&D investment and number of researchers. An advantage for our purpose, however, is that a patent represents an invention and does not indicate much about technology diffusion and adoption.

12. We chose 2000 as the starting year to have enough pre-sample data available to create weights and to control for fixed effects and because fuel economy performance data, which we need to compute our standard stringency measure, are only available from that year onward. We selected 2016 as the end year because this is the last year for which the October 2020 version of Patstat is complete. This is due to the delay between patent applications, grant decisions and updating of the database (Aghion et al. 2016).

13. Note that this approach yields much better aligned patent classifications than, for instance, Patstat's Y02 classification scheme for green technologies.

related to hybrid, electric, and hydrogen vehicles and fuel cells. We classify hybrid vehicle technologies as clean to keep consistency with the classification used by Aghion et al. (2016), though hybrid vehicles still use fossil fuels and could therefore also be classified as gray. Electric and hydrogen-powered vehicles have the potential to be purely clean from a GHG perspective if the electricity or hydrogen that powers them is generated using renewable energy. We refer to these as zero emission technologies. Tables C1 and C2 (tables A1, B1–B11, C1–C3 are available online) show the IPC codes belonging to each category and some examples of the technologies, respectively.

Patents are counted at the family level to prevent double counting of inventions. A patent family includes all patent applications that cover the same invention.[14] We count each family in the year of the earliest application within the family, as is standard in the literature. According to Griliches (1990), firms file a patent application early in the invention process, which means that the priority date is close to the date of invention.

A well-known issue with patent data is that the value distribution of patents is skewed. Many patents have little economic value, and the distribution has a long tail with some inventions that are highly valuable. In order to exclude inventions with little value we select only triadic patent families (see also Aghion et al. 2016). These families include at least one application at the EPO, one at the Japan Patent Office (JPO), and one at the US Patent and Trademark Office. The idea here is that applying for a patent is costly, which means that it is only worth the cost if the invention is likely to be profitable. Triadic patent families are highly correlated with other measures of patent quality, such as forward citations (Martinez 2010; Dechezleprêtre et al. 2017). Furthermore, this approach limits the sample to inventions with a potential for international application, because protecting an invention abroad is only worth the cost if there is a possibility to use or sell it internationally.

Figure 3 shows the total number of dirty and clean patents per year for the period 1978–2016. Dirty patents peak in 2010 and clean and total patents in 2011, which is broadly consistent with the findings of Probst et al. (2021). The figure shows that yearly clean patents have overtaken dirty ones in 2009 and stayed higher since. The total number of patent families selected for the sample period 2000–2016 is 34,622, of which 16,627 are classified as clean and 19,392 are dirty.[15]

14. A family may include multiple applications at the same patent office, and it may contain applications for the same invention in multiple countries. Each family has at least one priority patent, which is the first application of a certain invention. There are multiple ways of defining a patent family (Martinez 2010). We use DOCDB families, which are provided by Patstat. These families are constructed by patent examiners and may have multiple priorities.

15. Some patent families contain IPC codes that fall into both categories and are thus counted both as clean and as dirty. This is the case for 1,397 families (about 4% of all families), most of which (1,098) are for hybrid car technologies. Almost half (9,223) of the dirty patents are aimed at increasing fuel efficiency and are thus classified as gray, and the rest (10,169) are

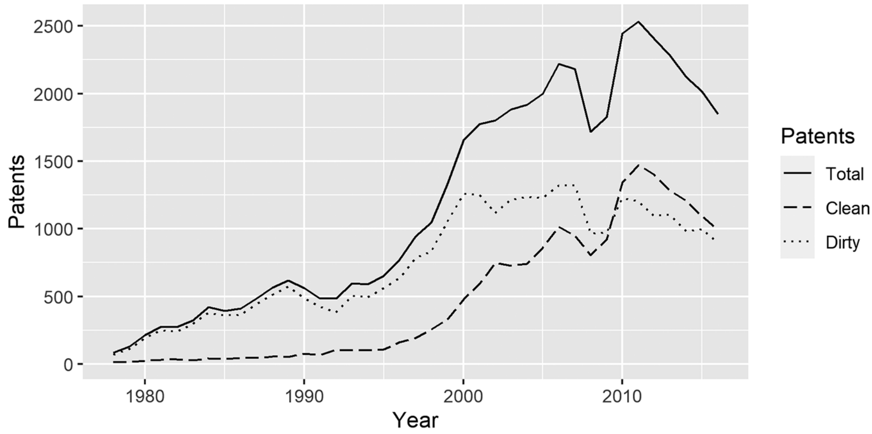

Figure 3. Patent counts. Number of triadic patent families per year. Total consists of all families used for this study but is not the sum of clean and dirty as some patent families fall into both categories. The sample period used is 2000–2016. *Data source*: Patstat.

The majority of patent applicants in our sample are companies (72%), and the remaining applicants are either individuals (20%), universities (4%), nonprofit organizations (2%) or unknown (1%).[16] All of the largest patent holders are companies. Though most car manufacturers do appear in our sample, the majority of firms that apply for car-related patents are suppliers of components or research firms. For instance, two of the firms that hold most patents in our data set are Toyota, a car manufacturer that does much of its R&D in-house, and Bosch, a large supplier of vehicle components. See table C3 for an overview of the largest patenters in our sample.

2.2. Fuel Taxes and Prices

Data on fuel taxes and prices are obtained from the International Energy Agency's (IEA) Energy Prices and Taxes database. This database contains annual energy prices for many countries and several energy sources, such as such as diesel, gasoline, liquified

purely dirty. About half of the clean families relate to hydrogen vehicles or fuel cells (8,497). The other half mostly consist of patents for electric vehicles (7,816). A total of 3,670 patents relate to hybrid technologies, most of which (2,923) are also classified as electric.

16. Most patent applications mention multiple applicants. We assigned a patent family to the organization or individual that is mentioned as applicant on the highest number of applications within that family. In case of a tie we assigned an equal fraction of the family to all those applicants that were tied. We then manually checked the list of applicants and matched those that were mentioned multiple times with slightly different names (e.g., Toyota Motor Corporation and Toyota Motor Europe). This reduced the number of different applicants from 4,279 to 3,646.

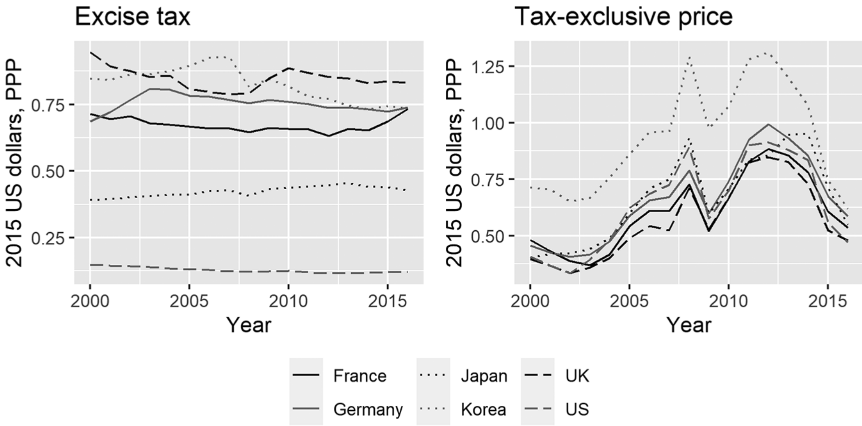

Figure 4. Excise taxes and tax-exclusive prices for selected countries. Excise tax and tax-exclusive fuel price in 2015 US dollars (PPP) for selected countries. Both are computed as the average of diesel and gasoline. *Data source*: International Energy Agency.

petroleum gas, and electricity. The country's source data are in local currencies and also distinguish between excise taxes and value added taxes (VATs).[17] We take excise taxes and tax-exclusive prices and convert them to 2015 US dollars using the OECD's purchasing power parities (PPP) conversion rates. For the purpose of this study we are interested in car fuels, so for each country we take the (unweighted) average of the diesel price and the gasoline price.[18] We include fuel prices and taxes for 30 countries.[19]

Figure 4 shows the evolution of excise taxes and tax-exclusive fuel prices for a selection of countries. Excise taxes vary considerably across countries. The United States has a a low excise tax, and European countries generally have high taxes. Japan is in

17. The database provides separate excises and VATs for all countries in our data set except the United States. We thus supplement this dataset with data from the American Highway Statistics, published by the Federal Highway Administration (see https://www.fhwa.dot.gov/policyinformation/statistics/2019/). The United States has federal excise taxes of 18.4 and 24.4 cents per gallon on gasoline and diesel, respectively. These have been at the same level since 1993. States also collect excise taxes, so we add the average state-level excise (weighted by volume taxed) to the federal one.

18. There are several types of gasoline (leaded, unleaded, regular, premium). We take premium unleaded 95 if it is available for a country in all years (2000–2016), and otherwise regular unleaded. Prices and taxes for at least one of those two fuels are available for all countries. Diesel prices are available for all countries in our dataset.

19. The countries are Australia, Austria, Belgium, Canada, Chile, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, South Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

between. Excises are relatively stable in the time dimension. This is not surprising, as many countries index their excise to the general price level and our measurement of the tax corrects for differences in purchasing power. Tax-exclusive fuel prices are much more volatile and follow a highly similar trend in all countries. A large part of the time series variation is due to (tax-exclusive) oil prices, which means that most countries experience the same shocks. Level differences between countries are largely due to variation in transportation costs and purchasing power.

Fuel taxes and prices are measured at the national level, whereas patents are measured at the innovating firm level. We therefore follow the method of Aghion et al. (2016), which has become standard in the literature, and compute firm-level excise taxes as the weighted average of country-level excise taxes as follows (prices are computed in the same manner).

$$\mathrm{FuelTax}_{it} = \sum_c w_{ci}^F \mathrm{FuelTax}_{ct}, \qquad \text{where} \qquad w_{ci}^F = \frac{w_{ci}^P \mathrm{GDP}_c^{0.35}}{\sum_{c'} w_{c'i}^P \mathrm{GDP}_{c'}^{0.35}}. \tag{2}$$

Here c indicates a country and w_{ic}^F is a weight that captures firm i's exposure to country c's market. The term w_{ci}^P is the share of firm i's pre-sample patent applications that were filed in country c. The pre-sample period runs from 1978 until 1999. We use all pre-sample patent applications by the firms in our dataset to construct these weights and not only those in triadic families concerning car technologies. The reason is to increase the number of firms for which pre-sample data are available. Following Dechezleprêtre et al. (2021) we further weigh by pre-sample GDP to reflect market size.[20]

The idea behind these weights is that a firm will protect its inventions in those places where it believes it is going to sell its innovation. Hence, a firm's patent portfolio should be a reasonable proxy for its sales distribution by country and thus its exposure to the signal provided by these countries' fuel prices and taxes. Aghion et al. (2016) introduce this method and defend it by showing that geographical sales weights and patent portfolio weights are highly correlated for some large automotive companies.[21] We use pre-sample portfolios to establish weights to assure their weak exogeneity. Almost half (1,722) of the 3,646 firms in the sample do not have any pre-sample patents. These firms are given the average weights of the other firms. We check the robustness of our results to using alternative weights in the appendix.

20. The exponent 0.35 is added because patent weights already partially reflect market size (see Dechezleprêtre et al. 2021). Setting the exponent to 0 or to 1 does not change our results in a meaningful way. Pre-sample GDP is computed as the average over the years 1995–99.

21. Specifically, see app. C, the section "More Descriptive Statistics on Patents Filing" and citations and table A1 in the online appendix to Aghion et al. (2016). Moreover, we find that portfolios are stable over time on average, that pre-sample and sample portfolios are highly correlated at the firm level, and that clean and dirty patenters have similar geographical portfolios.

2.3. Standards

Data on standards and their announcement dates are gathered from Transport Policy.net, which is a website created by the International Council on Clean Transportation (ICCT) and DieselNet.[22] It contains an overview of regulations on transportation for many countries and includes the standards that we study in this paper. We restrict our attention to standards for passenger vehicles.

Standards are measured in different units across countries (see also table A1). The EU, for instance, sets standards on GHG emissions, measured in grams of CO_2 per kilometer, whereas the United States initially used standards measured in miles per gallon of fuel and now has standards on emissions in grams of CO_2 per mile. Japan has standards expressed in kilometers per liter. In addition, countries use different test cycles to determine a car's fuel economy or emissions, which differ, among other things, in the amount of city driving relative to highway driving and the average speed during the test.[23] This means that even if the American standard (measured using the CAFE cycle) is converted from grams per mile to grams per kilometer, it is still not equivalent to the European standard (measured using NEDC). To circumvent this issue we use a conversion tool for standards, developed by the ICCT.[24] This tool allows one to convert standards across test cycles and units. We use this tool to convert all standards to grams per kilometer (NEDC). Canada, South Korea, and Mexico also have mandatory standards. For several reasons we have not included these countries in all specifications.[25]

Converting targets into the same units and test cycle does not give us a reliable measure of the stringency of the standards, however. As described in section 1, we use data on average performance in terms of CO_2 emissions per kilometer to compute

22. Some additional data were needed for Japan and were acquired from the website of the Energy Conservation Center Japan (https://www.eccj.or.jp). Japan's targets vary by weight group, which means that they are not straightforward to aggregate. We circumvent the aggregation problem by using the ECCJ's expected fuel economy as the target.

23. The four most used ones are the American CAFE test cycle, the New European Driving Cycle (NEDC), the Japanese JC08 cycle, and the Worldwide harmonized Light vehicles Test Cycles (WLTC).

24. This tool is available on the ICCT website. See https://theicct.org/pv-fuel-economy under "Sources and Tools." The conversion tool requires the fleet average diesel penetration (average of the two countries) as an input (Kühlwein et al. 2014). The share of diesels in new car registrations has been negligible in the United States and Japan, whereas in the EU it has risen from around 30% to around 50% in the sample period (Díaz et al. 2017). Since we convert American and Japanese standards to the European NEDC, we use a diesel penetration of 20%. None of the results hinge on this parameter choice.

25. First, none of these three countries has had mandatory standards for the entire sample period. Second, Canada and Mexico have some missing data points in their performance data. We use linear interpolation to fill in these values and compute stringency. Third, South Korea has had a target that was mandatory for all vehicles rather than for a sales-weighted average, making it difficult to compare across countries.

the required reduction to meet the most recently announced target. The average performance data are gathered from the ICCT, which collects the data from government agencies.[26] These data concern the sales weighted average of newly sold cars and are converted by the ICCT to the NEDC test cycle. The data are thus comparable with the targets discussed above.

Based on these data we compute our country-specific stringency measures for the different standards at the country level. To translate these stringency measures into firm-specific levels we take the same approach we use for fuel prices, that is, using weights that reflect market exposure. The weights are somewhat different from those for taxes as some countries are left out for standard stringency. Portfolio shares are computed over all pre-sample patents filed in EU countries, the United States, and Japan.[27] The standard stringency measure for each innovating firm i is thus computed as follows:

$$\text{Stringency}_{it} = \sum_{r=1}^{3} w_{ir}^{S}\text{Stringency}_{rt}, \qquad \text{where} \qquad w_{ir}^{S} = \frac{w_{ir}^{P}\text{GDP}_{r}^{0.35}}{\sum_{r'} w_{ir'}^{P}\text{GDP}_{r'}^{0.35}}, \quad (3)$$

and $r = 1, 2, 3$ represent the EU, Japan, and the United States. Since stringency is 0 when a standard is nonbinding, we take natural logarithms in our regressions, that is, we use $\log(1 + \text{Stringency})$.

2.4. Knowledge Stocks, Spillovers, R&D Subsidies, GDP

The same patent data discussed above are used to establish separate stocks of clean and dirty knowledge, which proxy for a firm's R&D experience and productivity. These stocks are updated each year using the perpetual inventory method:

$$K_{Cit} = (1 - \delta)K_{Cit-1} + P_{Cit} \qquad \text{and} \qquad K_{Dit} = (1 - \delta)K_{Dit-1} + P_{Dit}, \quad (4)$$

where δ is the depreciation rate of knowledge, which accounts for the fact that some knowledge becomes obsolete over time. We set the knowledge depreciation rate at 20%, which is a value often assumed in the literature (e.g., Aghion et al. 2016). Knowledge stocks are included as their natural logarithm.[28] In addition, we add three dummies to the regression: one to indicate that $K_{Cit} = 0$, one for $K_{Dit} = 0$, and one in case both are equal to zero (Blundell et al. 1999).

In addition to firm-level knowledge stocks, we include knowledge accumulation at the country level to account for geographical spillovers (see, e.g., Jaffe et al. 1993). Since

26. The data are available at https://theicct.org/pv-fuel-economy/.

27. In the specifications with Canada, Mexico, and South Korea these countries are also used to create weights. The weight assigned to the EU is based on all pre-sample patent applications in countries in our dataset that use the EU standard.

28. Since knowledge stocks are zero until the first patent application, we follow the standard approach in the literature and add an arbitrary constant to all knowledge stocks to avoid taking the logarithm of zero.

patents are recorded at the firm level and many firms operate from several countries, we compute spillover stocks using inventors' locations at the time of their patent applications, following Aghion et al. (2016). Note that these weights are different from those used for prices, taxes, and standards, which are based on patent applications (rather than inventor location). The spillover stock for firm *i* in country *c* consists of the cumulative knowledge stocks of all other firms that have inventors located in country *c*, weighted by the proportion of each firm's inventors that are located in country *c*.

Another potential determinant of innovation that we control for is R&D expenditures by national governments. We take these data from the IEA's Energy Technology R&D Statistics, which specifies government R&D budgets for a variety of technologies. We use government support for energy efficiency in the category transport (category 13). According to Aghion et al. (2016), these subsidies are largely aimed at gray technologies, that is, improving the efficiency of the internal combustion engine. We do not have data on which firms received subsidies, so we use weights again to measure the exposure to government support. Since governments subsidize firms that do research in their country, we use the inventor location weights that we use for spillovers, rather than the market exposure weights that we use for taxes and standards.

Our final control variable is GDP per capita, which is meant to capture overall economic conditions at the country level. We collect these data from the OECD database. We measure GDP in 2015 dollars (PPP). We use the same market exposure weights that we use for taxes and prices to transform GDP per capita to a firm-level variable.

2.5. Descriptive Statistics

Table 1 shows some descriptive statistics for our main variables. We show them separately for the sample of firms with at least one clean patent in the period 2000–2016 (clean sample) and the firms with at least one dirty patent (dirty sample). We do not use a balanced sample but only include firms in the years in which we know they were active, that is, from their first until their last observed patent application (in any technology). We show the alternative of using a balanced panel, which includes many more zeros in the dependent variable, in the appendix.

3. EMPIRICAL STRATEGY

3.1. Choice of Estimator

Our dependent variable is a count of patents, so we use a count model to estimate our regressions. Our regression equation is the following:

$$\begin{aligned} P_{ist} = {} & \exp(\beta_{s1}\log(S_{it-1}) + \beta_{s2}\log(\mathrm{FT}_{it-1}) + \beta_{s3}\log(\mathrm{FP}_{it-1}) + \beta_{s4}\log(\mathrm{RD}_{it-1}) \\ & + \beta_{s5}\log(\mathrm{KC}_{it-1}) + \beta_{s6}\log(\mathrm{KD}_{it-1}) + \beta_{s7}\log(\mathrm{SC}_{it-1}) + \beta_{s8}\log(\mathrm{SD}_{it-1}) \\ & + \beta_{s9}\log(\mathrm{PP}_{i}) + \beta_{s10}\log(\mathrm{PPD}_{i}) + w_{it}\gamma_{s}) + u_{ist}, \end{aligned} \tag{5}$$

Table 1. Descriptive Statistics

	Clean Sample		Dirty Sample	
	Mean	SD	Mean	SD
Clean patents	.624	4.619	.529	4.767
Dirty patents	.603	6.275	.782	6.537
Log(1 + standard stringency)	.684	.589	.655	.590
Log(fuel excise tax)	−1.117	.408	−1.103	.425
Log(tax-exclusive fuel price)	−.448	.291	−.452	.293
Log(R&D subsidy)	.165	.173	.158	.167
Log(1 + clean knowledge stock)	.536	.752	.311	.750
Log(1 + dirty knowledge stock)	.295	.777	.562	.818
Log(clean spillover)	6.258	1.184	6.160	1.258
Log(dirty spillover)	6.601	1.155	6.548	1.222
Pre-sample average	1.855	2.054	1.594	1.951
Pre-sample zero	.267	.442	.261	.439
Observations	26,580		24,716	
Firms	2,122		2,107	

where i denotes a firm, s denotes a technology (clean, dirty, or a subcategory), and t is a year. The term S is standard stringency, FT is the fuel excise, FP is the tax-exclusive fuel price, and RD are R&D expenditures. The terms KC and KD are the firm's own clean and dirty knowledge stocks, respectively. The terms SC and SD are clean and dirty spillover stocks, respectively. The terms PP and PPD are time-invariant variables based on pre-sample patenting to control for firm fixed effects. Finally, w includes control variable GDP per capita, dummies for when firm-level knowledge stocks are zero (three dummies: one for no clean knowledge, one for no dirty knowledge, one for when both stocks are zero), and a complete set of year dummies; u_{ist} is the idiosyncratic error term.

We use a negative binomial model for our regressions, for which we specify the mean and variance as follows:

$$\mathbb{E}(P) = \lambda, \tag{6}$$

$$\mathrm{Var}(P) = \lambda(1 + \delta), \tag{7}$$

where we parameterize λ for individual i, technology s, and year t as $\lambda_{ist} = \exp(X_{it}\beta_s + \eta_i + \nu_t)$. We prefer this estimator to the Poisson estimator, as it allows for overdispersion through parameter δ. If δ is zero the negative binomial and Poisson distributions are equal. An advantage of the negative binomial model is that its coefficients can be interpreted as elasticities, like for the Poisson model. We specify overdispersion to be constant across observations.[29]

29. That is, we use the NB1 model from Cameron and Trivedi (2013, chap. 3).

3.2. Identification

The main challenge in identifying the effect of regulation on innovation is to specify regulatory stringency for both taxes and standards in a manner that captures the impact on the decision to innovate. As discussed before, we separate the excise tax from the price, and we specify standard stringency to capture the anticipation of targets that have been announced but are not yet enforced.

In addition, we face two econometric challenges. First of all, there is the potential presence of unobserved firm characteristics that lead to differences in the propensity to patent. This is particularly relevant in patent regressions with knowledge stocks. Such stocks are an important determinant of new innovations and correlated to our variables of interest but they are not strictly exogenous (Blundell et al. 1995). Including them in the standard fixed effects count data model would violate the model assumptions (Hausman et al. 1984) and lead to biased results. Hence, in dealing with fixed effects we follow the approach of Blundell et al. (1995, 1999) and Noailly and Smeets (2015), who use firms' pre-sample patenting behavior to proxy for the firm fixed effect.

For pre-sample patenting we use average yearly patenting in any category (not only clean and dirty car technologies) from the first year in which a firm files a patent until 1999. We include all technologies to increase the number of firms that have pre-sample data available and because overall patenting is arguably a good proxy for the propensity to patent, and this is what the fixed effect should capture. In addition, we include a dummy that equals 1 if a firm has no pre-sample patents to account for the possibility that these firms are structurally different (in eq. [5] PP counts pre-sample patents and PPD is the dummy).[30] This is also the approach taken by Noailly and Smeets (2015).[31]

Our second concern is the presence of omitted variables that might correlate both with standard stringency and patenting and could thus bias our estimates. Importantly, we already mitigate this issue by explicitly controlling for knowledge stocks at the firm and country level. Including knowledge stocks in the estimation reduces the likelihood that past innovation, which potentially affects both current innovation and policy, biases the results.

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30. Blundell et al. (1995) defend this approach by arguing that under the assumption that a firm's innovative search process is stationary and follows an AR1 process, average yearly search activity is proportional (up to a constant) to the firm fixed effect η_i. If average pre-sample patenting is a good proxy for search activity, then it can be used to proxy for the fixed effect. They then show that the inclusion of these pre-sample variables strongly reduces serial correlation, which suggests that the fixed effect has been eliminated.

31. In our robustness section in the appendix we also include a specification with the clean and dirty knowledge stock in the last year of the pre-sample period. This approach is taken by Aghion et al. (2016) in the regressions they label as BGVR. Dummies for no pre-sample data are also included.

We have four other potentially omitted variables in mind that we cannot control for. The first two are lobbying and gaming. Omitting these variables, however, may lead us to underestimate the effect of standards on patenting. Automobile manufacturing is a large industry in several countries, which gives manufacturers some influence on future policies. Established manufacturers are likely to lobby against stricter fuel emission standards. Furthermore, car manufacturers are known to have gamed regulations by making their vehicles emit less in the lab where they are tested than on the road.[32] Both lobbying and gaming would make companies less active in the market for ideas as they offer an alternative to innovation, thus negatively affecting patenting. Stringency, in turn, is expected to affect both lobbying and gaming positively, as stricter rules give manufacturers a larger incentive to engage in these activities. Leaving out these variables, for which no data are available, may thus introduce a downward bias to our estimation.[33]

The third potentially omitted variable that could bias our results is expectations about clean innovation. If the expectation is that clean technologies will improve quickly over the next years, even in the absence of policy, then this may attract investment that positively affects patenting. At the same time, it could lead policymakers to implement more stringent regulations. Contrary to lobbying and gaming, the direction of this bias is such that we would overestimate the effect of stringency on clean patenting. No data are available to disprove that expectations played a role, but we argue that it is highly unlikely for several reasons.

During the first half of our sample, Japan was the only country with positive standard stringency. Japanese standards were part of the Top Runner program, which set targets based on the current top performer in the industry (see table A1). These standards were explicitly based on technologies that already existed at the time and are thus captured by our knowledge stock variables. The largest shocks to standard stringency, however, happened between 2009 and 2013 in the EU and the United States. During this period, the global electric vehicle (EV) fleet was negligible compared to the internal combustion engine (ICE) fleet, and only very expensive EVs were available (IEA 2024). Furthermore, nothing in the announcements of these standards suggests that policymakers were anticipating a large technological shift in the absence of policy in these years. In fact, the levels of the standards that were set during this time could be met with existing technologies

32. Dieselgate, also known as the Volkswagen scandal, is the most famous example of cheating.

33. Following Cinelli and Hazlett (2020), suppose we want to estimate $P = \hat{\alpha}S + X\hat{\beta} + \hat{\gamma}L + \hat{\varepsilon}_{\text{full}}$, but we do not observe lobbying L. We thus estimate the restricted model $P = \hat{\alpha}_{\text{res}}S + X\hat{\beta}_{\text{res}} + \hat{\varepsilon}_{\text{res}}$. We can then write our estimate $\hat{\alpha}_{\text{res}}$ as follows, $\hat{\alpha}_{\text{res}} = \hat{\alpha} + \hat{\gamma}\hat{\delta}$, where $\hat{\delta}$ comes from the regression $L = \hat{\delta}S + X\hat{\psi} + \hat{\varepsilon}_L$. It is the effect of stringency on lobbying, controlling for all other covariates. For both lobbying and gaming we expect $\hat{\gamma} \leq 0$ and $\hat{\delta} \geq 0$, i.e., $\hat{\alpha}_{\text{res}} \leq \hat{\alpha}$. In words, if lobbying or gaming biases our results, we expect our coefficient to be an underestimate. See Cinelli and Hazlett (2020) for details. Unfortunately, we cannot perform the tests proposed by that paper, as we do not use least squares to estimate our nonlinear model.

and fleets consisting of only ICE vehicles. In other words, additional innovation was not necessary to meet the targets. The EU legislation that was announced in 2009 states that it actively promotes eco-innovation and includes super-credits that support this claim.[34] If expectations about additional clean innovation were the reason for implementing the standard, then these incentives would be of no use.

One could even argue that the sentiment around zero emission driving technologies at the time was pessimistic rather than optimistic. For instance, only two manufacturers met the voluntary targets that were set by the EU for 2008 (see table A1). Moreover, during the late 1990s and the 2000s, California, which had targets for the share of the car fleet that should be zero-emission vehicles (ZEVs), made its targets more lenient several times because they were not met by carmakers (Hascic and Johnstone 2011). It both lowered the share that should be ZEVs, and allowed partial ZEVs (hybrid and natural gas vehicles) to be included as well. Though none of these developments disprove that optimism about clean technologies played a role, they convince us that this potential bias is unlikely to be a reason for concern.

The fourth potentially omitted variable is the introduction or expansion of other policies, such as incentives for electric vehicle adoption. We believe that other policies are not driving our results for two main reasons. First, electric vehicles made up such a small share of the total vehicle fleet in our sample period that other policies than standards had little "bite" for innovation decisions. Second, we do not find any policy changes that clearly correlate to our stringency measure for the most relevant countries. We elaborate on both arguments in appendix A.

As a final step we follow the literature and use the first lag of our explanatory variables in our main specifications. This makes sense in the context of patenting. A change in regulation may lead firms to respond by investing in R&D, but it takes time for this investment to result in patents. Hence, a lag of one year is reasonable. It also rules out that an invention in a particular year affects performance, which is part of our stringency measure on the right-hand side, and which would imply reverse causality. The effect of past patents on performance is already controlled for using knowledge stocks. Using lags makes sure that stringency is predetermined. We also test for specifications with different lag structures in the appendix.

4. RESULTS

4.1. Main Results

Table 2 shows our main results for counts of clean and dirty patents (cols. 1–3 and 4–6, respectively). All our estimations include fixed effects as described above, a full set of year dummies, GDP per capita, and dummies that indicate a knowledge stock of zero.

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34. Super-credits allow manufacturers to count clean vehicles (<50 g CO_2/km) as multiple cars when computing their weighted average during the phase-in period of the standard. We present a robustness exercise that deals with super-credits in table B11.

We use the negative binomial model for our baseline results. Column 1 shows that both our indicator of standard stringency and the excise tax have a positive and significant effect on clean patenting. The coefficient of 0.19 for stringency can be interpreted as an elasticity: a 10% increase in 1 + Stringency increases clean patenting by almost 2%. Similarly, a 10% increase of the fuel excise is associated with an almost 3% increase in clean patenting. The positive and significant impact of our two main variables of interest on clean patenting confirms the prediction that both (selective) taxes and standards induce clean innovation. The point estimates do not change much when we leave out either the fuel tax and price (col. 2) or stringency (col. 3).

The tax-exclusive fuel price and R&D subsidies have no significant impact. This is not entirely surprising. The tax-exclusive price mainly captures level differences in prices, while price shocks, which are highly similar across countries, are absorbed by the time fixed effects.[35] R&D subsidies are measured rather imprecisely, as we do not observe which firms are subsidized, and this might explain the absence of a significant effect. The marginally significant and negative impact of the R&D subsidy in column 2 is apparently related to the absence of the fuel price and might also reflect the fact that these subsidies are mainly aimed at gray technologies (Aghion et al. 2016), which shifts resources away from clean initiatives.

Firms' own clean knowledge stocks have a strong and positive effect on clean patenting, whereas own dirty knowledge is insignificant. This is in line with the DTC prediction that innovation is path dependent. A firm that has gained expertise in a particular area is likely to continue on the same path. The clean spillover has a positive, though slightly significant effect, while the spillover for dirty patenting is negative and significant. This indicates that local spillover effects are indeed a determinant of innovation. Pre-sample patenting is highly significant in all specifications, which suggests that it captures the propensity to patent. The coefficient for the average number of yearly patents is positive, meaning that firms that applied for more patents in the pre-sample period were also more likely to patent during the sample period. The dummy that indicates firms with no pre-sample patents is positive, which means that these firms are more likely to patent than other firms during the sample period. To a large extent, this captures patenting by firms that did not exist during the pre-sample period.

We find no evidence that standards and excise taxes affect dirty patenting negatively (cols. 4–6). The results for the tax-exclusive fuel price are in line with DTC theory. This negative effect, which is not statistically significant, could indicate that firms shift resources away from dirty to clean innovation. Interestingly, the effect of the standard is positive though insignificant. This confirms our idea that as long as car manufacturers have a mix of improvements available for compliance, a standard—which does not discriminate between technology classes—may still also induce further efforts to innovate

35. Figures C3, C4 show that the variation in fuel prices and excise taxes, conditional on country and year fixed effects, is limited for the most relevant countries in our sample.

Table 2. Clean and Dirty Patents

	Clean			Dirty		
	(1)	(2)	(3)	(4)	(5)	(6)
Standard stringency	.191***	.190***		.096	.115*	
	(.067)	(.063)		(.066)	(.067)	
Fuel excise tax	.284***		.245**	–.137		–.172
	(.107)		(.112)	(.151)		(.157)
Tax-exclusive fuel price	–.316		–.554	–.582*		–.751**
	(.415)		(.399)	(.305)		(.326)
R&D subsidy	–.143	–.298*	.007	.123	.152	.191
	(.168)	(.173)	(.164)	(.183)	(.192)	(.194)
Clean knowledge stock	1.034***	1.029***	1.022***	–.077**	–.072*	–.080**
	(.024)	(.025)	(.026)	(.035)	(.038)	(.035)
Dirty knowledge stock	–.002	.001	.002	1.090***	1.084***	1.089***
	(.016)	(.017)	(.017)	(.044)	(.049)	(.045)
Clean spillover	.193*	.0873	.143	.030	.088	.003
	(.099)	(.089)	(.098)	(.091)	(.104)	(.094)

Dirty spillover	−.189**	−.105	−.154*	−.022	−.063	.002
	(.090)	(.086)	(.090)	(.076)	(.082)	(.081)
Pre-sample average	.082***	.079***	.086***	.044**	.047**	.047**
	(.013)	(.013)	(.014)	(.022)	(.022)	(.021)
Pre-sample zero	.485***	.467***	.511***	.292***	.294***	.306***
	(.053)	(.053)	(.057)	(.059)	(.058)	(.059)
δ	.978	.982	.988	1.078	1.088	1.084
Observations	25,280	25,280	25,280	23,439	23,439	23,439
Log likelihood	−16,842.3	−16,853.2	−16,872.7	−15,265.4	−15,271.3	−15,273.0

Note. Estimation is done using the negative binomial model (with overdispersion parameter δ). Robust standard errors are clustered at the firm level and reported in parentheses. All regressions include knowledge stocks, spillover stocks, GDP per capita, dummies for knowledge stocks that are equal to zero, pre-sample patents and a dummy for no pre-sample patents (to account for firm fixed effects), and a full set of time dummies. All (time-variant) regressors are included as their first lag.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

in dirty technologies. The impact of own knowledge stocks is as expected, with a strong positive effect of dirty knowledge and a smaller, negative effect of clean knowledge. We do not find a significant effect of the spillover stocks on dirty patenting.

Our results on standard stringency contribute a new insight to the literature. The most closely related work to ours is Aghion et al. (2016), who study the innovation effects of tax-inclusive fuel prices. They find a strong, positive effect of fuel prices on clean patents (coefficient around 1.0) and no impact from standards.[36] Our coefficient for the fuel excise is smaller but also significantly positive, but the coefficient for the tax-exclusive price is not distinguishable from zero. For dirty patents Aghion et al. (2016) find a significant coefficient of around −0.5. The coefficient we find is of similar size but for the tax-exclusive price and not for the excise. We show the results of regressions that include the tax-inclusive price in our robustness analysis in the appendix. We also find a positive impact of the standard on dirty patents although it is not significant.

Our findings provide evidence that not only fuel taxes but also GHG emission standards strongly induce clean innovation for automobile technologies. Apparently our stringency indicator captures an important aspect of firms' innovation decisions. To interpret the magnitude of the effect it is best to consider the average value of $\log(1 + \text{Stringency})$ in our clean sample (used in cols. 1–3), which is 0.68, and its standard deviation, which is 0.59. A one standard deviation increase in $\log(1 + \text{Stringency})$ is associated with an 11% increase in patenting for clean technologies. Our finding that regulation did stimulate clean patenting but did not direct much research away from the dirty options is also interesting. Apparently regulation was not strong enough to reveal such an asymmetric impact, and car manufacturers still had confidence in the future of the dirty market during our sample period. This may also reflect the fact that all standards announced during our sample period could be met using only dirty technologies.

To put our estimates in perspective, we can do a simple back-of-the-envelope calculation based on our estimates and a policy scenario. Suppose that in 2017 all countries in our sample had adopted the target of zero emissions by new passenger vehicles in 2035 (i.e., the current EU target). This would have constituted a 103% increase in $1 + \text{Stringency}$, which, keeping all else equal, would be associated with a 19.7% increase in clean patenting. The tax increase that would be needed to achieve such an increase in patenting (keeping stringency constant) is 67%.[37] A tax increase of such a proportion

36. Aghion et al. (2016) use a measure of standard stringency of air quality standards (not fuel economy or GHG emission standards), while their patents are classified on GHG emission criteria. In other words, the policy measure does not perfectly match the relevant innovation decision.

37. Stringency in 2016 was 3.02 for the firm with the average weights. In 2017 the average firm would need to reduce its emissions from 129 to 0 in 18 years, that is, stringency becomes 7.17. The increase is in patenting is 0.191 times the percentage increase in $1 + \text{Stringency}$, and the tax increase is the patent increase divided by 0.284 (both coefficients are from table 2).

seems highly unlikely, while the equivalent target (in terms of patents, not welfare) is already being implemented. At least in this sense, our results seem economically meaningful and they show that the innovation dimension should not be dismissed when comparing the welfare effects of these two policies.

4.2. Disaggregated Technologies

In this subsection we take a closer look at the technologies that make up our clean and dirty categories. As noted before, we label electric and hydrogen vehicles and fuel cells as zero emission technologies and keep hybrid vehicles separate. All dirty patents relate to the internal combustion engine, but we consider the patents that aim to improve fuel efficiency as gray and the others as purely dirty. As described in section 2 some patent families belong to multiple categories.

Table 3 shows the results of our estimations for the disaggregated technologies. We include the same explanatory variables as in our baseline, so we do not compute separate knowledge stocks for each technology class.[38] Columns 1–3 show that the positive effect of stringency that we find for clean patenting is mostly driven by technologies for electric and hydrogen-powered vehicles. Interestingly, the effect of the fuel excise is not significant for the two zero emission categories, whereas we found a significantly positive effect for the aggregate measure of clean innovation in table 2. This difference could be due to the decreased sample size in our disaggregated estimations, but pooling of zero-emission and hybrid technologies also plays a role.

Indeed, our results for hybrid technologies are quite different from the zero emission categories (see col. 3). In fact these results are closely in line with the findings for the pooled dirty patents as shown in table 2 as well as the results for the purely dirty category (col. 5). The impact of the tax-exclusive fuel price on patenting is strong in both cases, but negative and highly significant. And, again, the fuel excise has a negative coefficient while the standard has a positive impact here, but both are insignificant. Interestingly, column 4 shows very different results for gray technologies, that is, technologies that aim to make the internal combustion engine more fuel efficient. Our stringency indicator also has a positive impact here, though only significant at the 10% level.

We believe that these findings could be well understood if one takes a closer look at the policy windows at that time. In Japan the Top Runner program has provided a strong incentive for hybrids in the early phase of our sample period, together with the inducement of standard setting in California (see also Hascic and Johnstone 2011). The Japanese policy gradually became more lenient, however, as well as standard setting in California which switched to standards allowing compliance based on the hybrid technology. The standards announced both in the United States at the federal level and in the EU

38. The differences in the number of observations come from the fact that we include only firms with at least one patent in the relevant category.

Table 3. Disaggregated Technologies

	Electric (1)	Hydrogen/ Fuel Cell (2)	Hybrid (3)	Gray (4)	Purely Dirty (5)
Standard stringency	.297***	.223***	.130	.115*	.048
	(.105)	(.080)	(.120)	(.065)	(.068)
Fuel excise tax	.202	.150	−.379*	−.005	−.246
	(.194)	(.154)	(.226)	(.166)	(.202)
Tax-exclusive fuel price	−.758	.185	−2.214***	.417	−1.024***
	(.778)	(.466)	(.545)	(.477)	(.357)
R&D subsidy	−.058	−.193	.150	−.039	.135
	(.294)	(.222)	(.380)	(.333)	(.221)
δ	1.523	1.035	1.195	1.155	.848
Observations	11,257	16,848	5,512	10,342	18,986
Log likelihood	−7,081.9	−11,316.3	−3,475.9	−6,779.6	−11,576.9

Note. Estimation is done using the negative binomial model (with overdispersion parameter δ). Robust standard errors are clustered at the firm level and reported in parentheses. All regressions include knowledge stocks, spillover stocks, GDP per capita, dummies for knowledge stocks that are equal to zero, pre-sample patents and a dummy for no pre-sample patents (to account for firm fixed effects), and a full set of time dummies. All (time-variant) regressors are included as their first lag.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

before 2010 were much more stringent and induced this search for much more radical technologies while switching away from the hybrid option.

The findings for the research impacts on the purely dirty technologies are in line with this interpretation (see col. 5). Apart from the radical alternatives, further improvements of fuel efficiency of the (very) large share of the typical mix of cars sold on the market would contribute strongly to compliance because zero emission technologies still had to find their way to consumers.

Our results clearly provide evidence for a strong impact of regulation on zero emission vehicle technologies, while neither fuel excises nor tax-exclusive fuel prices seem to play a role here. Though our estimation of the pooled clean technologies shows a positive and significant impact of the fuel excise, no such evidence could be found for the disaggregated technologies. Interestingly, research related to fuel efficiency, our gray category, resembles to some extent the pattern of research in electric and hydrogen cars. At the same time research on hybrid and purely dirty technologies resembles the (negative) predictions on research effort by the DTC literature, in particular through the tax-exclusive fossil fuel price channel.

4.3. Robustness Analysis

This subsection discusses a number of robustness exercises that we performed to test the sensitivity of our results. Appendix B presents the results and a more elaborate discussion of the robustness analysis. In these checks we find that the effect of stringency is highly robust. Among other things, we try alternative stringency specifications such as the target, distance to target, and a measure that includes California's GHG emission standards, and we account for super-credits. We find that the effect of fuel taxes and prices is less robust and quite sensitive to the choice of fixed effects specification. In addition to these tests, we also discuss the presence of other policies as potentially omitted variables; we use alternative estimators, alternative lag structures, and various restrictions on the sample. Moreover, we test the robustness of the pre-sample weights. The main conclusion from this battery of exercises is that the effect of standard stringency on clean innovation is strong and highly robust.

5. DISCUSSION AND CONCLUSION

Our findings show that car manufacturers and their innovators respond strategically to more intensive regulation by governments. We find strong evidence that fuel economy and GHG emission standards induced clean innovation in the 2010s. Our indicator of the stringency of these standards has a significantly positive effect on clean innovation in our baseline regressions. This effect is driven by inventions in electric and hydrogen vehicle technologies, and is robust to a variety of specifications. We also find that excise taxes on fuel seem to affect clean innovation positively, but these results are not as robust as those for standards. We do not find significant evidence of a negative impact of either policy on dirty patenting. Finally, we find no evidence that R&D subsidies impact innovation, while tax-exclusive fuel prices do affect dirty innovation, and existing stocks of knowledge affect both clean and dirty patenting.

Our attention so far has been on the statistical significance and causality of our results. To assess their economic significance, one would need a measure of the value that the additional patents bring in terms of welfare or saved emissions, which is not straightforward. Recent work shows that patented inventions have a significant impact of aggregate growth and productivity, though patent values are highly heterogeneous (Kogan et al. 2017). Moreover, Agnelli et al. (2023) show that more innovative carmakers (in clean and gray technologies) benefit from later rises in fuel prices. New vehicles' emissions per kilometer have been falling in recent years, in part due to the increasing share of electric and hybrid vehicles, which have quickly become competitive in price and cost of usage. We are, however, not aware of any study that causally links these developments to individual patents. As Aghion et al. (2016) point out, it is critical to the transition to increase the stock of available knowledge about clean technologies, so that clean can "overtake" dirty as early as possible. Due to path dependence, it will then stay ahead even when regulation becomes more lenient.

We believe our results show that not only prices and price instruments but also non-market or command-and-control instruments are an important driver of innovation. Identification of this impact requires measuring this regulatory stringency in a manner that is appropriate for innovation decisions. Our indicator of standard stringency accounts for anticipation effects, which are important for dynamic processes like innovation. In particular, our findings for the period 2000–2016 suggest that with strict enough standards innovators may be induced to additionally invest in radical alternative technology such as zero emission car technologies like electric vehicles and hydrogen fuel cells.

To get a sense of the importance of standards in innovation inducement we perform a set of simple counterfactual exercises. We use our estimates to predict total clean patenting over our sample period if no standards had been in place. We present the results in figure 5. If no standards had been in place anywhere, substantially fewer clean patents would have been filed. The estimated number of "additional patents" due

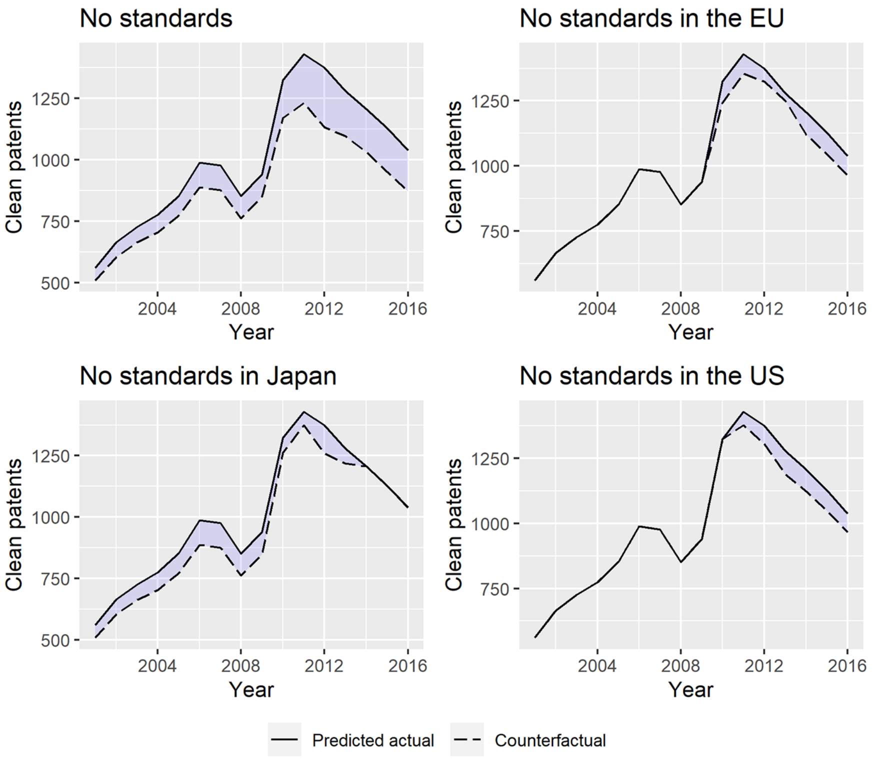

Figure 5. Counterfactual exercise. Predicted clean patents per year given actual stringency (*solid lines*) and for counterfactual scenarios in which stringency is zero either everywhere or in one country/region (*dashed lines*).

to standards is 2,041 over the period 2001–16. About half of these are due to Japanese standards, while European and American standards each induced approximately a quarter of the additional patents. Note that the actual number of clean patents over this period is 16,146, suggesting that about one-eighth of these patents is due to fuel economy and GHG emission standards. Note further that this finding can be interpreted as a lower bound, as we did not take the (positive) effect of patents on knowledge stocks and spillovers into account in this simple exercise.

Interesting extensions of our work would be to include fines in a similar stringency measure to test their effect and to measure stringency at the manufacturer level (an issue with this is that innovation also takes place at other firms, like component suppliers and research firms). We leave this for future work. It will also be interesting to test the effects of the stringent standards that have been introduced since 2016 and that we could not assess because of data limitations for patents.

Our finding that standards seem to provide important guidance for innovation may not be entirely surprising. Standards send out specific signals to engineers to which they can react with new targeted research. Whereas a tax is at best selective as far as its tax base is concerned, a standard provides clear guidance for firms and engineers to innovate in the physical dimension of the standard's attributes. In the case of car manufacturers and their innovators, research is directed toward the attributes of the car fleet sold to the market and which count for their compliance with the standard. And indeed, as a result of more stringent policies, one can now observe a trend toward more adoption of the zero emission technologies that were developed over the past decade. Moving forward, some recent work discusses the design of fuel economy standards aimed specifically at electric vehicle adoption (Holland et al. 2021; Gillingham 2022).

Note that we do not claim that our research shows that standards are preferable from an efficiency perspective. From that perspective the aim would be to reduce GHG emissions at the lowest cost, which means equating marginal costs across abatement strategies: driving less, changing the mix of vehicles, and innovation. A selective tax induces all three at the margin while the standard precludes driving less, which is a drawback. However, our study does add complexity to the comparison and is in line with earlier theoretical work that did not come up with a clear ordering of instruments when innovation is included.

Finally, we also do not claim that standards would provide a substitute for taxation or other price-related measures. Indeed, it is still important to reduce GHG emissions at lowest cost wherever we can. What our study does show, however, is that policies that aim to reduce particular emissions require smart design of policy instruments, providing the right signals for the different decisions that have to be made (see Vollebergh and Van der Werf 2014). Selling and using cars is one thing, creating zero emission technologies is something else. Standards and taxes are likely to play a complementary role in this respect.

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