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Shifting Gears: Environmental Regulation in the Car Industry and Technological Change Among Suppliers

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Shifting Gears: Environmental Regulation in the Car Industry and Technological Change Among Suppliers*

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Abstract

Decarbonizing industries to mitigate climate change requires technological change. Innovation by suppliers can play a crucial role in the technological transition, particularly when suppliers have expertise in zero-emission technologies. In this paper, I study the effect of environmental regulation in a downstream industry on the innovation outcomes of suppliers in the context of the European CO_2 emission standard for passenger cars. I construct a novel data set that links administrative data on car manufacturer compliance to supplier patent data using information on automotive supply chains. To identify the causal effect of changes in the stringency of the emission standard, I leverage the heterogeneous exposure of automotive suppliers to changes in the composition of the European car market in the aftermath of the 2015 Volkswagen diesel scandal. Exposure to more stringent environmental regulation increases innovation for zero-emission vehicle technologies among existing suppliers. In addition, the likelihood that car manufacturers form new supply chain links to firms with expertise in technologies to reduce vehicle emissions increases in response to more stringent environmental regulation. These results suggest that environmental regulation induces economically significant technology spillovers to the regulated firms.

Keywords: environmental regulation, global value chains, innovation, fuel economy standards, directed technological change
JEL Classifications: O30, Q55, Q58

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1 Introduction

Global climate change mitigation necessitates transitioning toward technologies that cause zero or low greenhouse gas emissions. In many industries, this transition requires non-incremental innovation for technologies on which firms currently lack expertise. Under these circumstances, technology spillovers from suppliers can be a crucial driver of technological change (Dugoua and Dumas, 2023). However, it is not clear to what extend innovation incentives imposed by environmental regulations in the downstream market spill over to suppliers (Greaker, 2006, Heyes and Kapur, 2011, Dugoua and Dumas, 2021), particularly when suppliers do not interact with all downstream firms due to persistent supply chain links. Environmental policies are typically implemented by national or regional policy makers. The innovation incentives of firms in a globalized market are, however, set by global demand. Can unilateral increases in the stringency of environmental regulation affect the direction of innovation among suppliers of a globalized industry?

I study this question in the context of the European carbon dioxide (CO_2) emission performance standard for passenger cars (Regulation EC 443/2009). CO_2 emission standards, or equivalently fuel economy standards, are present in all major car markets, including China, the United States, Europe, and Japan. However, the European Union's standards for 2020 required more ambitious CO_2 emission reductions than any comparable regulation in other jurisdictions (Yang and Bandivadekar, 2017). The car industry is well-suited to explore the effect of environmental regulation on non-incremental innovation along global supply chains. First, the industry is rapidly transitioning towards a low-emission technology in the form of electric vehicles (EVs),[1] which reached a global market share of 18% in 2023, up from just 2% in 2018 (International Energy Agency, 2024). Second, the car industry is characterized by a vertically disintegrated production process, in which suppliers are central drivers of innovation (Dugoua and Dumas, 2023). Third, the industry is highly globalized. Understanding the transition for the car industry is important since road passenger transportation accounted for 9.5% of global CO_2 emissions in 2016 (Our World in Data, 2020).

This paper provides firm-level evidence on the effect of environmental regulation in a downstream market on the global innovation outcomes of suppliers and the formation of supply chain links. I create a novel panel data set on automotive suppliers for the period 2016 - 2020. The data set links administrative data on manufacturer compliance with the CO_2 emission standard to supplier patent data using information on automotive supply chains. I quantify the effect of supplier exposure to an increase in the stringency of environmental regulation at the level of car manufacturers. In so doing, I use a "shift-share" instrumental variables approach (Bartik, 1991). I construct a new shift-share instrument that leverages the heterogeneous exposure of automotive suppliers to changes in the composition of the European car market in the aftermath of the 2015 Volkswagen diesel scandal. I document that changes in the stringency of environmental regulation create technology spillovers from suppliers to regulated firms. Automotive suppliers exposed to a one-percentage-point increase in stringency of the emission standard increase the number of patent applications for

[1] In the notation adopted in this paper, electric vehicles include both battery-electric vehicles and hybrid electric vehicles.

technologies relevant for zero- or low-emission vehicles by 11% in the following year. In addition, a one-percentage-point increase in regulatory stringency causes a 0.5 percentage point increase in the corresponding manufacturers likelihood to form supply chain links to firms with knowledge stocks on technologies relevant for low emission vehicles and technologies reducing the emission intensity of internal combustion engine vehicles (ICEVs).

The data used in this study combines i) monitoring data on vehicle registrations and CO_2 emissions of car models publicly available from the European Environment Agency, ii) information on supply chain links between car manufacturers and their direct suppliers (Tier 1 automotive suppliers) obtained from MarkLines, a company operating an information portal on the automotive industry, iii) firm- and technology-specific patent counts obtained from the World Patent Statistical Database (PATSTAT) and iv) balance sheet data and information on firm ownership structures obtained from Bureau van Dijks ORBIS database. I create a panel of supplier firms for the period 2016 - 2019, which comprises their innovation outcomes and exposure to regulatory stringency in the downstream car market. A unique feature of this data set is that it combines manufacturer-level measures of regulatory pressure imposed by an environmental regulation with supplier-level innovation outcomes.

In the empirical analysis, I study the impact of an increase in the stringency of the CO_2 emission standard for passenger cars in Europe (subsequently referred to as the standard). The standard limits the amount of CO_2 the average new passenger car sold by a manufacturer is allowed to emit per kilometer (subsequently referred to as the manufacturer's fleet-average emissions). Standard levels are binding for five years and are announced at least five years in advance. The emission target of the standard was 130 g CO_2 per km for 2015 and 95 g CO_2 per km in 2020. I measure the stringency of the standard using the ratio between a manufacturer's fleet-average emissions in the years 2015 - 2019 and the 2020 target of the standard.[2] Automotive suppliers are exposed to regulatory stringency based on the manufacturers to which they have pre-existing and persistent supply chain relationships.

The first outcome of interest is global innovation by automotive suppliers, which I measure using firm-level counts of technology-specific patent applications. Following the literature on directed technical change and the environment (Acemoglu et al., 2012, Aghion et al., 2016), I study three technological fields: "clean" technologies relevant for zero- or low-emission vehicles, such as electric vehicles, "dirty" technologies for Internal Combustion Engine Vehicles (ICEVs) and "grey" technologies reducing the emission intensity of ICEVs. I introduce an additional "benchmark" category to measure supplier innovation outcomes for technologies that are relevant to the car industry.[3] Patents are sorted into these categories based on patent classes of the Cooperative Patent Classification, which are assigned by patent examiners.[4] The second outcome of interest is the formation of supply chain links. I construct a cross-section of potential pairs (dyads) between car manufacturers and automotive suppliers in my sample. I then assess whether manufacturer-level regulatory stringency

[2] Reynaert (2021) shows that the European CO_2 emission standard induces manufacturer-level compliance before the announced emission targets become binding.

[3] The benchmark category is much broader in scope than the other technological fields. It comprises the most important CPC classes from all three fields.

[4] For details how technology categories are assigned, see Section 2.2 and Appendix Tables A1 - A2.

impacts a manufacturer's propensity to form supply chain links to suppliers with expertise in different technologies using additional supply chain data for the years 2021 and 2022.

Identifying the effect of exposure to higher manufacturer-level stringency of the emission standard requires an instrumental variable due to omitted variable bias and reverse causality. Reverse causality arises, e.g., if manufacturers adding an electric vehicle to their product portfolio reduce their fleet-average emissions and, at the same time, establish supply chain links to firms with expertise in electric vehicle technologies. Omitted variable bias arises since the European CO_2 emission standard interacts with other policies, particularly similar standards in other major car markets. I construct a new shift-share instrument, which combines a supplier's pre-2015 exposure to differences in manufacturer fleet-average emissions across different fuel types (diesel vs. other fuels, mostly gasoline) with changes in the manufacturers' share of diesel cars registered in a given year in the period 2015 - 2019. The identifying assumption is that the pre-2015 exposure of suppliers to car manufacturers relying on diesel cars for compliance with the emission standard is as good as random.[5]

The instrument leverages substantial variation in manufacturer-level reliance on diesel cars for compliance with the standard during the sample period. Since the CO_2 emissions per km of the average diesel car sold by a manufacturer used to be lower than the emissions of the average non-diesel car (see Figure 1), a high share of diesel cars facilitated compliance with the emission standard. Most car manufacturers in Europe made use of this compliance channel (see e.g. Schipper and Fulton, 2013). In the aftermath of the 2015 Volkswagen diesel scandal, the market share of diesel cars in Europe fell from more than 50% in 2014 to 34% (for the set of car manufacturers studied in this paper) in 2019. The scandal unfolded after the US Environmental Protection Agency accused the car manufacturer Volkswagen of cheating on federal air pollution emissions tests for many of their diesel cars on September 18, 2015. In the following years, it became apparent that this malpractice affected type-approval tests in the US and Europe, and was common among many car manufacturers. The scandal caused reputation damage for for diesel cars (Gross and Sonnberger, 2020), leading to heterogeneous reductions in the market share of diesel cars at the manufacturer level. This shock was limited mostly to the European car market, since diesel cars capture less than 5% of vehicle sales in other markets, compared to more than 50% in Europe before the scandal. After the scandal, the future of diesel cars in Europe became highly uncertain.[6]

The nature of my outcome variables imposes additional challenges. Standard fixed-effects count data models work under a strict exogeneity assumption. To include both firm fixed-effects and endogenous regressors in a panel regression with count data, I use a GMM quasi-differencing estimator developed by Wooldridge (1991) and Windmeijer (2000) to measure the effect on the innovation outcome. I estimate the effect of more stringent environmental regulation on the propensity that a manufacturer-supplier pair forms a supply chain relationship using a Probit control function approach (based on Papke and Wooldridge, 2008).[7]

[5]This approach follows arguments for identification based on exogeneity in the "share" component of shift-share instruments developed by Goldsmith-Pinkham et al. (2020).

[6]Additional information on the diesel scandal and how it affected the sales of diesel vehicles in Europe is provided in Section 2.1.

[7]Note that using a similar Poisson control function approach for the innovation outcomes is not possible. Correlation between the past innovation outcomes of automotive suppliers and the past supply chain links

I find that exposure to a one-percentage-point increase in regulatory stringency at the manufacturer level increases a supplier's number of patent applications for clean technologies by 11.2% in the following year. This increase corresponds to 1.34 additional patents per year for the average supplier. At the same time, I do not find evidence that exposure to more stringent regulation changed patenting for dirty or grey technologies. If anything, the sign of both coefficients suggests a negative response. The effect on dirty innovation might be masked by a substantial reduction in patenting for dirty technologies after 2017, which is observed independently of exposure to changes in the stringency of environmental regulation. I find some evidence suggesting that exposure to more stringent regulation in the downstream market increased the overall innovation outcomes of suppliers, as measured by patent applications in the benchmark category. However, this result is not backed by a statistically significant effect in the main regression, which is why I refrain from interpreting it as a causal effect. The increase in clean patent applications is consistent with theoretical predictions on directed technological change (Acemoglu et al., 2012, Aghion et al., 2016). The results show that unilateral changes in downstream environmental regulation create innovation incentives for suppliers.

The positive effect of environmental regulation on the number of patent applications for clean technologies is driven by suppliers with preexisting knowledge stocks. To assess whether path dependencies could explain the effect found in the main analysis, I re-estimate the main regression in using a long quasi-difference between the period 2011 - 2015 and the period 2016 - 2020. The results for clean innovation are robust to this alternative specification, with clean patent applications rising by 15.1% during the five-year period in response to exposure to a one-percentage-point increase in the stringency of the emission standard. Although no longer statistically significant at conventional levels, the size of the coefficient on clean patenting is robust to controlling for the supplier's past share of clean patents relative to the patent count in the benchmark category, suggesting that path dependencies are not sufficient to explain the observed results. The result underscores the importance of specialized innovators (Noailly and Smeets, 2015, Dugoua and Dumas, 2023, Dugoua and Gerarden, 2023).

I rule out several alternative explanations for the positive effect on clean innovation, including direct effects of the 2015 Volkswagen diesel scandal on the financial results of automotive suppliers, changes in average fuel prices across European countries, effects of EV market size not related to the stringency of environmental regulation, and differential pretrends in innovation outcomes among suppliers. In addition, the effect on clean innovation is robust to the exclusion of suppliers with exceptionally high annual numbers of clean patent applications and to studying innovation outcomes at the level of patent applicants observed in PATSTAT, instead of aggregating to the firm level.

Next, I turn to the effects of regulatory stringency in the downstream market on the formation of supply chain links in 2021 and 2022. In 2021, the more stringent emission target of the standard for the period 2020 - 2024 became fully binding. I find that a percentage-point increase in regulatory stringency at the manufacturer level increases the likelihood that the

used to construct the instrument still causes a violation of the strict exogeneity assumption, which would be needed for a Poisson control function approach incorporating firm fixed-effects. The GMM approach I use works under a sequential exogeneity assumption.

manufacturer sources components from a supplier who has previously applied for any patents by 0.27 percentage points. However, regulatory stringency does not affect the likelihood that the manufacturer forms supply chain links to non-innovating suppliers. Among innovating suppliers, the effect is driven by suppliers with expertise in both grey and clean technologies. In this group, a percentage-point increase in manufacturer-level regulatory stringency increases the propensity that the manufacturer sources a component from the supplier by 0.49 percentage points. This effect is 0.39 percentage points (significant at the 10%-level) larger than the effect among suppliers that are innovating but do not have knowledge stocks for either clean or grey technologies. Fully disentangling the effect between suppliers with clean and suppliers with grey knowledge stocks is inhibited by a large group of mixed suppliers. However, comparing pairs involving suppliers with and without knowledge stocks in the corresponding category shows that the difference is more pronounced for suppliers with expertise in grey technologies. This suggests that reducing the emission-intensity of ICEVs remained an important objective of car manufacturers for the period after 2020.

This paper makes three main contributions to the literature. First, it contributes to a large literature studying the effect of environmental regulation on innovation. This literature departs from seminal papers by Hicks (1932), Acemoglu (2002), Acemoglu et al. (2012) and Porter (1996), and provides robust empirical evidence that within the regulated industries, environmental regulation induces innovation (see Ambec et al., 2013, Popp, 2019, Dechezleprêtre and Hémous, 2022, for recent reviews). Both theoretical and empirical papers provide mixed results for the effects of environmental regulation on innovation by suppliers of the regulated industry. On one hand, theoretical work by Greaker (2006) and Heyes and Kapur (2011) points out that environmental regulation in a downstream sector should provide strong incentives for innovation by upstream technology suppliers. On the other hand, imperfect appropriation of the gains from technological progress might reduce innovation incentives among upstream firms relative to the directly regulated industry (Fischer et al., 2003, Dugoua and Dumas, 2021). Empirically, studies relying on sector-level measures of exposure to downstream environmental regulation provide contradictory results on the effects on innovation in upstream industries (Franco and Marin, 2017, Dechezleprêtre and Kruse, 2022). Several studies have analyzed the firm-level innovation response to specific regulatory changes in downstream industries, including standards for air pollution emissions of cars (Lee et al., 2011), deregulation in electricity markets (Sanyal and Ghosh, 2013) or a ban on certain dyes in the Indian leather and textile industries (Chakraborty and Chatterjee, 2017). My paper contributes to this literature by providing causal evidence for the role of heterogeneous supply chain relationships in the innovation response of suppliers to downstream regulatory changes.

Second, my paper contributes to the literature studying the effect of environmental regulation on innovation in the car industry. Fuel economy standards (Knittel, 2011, Klier and Linn, 2016, Reynaert, 2021) and vehicle air pollution standards (Jacobsen et al., 2023) have been shown to induce technology adoption in the car industry. Earlier papers studying the effect of environmental regulation on firm-level innovation in the car industry focused on changes in one major car market (Crabb and Johnson, 2010, Lee et al., 2011). Taking into account the globalized nature of the modern car industry, more recent papers have transitioned to approaches leveraging the heterogeneous exposure of firms to different markets (Aghion et al., 2016, Kiso, 2019, Rozendaal and Vollebergh, 2024, Barwick et al., 2024). In this study, I introduce a novel identification approach that utilizes differences in the exposure of automotive suppliers to a manufacturer-level shock that affects the stringency of a regional environmental policy. In contrast to previous work, my study explicitly focuses on the innovation response among upstream supplier firms. The paper most closely related to my study in that regard is Srinivasan (2017), who also studies the effect of environmental regulation on innovation by automotive suppliers. Three main features distinguish my work from her study. Instead of relying on the regulation in the manufacturer's country of origin, I can quantify the stringency of the environmental regulation in the jurisdiction where vehicles are sold. My paper provides causal evidence on the effect of changes in the stringency of environmental regulation using an instrumental variables approach. Finally, my study looks at technology spillovers more broadly by also studying the effect of environmental regulation on the formation of supply chain links.

Third, this study is related to papers that use cheating by car manufacturers on vehicle emission tests to obtain identifying variation. Existing studies have leveraged these scandals to study the effect of local air pollution on health (Alexander and Schwandt, 2022), collusion against environmental regulation (Alé-Chilet et al., 2023), the welfare effects of gaming environmental regulation (Reynaert and Sallee, 2021), reputation externalities in among firms with common characteristics (Bachmann et al., 2022) and consumer myopia regarding future energy expenditures (Gillingham et al., 2021). This paper contributes to this literature by developing an instrumental variable approach that uses variation in the exposure of upstream firms to car manufacturers relying on diesel technology. This instrument could be used to study the effects of the European CO_2 emission standard for cars on other supplier-level outcomes, such as firm competitiveness, investments, or labor market outcomes such as layoffs or wages.

The remainder of the paper is structured as follows: Section 2.1 introduces the context of the study. Section 2.2 introduces the data used. Section 3 presents the empirical strategy. Section 4 discusses the results. In Section 5, several empirical tests are conducted to rule out violations of the exclusion restriction. Section 6 concludes.

2 Context and Data

The following two sections provide details on the context of this study and the data used. Section 2.1 provides information on the European CO_2 emission standard for passenger cars, the 2015 Volkswagen diesel scandal, and manufacturer-supplier relationships in the car industry. Section 2.2 introduces the four data sources I merge and provides information on the final data set.

2.1 Context

Regulation:

Most major car markets regulate the CO_2 emissions of passenger cars (or equivalently, their fuel economy) by setting a standard on the average fuel consumption of all new vehicles sold by a car manufacturer in a given year (Yang and Bandivadekar, 2017). Examples of this type of regulation include the Corporate Average Fuel Economy Standards in the United States, Corporate Average Fuel Consumption Standards in China, the Top Runner Program in Japan, and the CO_2 emission performance standard for passenger cars in the European Union. In Europe, car manufacturer's must comply with a particularly stringent standard, limiting a manufacturers fleet-average CO_2 emissions for passenger cars[8] below 130 g/km in the period 2015 - 2019 and below 95 g/km in the period 2020 - 2024. The latter target exceeded the level of ambition in any other jurisdiction globally (Yang and Bandivadekar, 2017).

The emission target of the European CO_2 emission standard for passenger cars is updated every five years, with targets announced years ahead of their implementation. This timing explicitly takes into account the product development cycles in the car industry (European Commission, 2021). The most recent amendment (Regulation (EU) 2023/851) introduced a zero-emission target for 2035, effectively phasing out ICEVs.

The average emissions of the vehicle fleet must be below the current target value. The manufacturer's weight-adjusted fleet-average emissions are computed using the following formula:

$$\sum_{j \in J_o} \sigma_{ojt} \left(e_{ojt} - a_t(M_{ojt} - M_{0t}) \right) \leq Target_t \tag{1}$$

where $\sigma_{ojt} = \frac{q_{ojt}}{\sum_{j \in J_o} q_{ojt}}$ is the share of registrations q_{jot} for car model j produced by manufacturer o in year t among the total number of registrations by manufacturer o in year t, e_{ojt} are the model's CO_2 emissions in grams per km according to the European type approval testing procedure,[9] a_t is a vehicle weight adjustment factor, M_{ojt} is the weight of the model, M_{0t} is the weight of the average new vehicle registered in Europe in a base year, and $Target_t$ is the emission threshold. During the five-year regulatory periods, a_t, M_{0t}, and $Target_t$ are constant.

Noncompliance with the standard leads to heavy fines proportional to the number of vehicles sold and the degree to which the standard is exceeded. As a consequence, almost all manufacturers comply with the standard during the period 2015 - 2019.[10] In contrast to the United States Corporate Average Fuel Economy (CAFE) standards, over-compliance cannot be traded between manufacturers, which implies that the regulation requires different

[8]In Europe, separate standards apply for passenger cars and light-duty commercial vehicles. This paper focuses on passenger cars.

[9]During the sample period, the type-approval tests in Europe were conducted using the New European Driving Cycle (NEDC). In 2017 - 2020, vehicles were already tested using the Worldwide Harmonized Light Vehicle Test Procedure (WLTP). However, to ensure consistency in the evaluation of the CO_2 emission standard, test results were converted to NEDC using statistical software.

[10]In this study, only car manufacturers registering at least 10,00 passenger cars in Europe in 2015 are considered. Smaller manufacturers are eligible for derogations from the standard, implying less stringent emission targets. Among manufacturers selling more than 10,000 cars, the following were in noncompliance: Mazda in 2017 and SsangYong in 2019.

abatement efforts from different manufacturers. Manufacturers can, however, decide to pool their vehicle fleets to achieve compliance as a so-called manufacturer pool. Manufacturers with a common owner (holding more than 50% of company shares) are required to pool their vehicle fleets and must comply with the standard as a "group of connected manufacturers". Monitoring data, including all relevant components to evaluate the formula in (1), is publicly available (European Environment Agency, 2023) and will be introduced in Section 2.2.

In this paper, I evaluate regulatory stringency at the level of car manufacturer pools using a modified version of the above formula, where $Target_T$ is the target level of the standard in 2020. This measure is similar to that found in Rozendaal and Vollebergh (2024).

$$S_{ot} = \frac{\sum_{j \in J_o} \sigma_{ojt} \left(e_{ojt} - a_t(M_{ojt} - M_{0t}) \right) - Target_T}{Target_T} \tag{2}$$

To estimate the gap between manufacturer fleet-average emissions in 2010 to 2019 and the 2020 emissions target of the standard, I ignore all time-varying components of the regulation besides changes in the composition of manufacturer pools, average vehicle weight, and the weight adjustment factor and the 2020 emissions target. Ignored time-varying components include, for example, phase-in periods where only a fraction of a manufacturer's fleet has to comply with the regulation or temporary "supercredits", implying that a higher weight is assigned to vehicles with particularly low emissions. Since the withdrawal of these measures is anticipated in the legislation, they do not affect the manufacturer-level abatement efforts needed to comply with the future target of the standard. To obtain a measure of regulatory stringency at the manufacturer level based on these abatement efforts, I hold the average weight of the European vehicle fleet and the vehicle weight adjustment factor constant at their 2016 levels.

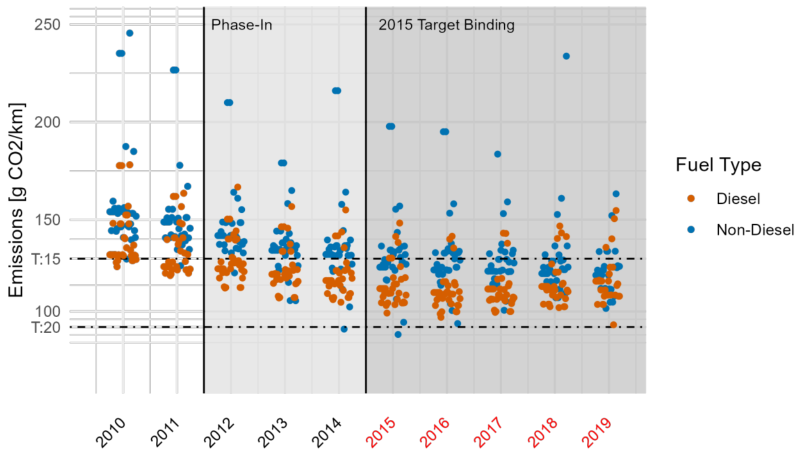
The 2015 diesel scandal:

Before 2015, many car manufacturers in Europe were using high market shares of diesel cars as a tool to comply with the CO_2 emission standards for cars. On average, the weight-adjusted CO_2 emissions of diesel cars were lower than the corresponding average in the remaining vehicle fleet, predominantly gasoline cars. One can see in panel (a) of Figure 1 that his pattern holds for almost all car manufacturers in my sample throughout the period 2010 - 2019. In the remainder of this paper, this pattern will be referred to as car manufacturers using diesel cars as a compliance tool.

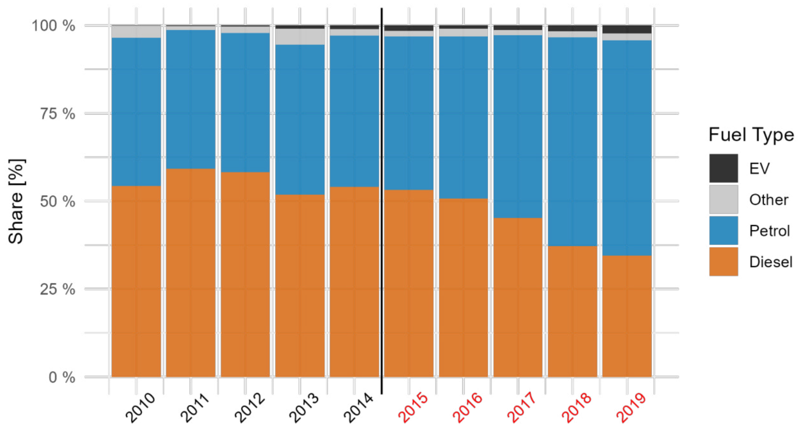
Governments in Europe historically promoted diesel cars as a means of reducing CO_2 emissions. They supported high market shares of diesel cars, for example, by charging lower excise taxes on diesel than on gasoline (Schipper et al., 2002). Thus, a high market share for diesel became a distinguishing feature of the European car market. In 2015, the market share of diesel cars in Europe was higher than 50%, dwarfing market shares in most other major car markets (as of 2015 for the largest car markets by volume, in order: $< 1\%$ China (Zhang et al., 2023), 3% USA (Chambers and Schmitt, 2015), 52% European Union (Mock, 2016), $< 5\%$ Japan (Diaz et al., 2017)). In combination with the emissions advantage of diesel cars, this implies that a substantial reduction in the market share of diesel cars, all

Figure 1: Market share and emissions of diesel powered cars vs. other fuel types

(a) Manufacturer compliance diesel vs. non-diesel fleet



(b) Market share of different fuel types



Notes: *Panel (a):* Points indicate weight-adjusted CO2 emissions per km for the average passenger car of a manufacturer in a given year with the corresponding fuel type. T15 indicates the 2015 CO_2 emission standard, T20 indicates the 2020 CO_2 emission standard. Phase-in indicates the phase-in period for the 2015 emission standard, during which several measures facilitated the compliance with the standard. Both the 2015 standards and the 2020 standards were announced when the policy was adopted in 2009. *Panel (b):* Market share of different fuel types pooling vehicle registrations in the European Community. Excluding car manufacturers with less than 10,000 vehicles sold in 2015 in both panels. Years after the beginning of the diesel scandal highlighted in red.

other things equal, will increase the stringency of the European fleet-average CO_2 emissions standard but will not affect fleet-average CO_2 emissions in other jurisdictions much.

A substantial reduction in the market share of diesel cars occurred in the aftermath of the 2015 Volkswagen diesel scandal. The scandal became public in September 2015, with the US Environmental Protection Agency notifying the Volkswagen Group that some of their diesel models violated air pollution emission standards under the Clean Air Act, emitting up to 40 times more nitrogen oxides (NO_x), an air pollutant detrimental to human health, than permitted by the standard.[11] The diesel scandal had major consequences for the car industry. Some manufacturers faced heavy fines for noncompliance with air pollution emissions standards, and many had to call back and retrofit a large number of diesel cars sold both in Europe and the United States (Breitinger, 2018). In Europe, the scandal ignited a prolonged debate about the impact of diesel cars on local air pollution concentrations, particularly in city centers (Amelang and Wehrmann, 2020). Municipal governments were discussing driving bans for diesel cars in cities throughout the continent (Tietge and Diaz, 2017), but particularly in Germany. In addition, major car markets in Europe debated changes to vehicle and fuel taxation to discourage the purchase of diesel cars. This included higher road taxes for diesel cars adopted in Great Britain in 2018 (Griffiths, 2018), and an equalization of taxes on diesel and gasoline in France (The Connexion, 2017) that was withdrawn only after fierce public protests. Panel (b) of Figure 1 shows that these uncertainties for the future value of diesel cars manifested in a reduction in market share among new vehicle registrations in Europe from more than 50% in 2015 to 34% in 2019.[12] Since I focus on the long-term abatement efforts needed to comply with the 2020 standard as a measure of regulatory stringency, the coincidental temporal overlap between the CO_2 emission standard becoming binding and the beginning of the Volkswagen diesel scandal in 2015 should not affect my identification strategy.

Manufacturer-supplier relations in the European car industry:
Supply chain links between car manufacturers and their Tier 1 suppliers tend to be persistent and involve substantial relationship-specific investments. This section summarizes several important insights from a case study on buyer-supplier relationships in the German car industry (Calzolari et al., 2019, Mueller et al., 2016).

Mueller et al. (2016) finds that supply chain relationships in the automobile industry are persistent and often last more than 8 years. On the one hand, this is due to long development cycles. Suppliers play a substantial role in the development process of new car models, particularly since manufacturers largely outsourced the production of parts in the 1990's. They often get involved early on, conducting both independent R&D for new car parts and R&D ordered by car manufacturers in development contracts. Car manufacturers often approach suppliers to develop the innovative parts they need. According to Mueller et

[11] This highlights an important feature of the diesel technology: while the weight-adjusted CO_2 emissions of diesel cars are lower than those of a comparable gasoline car, emissions of other air pollutants such as NO_x are higher.

[12] Among manufacturers selling more than 10,000 cars in Europe in 2019. Smaller car manufacturers are not included in the analysis in this study due to the derogations from the CO_2 emission standard that these manufacturers are eligible for.

al. (2016), manufacturer-specific R&D accounts for the bulk of supplier R&D efforts. On the other hand, repeated interactions between car manufacturers and suppliers across different car models are common.

Given the persistence of supply chain links and the high share of relationship-specific innovation, the analysis in this paper is based on the assumption that suppliers are exposed to the car manufacturers with whom they have interacted in the past. This allows measuring the exposure of different suppliers to changes in the abatement efforts needed at the manufacturer level to comply with the future emission target of the manufacturer set by the European CO_2 emission performance standard.

2.2 Data

This section first provides information on the four data sources used in this study before summarizing the dataset used in the main analysis. For details on the data merging procedure, see Appendix B.

Patent data:
In this paper, I use patent data for 2005 - 2020 from the spring 2024 version of the World Patent Statistical Database (PATSTAT). The database contains data on more than 100 million patent documents from more than 40 patent authorities and is maintained by the European Patent Office (EPO).

Patent offices classify innovations as related to specific technologies. Since 2013, the EPO and the United States Patent and Trademark Office (USPTO) use a common classification scheme called Cooperative Patent Classification (CPC). Older patents are retroactively classified using the CPC scheme, and additional patent offices use the CPC classification scheme in addition to their national classification (CPC, 2019), including China and Korea. Using a selection of CPC codes based on previous work by Haščič and Migotto (2015), Aghion et al. (2016), EPO and OECD/IEA (2021) and Dugoua and Dumas (2023), I extract patents for innovations pertaining to three technological fields: clean innovation summarizes patents for zero emission or low emission technologies. In the car industry, these technologies are electric, hybrid electric or fuel-cell electric vehicles.[13] Dirty innovation pertains to technologies based on fossil fuels, which in the car industry corresponds to the internal combustion engine. Grey innovation helps to reduce the CO_2 emission intensity of fossil-fuel-based technologies. Note that grey innovation is a subset of dirty innovation. The selection of CPC codes for each technological field can be found in Tables A1 and A2.[14] To asses, whether changes in the patenting behavior of firms are technology-specific or driven by larger trends in patenting, I additionally measure the overall innovation output of firms in my sample for

[13]Emissions caused by electricity consumption or during the production process of the vehicle are not regulated under the European CO_2 emission standard for cars. Thus, electric, hybrid electric, and fuel-cell vehicles can be considered clean technologies in the sense that they facilitate compliance with the environmental regulation.

[14]In contrast to earlier papers, which rely on both CPC and the International Patent Classification to identify relevant patents, I use only the CPC classification in my search strategy. Since the clean patent category relies heavily on the Y02 classes only assigned in the CPC scheme, this should reduce biases between patent counts across the three classes.

related technologies based on patents that are assigned one of the following CPC classes: vehicles in general (B60), electrical equipment (H01) or combustion engines (F02).

I measure the quantity of technology-specific innovation at the firm level using patent counts for the technological fields described above. Based on patent applicants (the firm or the individual who would own the patent once it is granted), I match patents to firms in the car industry, namely car manufacturers and their Tier 1 suppliers. I follow two common approaches recommended by the OECD Patent Statistics Manual (OECD, 2009) to avoid double counting innovations. First, since patents can be held by multiple applicants, I use fractional counts, dividing by the number of applicants on a patent before counting patents at the firm-by-year level.[15] Second, I count patent families instead of patent applications. This is necessary since the same innovation is often patented in multiple countries. The first patent application for an innovation is called a priority. Patents connected by a common priority are referred to as a patent family. To measure innovation output at the firm level, I use fractional counts of DOCDB patent families.[16] I determine the timing of the innovation using the priority application year, i.e., the year in which the first patent in the family was filed for application. The priority application date is the closest date to the time of the actual invention available in patent data (OECD, 2009).

Using patent data to measure innovation output is a standard approach in economics (see e.g. Lanjouw and Mody, 1996, Popp, 2002, Noailly and Smeets, 2015, Aghion et al., 2016, Calel and Dechezleprêtre, 2016, Calel, 2020, Rozendaal and Vollebergh, 2024). Its popularity stems from the ability to measure innovation specific to highly disaggregated technological fields and the availability of patent data for innovation outcomes of firms that are not required to report expenditures for Research and Development (R&D) in their annual accounts (e.g., small- and medium-sized firms in Europe and privately owned firms in the United States). While patents are not the only means to protect innovations, there is evidence that in the car industry, patents are considered an effective means to protect innovation (Cohen, 2000). However, the economic value of patents is very heterogeneous. To set a lower bound on the economic value of patents included in my study, I include only non-domestic patent families, i.e., patent families extending across at least two jurisdictions or being filed at the EPO or internationally under the Patent Cooperation Treaty (PCT). I deviate from previous literature using so-called "triadic" patent families (Aghion et al., 2016)[17] to accommodate the increasing role played by developing economies, in particular China, for innovation on EV technologies. An alternative measure often used to correct for the heterogeneous economic value is a citation-weighted patent count, i.e. weighting each patent by the number of later patents citing it. Given the recent sample period and time lags in the publication of patents, constructing sensible citation weights for my sample is not feasible. A thorough discussion

[15] I conduct this adjustment after dropping patent applicants not observed in the other data sets and after aggregating all patent applicants belonging to the same global ultimate owner, since the sampling procedure would otherwise affect my patent counts.

[16] DOCDB simple patent families are assigned to a patent by EPO patent examiners based on common priorities and the examiner's evaluation of whether these priorities patent the same innovation. For details on the construction of DOCDB patent families, see Martinez (2010). DOCDB is the EPO's master DOCumentation DataBase (DOCDB) which has worldwide coverage.

[17] Triadic patent families are patent families comprising a patent application at the United States Patent and Trademark Office, the Japan Patent Office and at the EPO.

of the benefits and limitations of using patent data to measure innovation outcomes can be found in Griliches (1990).

Car registrations in Europe:
Since 2010, the European Environment Agency publishes data on all new passenger car registrations in the 27 member states of the European Union, and Iceland, Norway and the United Kingdom under a transparency requirement of Regulation (EC) 443/2009. The data contain information on the manufacturer, the vehicle model (model name and type-variant-version codes), as well as all the information required to determine the compliance of the manufacturer with the fleet-average emission standard, such as the car models CO_2 emissions per km according to type-approval tests, its weight, fuel type and the number of vehicle registrations. In addition, the data set tracks manufacturer pools formed to comply with the regulation over time. The data allows me to calculate year-to-year changes in the fleet-average emissions of a manufacturer and the manufacturer pool to which it belongs, as well as the number of new cars registered by these entities in a given year between 2010 and 2019.

Manufacturers and manufacturer pools with vehicle sales below certain thresholds can apply to receive a less stringent manufacturer-specific standard.[18] The emissions targets under these derogations take into account the structure of a manufacturer's vehicle fleet and typically require lower abatement efforts. In this study, all car manufacturers belonging to a pool selling more than 10,000 passenger cars in Europe in the year 2015 will be considered. This includes car manufacturers that are subject to more lenient emissions reduction targets under a niche manufacturer derogation. For manufacturers with such derogations in a given year, I manually match the 2020 target implied by the targets communicated in so-called monitoring reports published by the European Commission (see e.g. European Commission, 2022). In cases where the manufacturer belongs to a different pool in 2020, I reduce the 2015 emissions target by 20% to obtain a 2020 target for the manufacturer.

Supplier-manufacturer relationships:
To measure the exposure of suppliers to car manufacturers, I use the *MarkLines "Who Supplies Whom"* database, which provides information on parts provided by supplier companies for different car models. MarkLines is a private market research company, operating an information platform on the global automotive industry. In their "Who Supplies Whom" database, I observe 142,783 components for 2,352 model names provided by 2,478 suppliers for 92 car makers globally over the period 2010 - 2015.[19] Combining this information with

[18] Manufacturers with less than 1,000 passenger cars registered in the European Community per year are fully exempt from the regulation. Manufacturers with less than 10,000 cars registered can apply for a manufacturer-specific standard (small-volume derogation), manufacturers with less than 300,000 passenger cars registered in the European Community per year can apply for a standard requiring a 45% reduction of their fleet-average emissions by 2020 compared to the manufacturer's average emissions in 2007 (niche derogation) (European Parliament and Council, 2009, 2019).

[19] MarkLines Who Supplies Whom database contains information on the supplier companies from which OEMs source 300 important car model components for different car models they produce. These components fall into one of the following categories: e-Powertrain, Internal Combusion Engine Powertrain, Driveline, Electrical and Electronic, Interior, Exterior, Chassis, Body and General / Small Parts.

data on the number of registrations of car models in Europe, I obtain exposure weights that should proxy for the share of components delivered from a supplier to a manufacturer (for details on the exposure weights, see Section 3). In addition to the pre-2015 supply chain links, I gather information on 8,126 manufacturer-supplier pairs with supply chain links observed in the period 2021-2022 from MarkLines Who Supplies Whom. Note that while the MarkLines data cannot be considered a complete census of supply chain links between car manufacturers and their Tier-1 suppliers, supply chain links to large, innovative suppliers are more likely to be covered. This is, e.g., due to the greater attention paid to electric vehicles in so-called teardown reports by MarkLines, where a vehicle is disassembled to see which components it uses.

To check whether the supply chain links are as persistent as assumed, Appendix Figure E.2 tracks manufacturer-supplier pairs forming additional supply chain links over time. One can see that in 2021, 42% of all manufacturer-supplier pairs for which a supply chain link is observed in 2010 still form at least one additional supply chain link per year. These links are observed in the form of an additional component supplied for a specific car model. Given the long production phase of these car models, this should result in a share of persistent manufacturer-supplier relationships over a ten-year time horizon substantially higher than 50%. Additionally, this figure provides evidence that repeated interactions between car manufacturers and their Tier 1 suppliers are, in fact, widespread.

Corporate data:
Linking the firm-level patent data obtained from PATSTAT to the manufacturer supplier links in MarkLines Who Supplies Whom is complicated by the fact that the subsidiary providing parts and components to a car manufacturer and the subsidiary in charge of research and development may not always work under the same name. To alleviate that concern, I match both the patent data and the companies in the manufacturer-supplier data to Bureau van Dijks Orbis database. Orbis contains data on ownership links for 462 million companies worldwide, as well as balance sheet data for many of these companies. The data set is standardized for cross-border comparisons. I use Orbis to merge all companies in PATSTAT, European car registrations, and in MarkLines Who Supplies Whom to their global ultimate owner in 2015 (a firm owning more than 25% of the subsidiary is assigned to be its global ultimate owner).[20] Since I will rely on predetermined exposure weights for the instrumental variables approach in this paper, fixing ownership links in 2015 for the sample of automotive suppliers does not affect my results. For the car manufacturers, the registration data allows me to track manufacturer pools over time, such that I can measure the regulatory stringency implied by the current ownership structures of car manufacturers. In addition to the ownership structure of firms, I obtain balance sheet data for 140 firms in my final sample for the period 2010 - 2020.

Merged data and descriptive statistics:

[20] There are ten entities in the MarkLines data where the global ultimate owner of a firm is not unique based on the 25% ownership threshold. In these cases, I randomly assign one firm as the global ultimate owner.

In this section, I briefly summarize the data merging procedure and descriptive statistics on the final data set obtained. A more detailed description of the data merge is relegated to Appendix B.

In the first step, I merge the car registration data, the patent data, and the manufacturer-supplier links to ORBIS using the company names. In the second step, I use the historical firm ownership information for the year 2015 from ORBIS to assign a global ultimate owner holding more than 25% of the company to each firm. For these GUOs, I create firm-level patent stocks by counting all patent families held by patent applicants belonging to the GUO. I aggregate information on the regulatory stringency on the level of pools of car manufacturers that are specified in the registration data. I measure regulatory stringency by calculating the distance between the sales-weighted average emissions of the manufacturer pools new vehicle registrations and the 2020 target for manufacturer fleet-average emissions levels specified by the standard.

Linking the manufacturers in the MarkLines Who Supplies Whom data to the car manufacturers in the EU car registrations based on company names and car model names, I create sales-weighted exposure shares to the 34 regulated car manufacturers (held by 22 GUOs in 2015) for all supplier companies. These first merging and harmonization steps reduce the size of the sample from 2,172 supplier companies (after only a basic name harmonization) to observing 1,324 firms held by 542 global ultimate owners of supplier companies providing components for 494 car models, where I use model type series as the definition of a car model. To provide an example, I would treat all BMW 2-Series as the same car model, not distinguishing between, e.g., the BMW 2-Series Coupe, Coupe M and Gran Coupe, Gran Coupe M and Active Tourer, the last being a plug-in hybrid. This model specification not only ignores model trims but also different model face-lifts produced over time.[21] I include supplier links for 30 out of 34 car manufacturers, and I observe at least one component supplier for 79.5% of all new car registrations in Europe between 2010 and 2015 by those manufacturers.[22] In the third step, I merge the data measuring innovative activity and the data measuring exposure to regulatory stringency using the GUOs ID in the ORBIS data. This leaves me with 410 GUOs observed in all three data sets. In the main sample, I keep only GUOs that applied for at least one non-domestic patent family for any of the four technological fields, clean, grey, dirty, or benchmark in the period 2015 - 2020, and that applied for at least one patent in the benchmark category before 2015. In doing so, I restrict my sample to firms that are actively patenting in technological fields relevant to the car industry before and at least once during the sample period. These restrictions reduce the size of the final sample to 339 GUOs of automotive suppliers and additionally 22 GUOs of car manufacturers. The supplier's GOUs correspond to 1,737 patent applicants (before name-disambiguation). In total, I merge 81,155 of 384,964 patent families for clean technologies with an application

[21] Note that the model specification is only used to construct supplier exposure weights and thus does not affect the calculation of manufacturer fleet-average emissions.

[22] The brands excluded are Avtovaz, Bugatti, Rolls Royce, and Tata Motors. Avtovaz is a Russian car manufacturer belonging to Renault. Bugatti is owned by Volkswagen. Rolls Royce is owned by BMW. All three brands are regulated but do not sell any diesel cars in 2015, which is why the instrumental variable used in this paper is not well-defined for these firms. Tata Motors owns Jaguar Landrover, but the brand Tata itself stopped selling cars in Europe in 2018 and is thus excluded from the sample.

date between 2015 and 2020 (21%).[23][24] In the final sample, 55% of all clean patents are held by supplier companies, with the remaining 45% held by the GUOs of car manufacturers. While this highlights the importance of supplier companies for innovation in the car industry in Europe, it also underscores the disproportional role played by the 22 GUOs of the car manufacturers in my sample. I use these data to study the innovation outcomes of firms in the period 2016 - 2020.

Table 1: Descriptive Statistics

Variable	Unit	Mean	Sd	Min	Pctile[25]	Pctile[50]	Pctile[75]	Max
Panel A: Supplier patenting between 2015 and 2020								
Benchmark Patents	Count	50	158	0	1	5.5	29	1674
thereof Clean Patents	Count	12	59	0	0	0	3	942
thereof Grey Patents	Count	2.1	15	0	0	0	0	284
thereof Dirty Patents	Count	4	20	0	0	0	1	344
Panel B: Manufacturer car market outcomes in 2015								
Emissions^{15} - Target^{20}	gCO_2/km	23	11	0	16	24	32	41
Diesel Emissions Disadvantage	gCO_2/km	-14	20	-67	-20	-17	-11	47
without weight-adjustment	gCO_2/km	-2.8	22	-63	-10	-4	5	60
Diesel Market Share	%	50	20	14	38	48	60	92
Panel C: Supplier exposure to car market outcomes in 2015								
Emissions^{15} - Target^{20}	gCO_2/km	23	5.1	0	21	24	25	41
Diesel Emissions Disadvantage	gCO_2/km	-12	13	-67	-17	-14	-11	47
without weight-adjustment	gCO_2/km	0.8	14	-63	-4.6	-1.6	2.7	60
Diesel Market Share	%	47	13	14	40	51	56	92
Panel D: Change insupplier exposure to car market outcomes from 2015 to 2019								
Δ Emissions - Target	gCO_2/km	0.34	4.7	-19	-1.9	0.82	2.3	36
Δ Diesel Market Share	%-points	-21	4.8	-48	-23	-20	-18	-14

Notes: Descriptive statistics on the final sample of 339 global ultimate owners of tier-1 automotive suppliers, annual observations. Panel A displays fractional patent counts for the corresponding technological fields. Panel B displays regulatory outcomes for 22 global ultimate owners of regulated car manufacturers. Emissions - Target is the firm-specific exposure to manufacturer-level differences between fleet-average CO2 emissions and the 2020 target set by the European CO_2 emission performance standards for passenger cars. Diesel Market Share is the supplier's exposure to manufacturer-level shares of diesel-powered vehicles by firm i in year t (σ_{it}^D), Diesel Emissions Advantage is the supplier's exposure to manufacturer-level differences in weight-adjusted emissions between the average diesel and the average non-diesel car sold by the manufacturer ($\overline{e}_{it}^D - \overline{e}_{it}^{ND} - a_t(\overline{M}_{it}^D - \overline{M}_{it}^{ND})$, where $\overline{e}_{it}^D(\overline{e}_{it}^{ND})$ is the exposure to the diesel-fleet (non-diesel-fleet) average emissions of a manufacturer, $\overline{M}_{it}^D$ ($\overline{M}_{it}^{ND}$) is the exposure to the diesel-fleet (non-diesel-fleet) average vehicle weight of a manufacturer and a_t is the regulatory weight adjustment factor in year t. Δ denotes the indicated year-to-year differences in the corresponding variables.

Table 1 provides descriptive statistics on the final sample of automotive supplier companies. Panel A shows that the distribution of patent applications per year is positively skewed, with the median firm applying for 5.5 patents in a given year, compared to 50 patents by the average firm and a maximum of more than 1,600 patents per year. A similar pattern is also

[23]This comparison uses raw patent applications since fractional, non-domestic counts are only created after the data merge. Fractional counts consider only merged suppliers.

[24]Appendix Figure E.1 compares trends in the average number of patent applications per year in the categories clean, grey, and dirty between all patent applicants observed in PATSTAT and my sample.

observed for technology-specific patent counts. The average firm in my sample applies for 12 patents for clean technologies per year. Clean innovation thus makes up a sizable proportion of overall innovation outcomes for automotive suppliers. In particular, the number of patents for clean technologies is higher than the number of patents for dirty technologies. In a given year, only 25% of the firms in my sample apply for either a clean or a dirty patent in a given year.

Panel B provides details on the fleet-average emissions of car manufacturers in my sample. For the average car manufacturer in the sample, the 2020 emission performance standard will be binding since its current fleet average emissions are 23 g CO_2 per kilometer higher than the level of 95 g CO_2/km prescribed by the standard after 2020. There are, however, car manufacturers (SsangYong), for whom the 2020 target is not binding already in 2015.[25] The second important observation is that for almost all manufacturers, the average diesel car sold has lower weight-adjusted CO_2 emissions per km than the average non-diesel car sold. For the average manufacturer, the weight-adjusted emissions of the fleet of diesel cars sold is 12 g below the emissions of the non-diesel fleet. This emissions advantage is much less pronounced without the adjustment of emissions for vehicle weight: for at least 25% of car manufacturer by year observations, the diesel fleet actually has slightly higher emissions than the fleet of non-diesel cars before adjusting for vehicle weight. Third, diesel cars make up a substantial share of new vehicle sales for all manufacturers over the sample period, ranging between 12 and 92% (48% on average).

Panel C provides details on the supplier's exposure to the car market outcomes of car manufacturers. A comparison between panel B and panel C provides three important insights: First, the average supplier seems to be exposed to car market outcomes that are close to the average outcomes across all car manufacturers, suggesting that the exposure weights obtained from the MarkLines data do not introduce bias in terms of the observed suppliers being exposed to a non-representative fraction of the car market.[26] Second, we see that there are meaningful differences in terms of the exposure to car market outcomes across suppliers: while some suppliers are exposed to car manufacturers with a large market share of diesel cars, others are exposed to firms not relying on diesel cars as much. Third, the variability in the outcomes of car manufacturers is much higher than the variability observed in the exposure of suppliers to these outcomes. While the previous insight suggests that automotive suppliers are not exposed to the car market as a whole, the lower variabiliy indicates that many suppliers are in fact exposed to more than one car manufacturer. A graph illustrating the network between car manufacturers and their suppliers is provided in Appendix Figure B.4.

Finally, panel D displays changes in exposure to car market outcomes for automotive suppliers from 2015 to 2019. On the one hand, exposure to compliance gaps between the 2020 level of the emissions standard and the manufacturer's fleet-average CO_2 emissions increased slightly by 0.34 g CO_2 per km for the average supplier. On the other hand,

[25] Note that none of the famous EV manufacturers like Tesla or BYD were subject to the regulation in 2015 due to their low vehicle sales in Europe at that time. Thus, they are not included in this study.

[26] A graph showing the average weight assigned to different car manufacturers can be found in Appendix Figure B.3.

for more than 25% of the sample, exposure to compliance gaps dropped by at least 1.9 g CO_2/km. This implies that for some suppliers, the exposure to regulatory stringency in terms of emissions abatement efforts required in the downstream market increased, while it decreased for others. The market share of diesel cars sold by the manufacturers a supplier is exposed to, however, dropped for all Tier-1 suppliers. Reductions range between 14 and 48 percentage points.

3 Empirical Strategy

To quantify the effect of exposure to stringency of the European CO_2 emission performance standard for cars on innovation by automotive suppliers, the following equation will be estimated:

$$PAT_{it} = exp(\beta S_{it-1} + \gamma X_{it-1} + \eta_i + \mu_t)u_{it} \tag{3}$$

where PAT_{it} is supplier i's number of technology-specific patent applications in year t, S_{it-1} is the supplier's exposure to the stringency of the EU CO_2 emissions standard for cars in the previous year (to be introduced in Equation (4)), X_{it-1} are additional control variables, including either lags of a firms share of patents pertaining to the technological field under consideration, exposure to country-level fuel prices, or firm financial outcomes such as the firms revenues.[27] Furthermore, η_i is a firm fixed-effect, μ_t is a year fixed-effect and u_{it} is the error term.

Suppliers are not directly subject to regulation in the downstream car market. Given the persistence of manufacturer-supplier relationships in the car industry, I assume that suppliers are exposed to environmental regulations in the car market via the car manufacturers with whom they have pre-existing relationships. I calculate the exposure to regulatory stringency on the supplier level as

$$S_{it-1} = \sum_{o \in O} w_{io} S_{ot-1} \tag{4}$$

where O is the set of regulated car manufacturers, ω_{io} is a weight reflecting supplier i's exposure to manufacturer o (to be introduced in Equation (5)), and S_{ot-1} is the stringency of the European CO_2-emission standard for cars for manufacturer o in year $t-1$ defined in Equation (2).

After counting new vehicle registrations for all car models over the period 2010 - 2015, I define supplier i's exposure to manufacturer o using a registration-weighted share of supply chain links to manufacturer o relative to all supply chain links of supplier i:

$$w_{io} = \frac{\sum_{j \in (J_o \cap J_i)} q_{j,2010-2015}}{\sum_{j \in J_i} q_{j,2010-2015}} \tag{5}$$

where $q_{j,2010-2015}$ is the number of newly registered vehicles of car model j in the regulated market in the years 2010 to 2015, J_o is the set of car models produced by car manufacturer o, and J_i is the set of car models for which supplier i provides at least one component in the period 2010 - 2015. I resort to manufacturer-supplier relationships before 2015, such that the

[27] In the preferred specification, I do not include any additional control variables.

exposure weights are pre-determined over the sample period. Note that the list of supplied components in MarkLines Who Supplies Whom does not cover all manufacturer-supplier relationships in the European car market. I thus regard these exposure shares as a proxy for the relationships suppliers have with different manufacturers.

In some specifications, additional control variables $X_{i,t-1}$ include firm knowledge stocks. In contrast to other papers working with patent data, the estimator used in this study allows me to directly include firm fixed effects, such that controlling for level differences in the patenting outcomes of firms is unnecessary. Clean patenting, however, is growing substantially during the sample period. Controlling for the share of a firm's technology-specific patent applications in the past year should take into account changes in the firm's innovation strategy.

$$A_{it-1} = \frac{PAT^k_{it-1}}{PAT^b_{it-1} + 1} \tag{6}$$

where PAT^k_{it-1} is the number of patent applications for technology k corresponding to patenting for either clean, grey, or dirty technologies. In the denominator, I divide by the number of patent applications in the benchmark category.

In some specifications, I also estimate a version of the above model using a Poisson Quasi-Maximum Likelihood Estimator (PQMLE). To account for time-invariant differences in the patenting outcomes of firms in these regressions, I include a firms technology-specific knowledge stocks as controls.[28] The knowledge stock K^k_{it} for technology k is calculated using the perpetual inventory method, (following Cockburn and Griliches, 1988, Peri, 2005) including patent applications dating back to 2005 and assuming a knowledge depreciation rate of $\delta = 0.2$, following Aghion et al. (2016):[29]

$$K^k_{it} = \sum_{l=2005}^{t} (1-\delta)^l PAT^k_{it} \tag{7}$$

A key challenge in estimating the effect of exposure to regulatory stringency in the downstream car market on the innovation outcomes of upstream automotive suppliers is the endogeneity of supplier exposure to regulatory stringency S_{it-1}. This endogeneity arises since both the additional abatement efforts demanded from manufacturer o (S_{ot-1}) and a supplier's future innovation efforts are driven by the manufacturer's current product portfolio. The main concern is reverse causality: adding a low-emission vehicle, e.g. an EV, to a manufacturers product portfolio will most likely reduce the manufacturers fleet-average emissions. Simultaneously, components for the low-emission car model will come from suppliers with an expertise in clean vehicle technologies. This creates a spurious, negative correlation between exposure to regulatory stringency in the downstream market and supplier innovation for clean technologies.

[28] For details on the alternative estimation approach, see Appendix B.

[29] Note that the knowledge stock in the benchmark category will be non-zero in every year after 2015, since firms without any patents before 2015 were removed from the sample as outlined in Section 2.2.

The high degree of globalization in the car industry poses an additional challenge. Large car manufacturers sell cars in almost all major markets. Previous research (e.g. Kiso, 2019) shows that the fleet-average emissions of car manufacturers are correlated across jurisdictions. Given that all major car markets are subject to some sort of fuel economy or fleet-average CO_2 emission standard (e.g., the Corporate Average Fuel Economy Standards in the US or Corporate Average Fuel Consumption standards in China), the exposure to binding environmental regulation is correlated across jurisdictions. This might introduce omitted variable bias in a regression focusing on the effect of the European CO_2 emission performance standard for passenger cars on global innovation outcomes.

Finally, anticipation of changes in the stringency of environmental regulation inhibits the identification of short-term effects on innovation outcomes. Changes in the target levels of emissions standards are often adopted or announced years before they become binding. This is particularly true in Europe, where the target level of the 2020 standard has been anticipated since 2009.

3.1 Construction of the instrument

To overcome the endogeneity problems described in the previous section, I construct a shift-share instrumental variable (Bartik, 1991) that combines cross-sectional variation in the pre-2015 exposure of Tier 1 automotive suppliers to car manufacturers relying on diesel cars as a compliance technology (the "share") with temporal variation in the share of diesel cars sold at the manufacturer level (the "shift"). Identification is based on a sequential exogeneity assumption on the shares , following Goldsmith-Pinkham et al. (2020). The identifying assumption will be discussed after introducing the instrument formula.

Instrument Formula:
I obtain a formula instrument for exposure to the stringency of the fleet-average CO_2 emission standard by re-writing its definition:

$$S_{it-1} = \sum_{o \in O} \omega_{io} \underbrace{\frac{\sum_{j \in J_o} \sigma_{ojt-1} \left(e_{ojt-1} - a_t (M_{ojt-1} - M_{0t-1}) \right) - Target_T}{Target_T}}_{S_{ot-1}} \tag{8}$$

All components are defined exactly as in equation (4), except for the registration share of model j in the fleet of manufacturer o $\sigma_{ojt} = q_{ojt} / \sum_{k \in J_o} q_{okt}$, where q_{okt} is the number of cars of model k (produced by manufacturer o) registered in year t. Decomposing the sales-weighted average emissions S_{ot-1} by fuel type, I obtain a formula for exposure to regulatory stringency at the supplier level.

$$S_{it-1} = \sum_{o \in O} \omega_{io} \left(\sigma^D_{ot-1} S^D_{ot-1} + (1 - \sigma^D_{ot-1}) S^{ND}_{ot-1} \right) \tag{9}$$

$$= \sum_{o \in O} \omega_{io} \left(S^{ND}_{ot-1} \left(1 + \sigma^D_{ot-1} \frac{S^D_{ot-1} - S^{ND}_{ot-1}}{S^{ND}_{ot-1}} \right) \right) \tag{10}$$

where $\sigma_{ot}^{D} = \sum_{j \in J_{o|D}} \sigma_{ojt}$ is the share of diesel cars among manufacturer o's new vehicle registrations in year t, $J_{o|D}$ is the set of diesel models sold by manufacturer o,

$$S_{ot-1}^{D} = \sum_{j \in J_{o|D}} \sigma_{ojt-1} \left(e_{ojt-1} - a_t(M_{ojt-1} - M_{0t-1})\right) - Target_T \tag{11}$$

is the gap between the fleet-average emissions of manufacturer o's fleet of diesel passenger cars sold and the future target emissions level of the standard, and $S_{ot-1}^{ND}$is the corresponding gap for a manufacturer's fleet of non-diesel passenger cars.

Equation (10) shows that a supplier's exposure to regulatory stringency directly depends on the supplier's exposure to car manufacturers that rely on diesel cars for compliance with the standard. Holding the average emission level of a manufacturer's diesel and non-diesel fleet constant at 2014 levels, the second term of Equation (10) should provide a relevant, time-varying instrument for the stringency of the European CO_2 emission standard for passenger cars.[30] To gain precision, I focus on changes in the manufacturer-share of diesel cars relative to 2014 $\Delta\sigma_{ot-1}^{D} = \sigma_{ot-1}^{D} - \sigma_{o,2014}^{D}$.

$$IV_{it-1} = \sum_{o \in O} \omega_{io} \frac{S_{o,2014}^{D} - S_{o,2014}^{ND}}{S_{o,2014}^{ND}} \Delta\sigma_{ot-1}^{D} \tag{12}$$

This instrumental variable has a shift-share structure, combining supplier-level pre-2015 exposure weights $\omega_{io}\frac{S_{o,2014}^{D} - S_{o,2014}^{ND}}{S_{o,2014}^{ND}}$ with manufacturer-level shocks to the market share of diesel cars $\Delta\sigma_{o,t-1}^{D}$.

Exclusion restriction:

The instrumental variable addresses three previously raised concerns for identification. It resolves concerns about a reverse causality between manufacturer-level regulatory stringency and supplier-level innovation. Controlling for supplier fixed-effects and relying on the pre-2015 exposure of suppliers to different car manufacturers, the variation isolated by the instrument is driven by the heterogeneous exposure to manufacturer-level demand shocks. The exposure is correlated to future changes in the exposure to regulatory stringency, but plausibly exogenous to confounding future shocks to supplier innovation. The approach also resolves concerns about omitted variable bias that could arise due to the omission of controls for foreign fuel economy or CO_2 emission standards. Since the large market share of diesel cars is a distinctive feature of the European car market, the supplier exposure to manufacturer-level shocks in the sales of diesel cars should affect the exposure to regulatory pressure from European regulation, but should be orthogonal to changes in the stringency of similar standards in other major car markets, such as the United States or China. Finally, since the diesel scandal was not anticipated by market participants, the instrumental variables approach isolates unanticipated changes in the stringency of the standard.

Formally, the instrumental variables approach developed above relies on the following

[30] The first term is constant over time after fixing the stringency outcomes at 2014 levels and will thus be eliminated by the firm fixed-effect.

exclusion restriction:

$$\mathbb{E}\left(\sum_{o\in O}\omega_{io}\frac{S^{D}_{o,2014}-S^{ND}_{o,2014}}{S^{ND}_{o,2014}}\Delta\sigma_{o,t-2}(u_{i,t}-u_{i,t-1})\right)=0 \tag{13}$$

I assume that the suppliers exposure to manufacturers relying on diesel cars is as good as random, while manufacturer-level shocks to the number of diesel cars sold can be non-random, following the approach to identification with shift-share instruments developed by Goldsmith-Pinkham et al. (2020).[31] In particular, this assumption implies that the pre-2015 exposure of suppliers to car manufacturers relying on diesel cars for compliance with the CO_2 emission standard cannot be correlated to future shocks to the supplier's innovation outcomes (conditional on supplier and year fixed effects).

A number of observations on the car market corroborate this assumption. First, the exposure to diesel cars does not seem to be correlated to future shocks to the market share of clean technologies such as EVs. Up to 2019, the market share of electric vehicles in Europe increased only by 1.2 percentage points (see Figure 1), in contrast to a reduction of 19.6 percentage points in the market share of diesel cars. Since both diesel and gasoline cars, the latter being the predominant substitute for forgone diesel sales, rely on internal combustion engines, the scandal itself should not have changed the relative incentives to innovate for dirty or clean technologies.

Second, suppliers should not be able to select into relationships with car manufacturers based on anticipated shocks to the size of the market for clean, grey, or dirty technologies. For most car manufacturers, the market share of EVs was almost zero in 2014. Thus, the average supplier's exposure to different car manufacturers does not seem to be driven by EV components, alleviating concerns about selection into exposure to car manufacturers with above-average EV market shares. Furthermore, Appendix Table A2 shows that supplier exposure to manufacturers relying on diesel cars as a compliance technology is not correlated with changes in EV market shares before 2015.

Third, it implies that supplier exposure to changes in the stringency of other relevant domestic regulations are not correlated to a supplier's exposure to car manufacturers relying on diesel cars. Domestic regulations that could affect incentives for clean versus dirty innovation include subsidies for EVs or standards for other air pollutants emitted by passenger cars. In the aftermath of the 2015 Volkswagen diesel scandal, emission standards for air pollutants such as nitrogen oxides or fine particulate matter were tightened. In contrast to the CO_2 emission standards for passenger cars, air pollution standards apply to any single vehicle sold. For a single vehicle, cheaper compliance technologies than shifting production to EVs entirely are available, such as selective catalytic reduction to reduce NO_x emissions or software updates and smaller changes to the vehicle's mechanical makeup to reduce air pollutant emissions from fuel combustion. Thus, it is unlikely that the regulation on air pollutants other than CO_2 would have increased incentives for innovation on low to zero

[31] Borusyak et al. (2022) show that exogeneity in the "shift" component of shift-share instruments can also provide a valid exclusion restriction. Prerequisites for this approach are a large number of independent shocks and exposure weights to the individual shocks converging to zero as the number of shocks grows. In the context of an oligopolistic car market, neither assumption is given for changes at the level of car manufacturers.

CO_2 emission technologies. EV subsidies, on the other hand, incentivize innovation for EV technologies. The extent to which these incentives are passed through to suppliers depends on the manufacturer-level share of EVs sold. As I have argued before, supplier exposure to manufacturers relying on diesel cars as a compliance technology is not correlated with changes in EV market shares before 2015.

Estimator:
With the instrument at hand, I proceed to estimate the specification in equation (3) using a GMM quasi-differencing estimator proposed for fixed-effects count data models with endogenous regressors by Wooldridge (1991), Windmeijer (2000) and Jochmans (2022). This estimator relies on sequential moment restrictions

$$\mathbf{E}(u_{it}|\eta_i,\ \mu_t,\ \omega_{io},\ S^D_{o,2014},\ S^{ND}_{o,2014},\ PAT_{i,1},\ldots PAT_{i,t-1}) = 1 \tag{14}$$

, which include the exclusion restriction for the exposure to manufacturers relying on diesel cars as a compliance technology $\omega_{io}\frac{S^D_{o,2014}-S^{ND}_{o,2014}}{S^{ND}_{o,2014}}$ and a sequential exogeneity assumption for PAT_{it}, implying that past patent stocks K_{it} may be correlated with future error terms $u_{ir}, r > t$.[32] In the main specification, I set $X_{it} = (S_{i,t-1})$ and $Z_{it} = (IV_{it-1})$. Given these variables, the GMM quasi-differencing estimator uses moment conditions of the following form:

$$\mathbf{E}\left(Z_{it}\left(\frac{y_{it}}{\exp(X_{it}\beta)} - \frac{exp(\mu_t)}{exp(\mu_{t-1})}\frac{y_{i,t-1}}{exp(X_{i,t-1}\beta)}\right)\right) = 0 \tag{15}$$

which is equivalent to $\mathbf{E}\left(Z_{it}(u_{i,t} - u_{i,t-1})\right) = 0$. Since Wald-tests based on two-step GMM estimators tend to over-reject the null hypothesis in finite samples I bootstrap the standard errors using a re-weighting method for bootstrapping GMM estimators developed by Brown and Newey (2002).[33]

4 Results

Before discussing the results of the GMM estimation in Section 4.2, Section 4.1 shows trends in patent outcomes for suppliers with high and suppliers with low exposure to manufacturers relying on diesel cars for compliance with the standard in 2014.

4.1 Trends

Figure 2 shows trends in patent counts for different technologies for firms with a high and firms with a low exposure to manufacturers that rely on diesel cars as compliance tech-

[32]Note that the estimator does not converge for independent variables that are either non-negative or non-positive. As suggested by Windmeijer (2000), I subtract the overall mean from all variables in X_{it} and the instrument.

[33]I implement the GMM estimation in R, using matrix algebra and the *gmm* package in R for the optimization procedure (Chausse, 2010).

nology in 2014.[34] I classify a firm as having a high exposure using the exposure weights $\sum_{o \in O} \omega_{io} \frac{S^{D}_{o,2014} - S^{ND}_{o,2014}}{S^{ND}_{o,2014}}$. I classify a supplier as "high exposure" when the exposure weight is smaller than the median in the sample of all suppliers. That is, the supplier is exposed to manufacturers with a below-median emissions disadvantage (i.e., an above-median emissions advantage) of diesel cars.

One can see that for automotive suppliers, patenting in the period before 2015 evolves mostly in parallel for firms with a high vs. a low exposure. Across both groups, two trend breaks are visible in the period 2015 - 2017. First, the average firm increases patenting for clean technologies around 2015. Second, roughly two years later, the trend in patenting for dirty technologies changes dramatically, with patent counts decreasing every year after 2017. This seems to reflect a broader trend in patenting by the firms observed in my sample, which can be seen in panels (e) and (f).

Comparing companies with high versus low exposure to manufacturers using diesel cars as a compliance technology, Figure 2 shows that both trends seem to change more dramatically in the subsample of firms that were more exposed to manufacturers using diesel cars as compliance technology: After 2015, suppliers with a higher exposure appear to increase their patenting for EV technologies faster than suppliers with low exposure. This is particularly visible in the average number of patent applications for clean technologies in panel (a) and much less pronounced when looking at the logarithm of patent counts in panel (b), suggesting that the increase might be driven by a few larger firms substantially increasing their number of patents for clean technology. At the same time, suppliers with high exposure appear to reduce the number of patent applications per year for dirty technologies more than the group of suppliers with low exposure, which can be seen in panels (c) - (f). For this outcome variable, taking the logarithm of patent counts does not change the visible trends as much. For the number of patents in the benchmark category, which serves as a proxy for the total innovation activity of a firm relevant to the car industry, firms with high exposure to diesel technology seem to experience a weaker reduction in the number of patents in both panels (c) and (d).

4.2 Regression analysis and main results

First stage results:

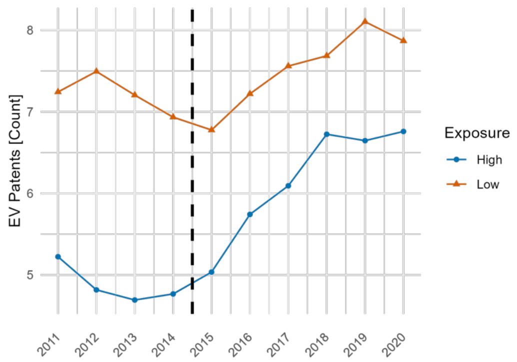
The GMM approach depends on a non-zero correlation between the shift-share instrument developed in Section 3 and supplier exposure to regulatory stringency at the manufacturer-level. I test for the joint significance of the first-stage relationship between the instruments used in the GMM estimation and the endogenous supplier exposure to regulatory stringency to assess the relevance of my instrument.

Table 2 shows the result of two first-stage regressions. In congruence with the main analysis, I analyze the first-stage relationship in a panel regression including annual observations from 2015 - 2019 and in a long quasi-difference, comparing the period 2015 - 2019 with 2010

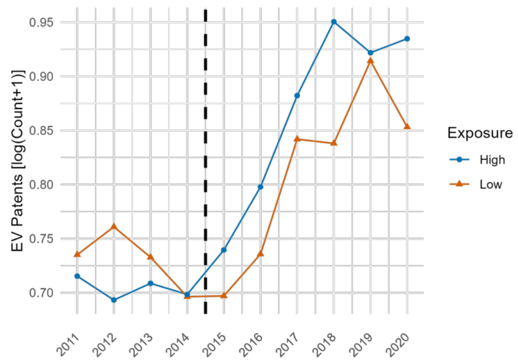
[34]The trends in patent counts for clean, grey, and dirty technologies over the full sample is displayed in Appendix Figure E.1.

Figure 2: Exposure to loosing Diesel cars as a compliance technology and trends in patenting

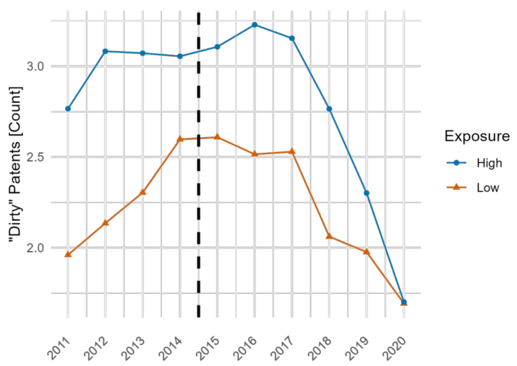
(a) Patent count Clean technology



(b) Log patent count Clean technology

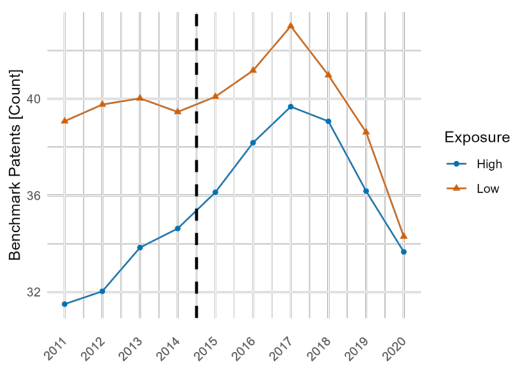


(c) Patent count Dirty technology

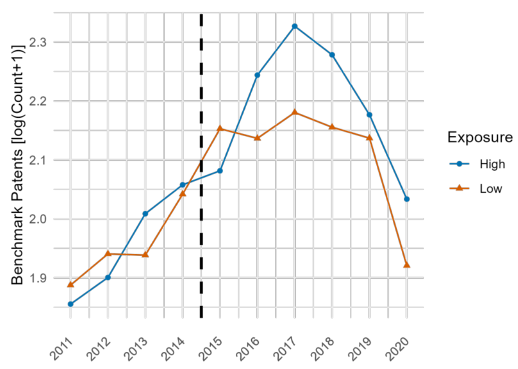


(d) Log patent count Dirty technology

(e) Overall patent count



(f) Log Overall patent count



Notes: High vs. low exposure is defined based on a median split of supplier exposure to manufacturers using diesel cars as a compliance technology in 2014. Exposure variable defined in Equation (12). High exposure is defined as being below the median of that (negative) variable. Panels (a), (c), (e) display the average number of patents per year for the sample of suppliers (winsorized at the 97.5th percentile before taking averages). Panels (b), (d), and (f) display the average in the logarithm of the patent count + 1 (not winsorized) for the sample of suppliers. Patents are classified as protecting Benchmark, Clean, or Dirty technologies based on the classification in Table A1.

- 2014. In both regressions, I can reject the hypothesis that the instruments are irrelevant based on a large F-statistic. Given the formula for exposure to regulatory stringency in Equation (10), one would expect a positive correlation between the instrument and supplier exposure to regulatory stringency. This initial conjecture is confirmed in the first stage for the long quasi-difference regression in column (2) of Table 2: suppliers more exposed to manufacturers relying on diesel cars as a compliance technology are exposed to a larger compliance gap in the downstream car market. Note that in both first stage regressions, I loose one time period compared to the main regression due to the quasi-differencing approach and the assumed lag structure. This implies that in the first-stage for the long quasi-difference, I am left with only one period and can no longer control for firm and year fixed-effects. Controlling for supplier fixed-effects in column (1), I use only variation in the instrument and exposure to regulatory stringency within the same supplier. The coefficient measuring the correlation between the excluded instrument and exposure to regulatory stringency in this regression is negative and statistically significant.

Table 2: First-stage relationship between regulatory stringency and the instrumental variable

	Stringency	
	Panel	*Long Difference*
IV_t	-0.322^{***}	
	(0.048)	
$\overline{IV}_t$		0.998^{***}
		(0.122)
F	68.041	94.259
Firm FE	X	
Year FE	X	
Firms	339	339
Periods	5	1

Note: First-stage regressions for the period 2015 - 2019. IV_t is the annual instrumental variable developed in Equation (12). $\overline{IV}_t$ is the average of this annual instrumental variable. Firms is the number of firms observed. Periods is the number of years in column (1) and the one of five-year period 2016 - 2020 in column (2). First-Stage F after within-transformation in column (1). Standard errors in column (1) clustered at the firm level. Heteroskedasticity-robust standard errors are used in column (2). *p<0.1; **p<0.05; ***p<0.01.

The following considerations rationalize the negative sign of the coefficient on the excluded instrument in column (1) of Table 2. Given the assumption about persistent supply chain relationships and the use of pre-determined shares in the shift-share instrument, suppliers are exposed to a constant set of manufacturers over time. Among these manufacturers, those facing a lower reduction in regulatory stringency than the average manufacturer will be reluctant to lower their share of diesel cars sold, since a higher share of diesel cars sold reduces their fleet-average emissions. This behavior implies that there is a positive correlation between the exposure to a (potentially endogenous) change in diesel sales and exposure to regulatory stringency, which can be seen in panel (c) of Figure 3. The correlation between the exogenous share component of the shift-share instrument (following Goldsmith-Pinkham et al., 2020) and exposure to regulatory stringency is displayed in panel (b). As expected, the supplier exposure to manufacturers relying on diesel cars for compliance in 2014 positively correlates with the exposure to regulatory stringency. Taken together, this implies a negative correlation between the instrument and stringency exposure, as seen in Panel (a) of Figure 3.

Table 3: Effect of exposure to more stringent environmental regulation on clean innovation

	Panel		*Long Difference*			
	GMM (IV) (1)	Poisson (2)	GMM (IV) (3)	GMM (IV) (4)	Poisson (5)	Poisson (6)
Stringency_{t-1}	11.233**	2.834	15.104**	13.397	4.853	5.604*
	(4.588)	(2.022)	(7.578)	(8.511)	(4.257)	(2.950)
Clean Share_{t-1}				0.646		2.836***
				(0.893)		(0.464)
First Stage						
Instrument	-0.322***		0.998***	0.997***		
	(0.048)		(0.122)	(0.122)		
F	68.041		94.539	47.305		
Periods	6	6	2	2	2	2
Firms	339	339	339	339	339	339
Firm FE	X		X	X		
Controls		X			X	X
Period FE	X	X	X	X	X	X

Notes: Models titled GMM (IV) estimate the specification in Equation 3 using the moment conditions in Equation 15 for the panel of five years and C.3 for the long quasi-difference. Details on the long difference approach are provided in Appendix C. Models titled Poisson estimate the specification in Equation C.1. Firms is the number of firms (companies or global owners) observed. Controls indicates that the logarithm (log(x+1)) of the presample patent stock in the benchmark category (corresponding technology) were included as controls. First-Stage F in column (1) after within-transformation. Block-bootstrapped standard errors for GMM models (100 draws, clustered at the level of firms, using re-weighted bootstrapping procedure by Brown and Newey (2002)). Standard errors for non-instrumented regressions clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Effect on innovation for clean technologies:
Table 3 shows the effect of exposure to a more stringent CO_2 emission standard on the number of patent applications for clean technologies by automotive suppliers. The preferred specification in column (1) shows that the number of applications for clean patents increases by 11% in response to a percentage point increase in emissions, relative to the future level of the standard. The 11% increase corresponds to 1.34 additional clean patents for the average supplier per year. This response is both statistically (at the 5% level) and economically significant. A percentage-point increase in emissions relative to the target corresponds to an

Figure 3: Stringency of the fleet-average CO_2 emission standard and exposure to diesel cars

Notes: Stringency is defined in equation (4). *Panel (a):* IV is the instrumental variable obtained in equation (12). *Panel (b):* The relative emissions gap is the supplier's exposure to manufacturer-level differences (as of 2014) between the emissions of the diesel and non-diesel fleet, divided by the emissions of the non-diesel fleet. *Panel (c):* Supplier exposure to diesel market shares at the manufacturer level. Manufacturer-level variables aggregated to the supplier level using time-constant supplier exposure weights introduced in Equation (5). The black lines show the slope of a regression of the regulatory stringency on the corresponding variable, controlling for time and individual fixed effects in panels (a) and (c) and for time fixed-effects in panel (b).

increase in fleet-average emissions by 0.95 g CO_2 per km. The average supplier was exposed to a 0.34-gram increase in CO_2 emissions over the period 2015 - 2019, although this figure masks substantial heterogeneity between suppliers (see Table 1). The average increase in exposure to regulatory stringency over the sample period would correspond to a 4% increase in the number of clean patents. The 2020 target level of the standard (95 g CO_2/km) is 36.8% lower than the 2015 target level (130 g CO_2/km). Linearly extrapolating the estimated effect size would lead to an increase in clean patenting by 412%. This number seems to exaggerate the effect of environmental regulation when compared to the observed increase in the average number of clean patents by firms in our sample since 2015 in Appendix Figure E.1, panel (b). However, we would not expect to see the full effect of the increase in stringency after 2015, since this policy change was anticipated since the adoption of the standard in 2009.

To assess whether this change in supplier innovation strategies is a response to the more stringent environmental regulation, I estimate a long quasi-difference, comparing the period 2016 - 2020 to the period 2011 - 2015, i.e., the five years after the scandal to the five years before.[35] In column (3) of Table 3, one can see that the magnitude of the overall reaction is similar to the coefficient estimated in column (1), implying that a percentage-point increase in regulatory stringency in the downstream market in the five-year period preceding the scandal translates into 15% more patents for clean technologies (significant at the level 5%) over the next five years. Controlling for the share of clean patents in period $t-1$ does not change the size of the coefficient substantially, although it renders the coefficient insignificant. This suggests that initial differences in knowledge stocks between automotive suppliers are not sufficient to explain the observed innovation response.

Comparing the effects estimated in the GMM specifications to the non-instrumented Poisson Fixed-Effects Quasi-Maximum Likelihood estimates in columns (2), (5), and (6), two things become apparent. First, the coefficients in the non-instrumented regressions are much smaller, which is in line with supplier anticipation of changes in regulatory stringency. As patenting is driven by expectations about future incentives, anticipated changes in regulatory stringency, such as the introduction of cleaner car models by some car manufacturers, should not alter the future innovation outcomes of suppliers. The IV approach purges the measure of exposure to regulatory stringency from this variation by holding constant a manufacturer's product portfolio and a supplier's exposure to different car manufacturers. Second, the coefficient of regulatory stringency in period $t-1$ is significant at the 5% level when controlling for the share of clean patents filed in period $t-1$.

Effects on innovation for other technologies:

To assess whether being exposed to a more stringent environmental regulation has an effect on innovation outcomes in other technological fields, I repeat the analysis in columns (1) and (3) of Table 3 for the number of patents in the grey and dirty category, as well as for the overall number of patent applications of the firm in technologies related to passenger cars using the benchmark patent category. The results can be found in Table 4.

[35] For details on the alternative regression specifications employed in this section, the interested reader is referred to Appendix B.

Table 4: Exposure to regulatory stringency and innovation for other technologies

	Dirty Patents		Grey Patents		Benchmark Patents	
	GMM (IV)	Poisson	GMM (IV)	Poisson	GMM (IV)	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Stringency_{t-1}	-3.924	-1.042	-7.314	-0.695	0.996	2.423**
	(3.691)	(0.935)	(6.770)	(1.214)	(4.401)	(1.166)
First Stage Regression						
Instrument	-0.322***		-0.322***		-0.322***	
	(0.048)		(0.048)		(0.048)	
F (within)	68.041		68.041		68.041	
Years	6	6	6	6	6	6
Firms	339	339	339	339	339	339
Firm FE	X		X		X	
Controls		X		X		X
Time FE	X	X	X	X	X	X

Notes: Models titled GMM (IV) estimate the specification in Equation 3 using the moment conditions in Equation 15. Models titled Poisson estimate the specification in Equation C.1. Firms is the number of firms observed. Controls indicates that the logarithm (log(x+1)) of the pre-sample patent stock in the benchmark category (corresponding technology) were included as controls. First-Stage F after within-transformation. Block-bootstrapped standard errors for GMM models (100 draws, clustered at the level of firms, using re-weighted bootstrapping procedure by Brown and Newey (2002)). Standard errors for non-instrumented regressions clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

The theory of directed technological change predicts that environmental regulation directs technological change towards clean and away from dirty technologies (Acemoglu et al., 2012). As one can see in column (1) of Table 4, I do not find evidence for the latter effect in the data.

The sign of the effect of environmental regulation on grey technologies is not determined by theory. My paper also provides no empirical evidence on the sign of this effect since the coefficient for the effect of exposure to regulatory stringency on innovation for grey technology in column (4) is not statistically significant at conventional levels. If anything, exposure to more stringent environmental regulation in a downstream market seems to decrease innovation for grey technologies.

Finally, to assess whether the observed increase in patenting for clean technologies could be explained by an innovation response of automotive suppliers that is not technology-specific, I estimate the effect of exposure to regulatory stringency on patenting in the benchmark technology in column (5) of Table 4. I do not find evidence that exposure to more stringent environmental regulation changes the overall patenting activity of supplier firms.

4.3 Effects on the formation of new supply chain links

In addition to creating incentives for existing suppliers to produce innovations for clean technologies, more stringent environmental regulation for a car manufacturer might also affect the formation of new supply chain links. To produce cleaner vehicles, manufacturers could try to source components from suppliers with expertise in clean or grey technologies. To study this response, I use data on manufacturer-supplier links between 908 suppliers and 23 car manufacturers in the years 2021 and 2022. After constructing a cross-section of all potential manufacturer-supplier pairs, I estimate the following probit model:[36]

$$\begin{aligned}\mathbb{E}\left(\mathbb{1}\left[J_i \cap J_o \neq \emptyset\right] | S_o, J_{i,0}, J_{o,0}, D^k_{i,0}\right) = \phi\Bigg(&\beta_0 S_o + \sum_{k \in K}\left(\beta^k_1\left(D^k_{i,0} \times S_o\right) + \beta^k_2 D^k_{i,0}\right) \\ &+\beta_3 \mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] + \beta_4 \frac{1}{|O|}\sum_{o \in O}\mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] + \epsilon_{io}\Bigg)\end{aligned} \tag{16}$$

Here, J_i is the set of car models for which supplier i provides at least one component in the period 2021 - 2022, J_o is the set of car models produced by manufacturer o in that period. Subscript 0 indicates that the corresponding variable is evaluated before 2015. In addition, $\mathbb{1}$ is an indicator assuming the value one when the condition inside the brackets holds and zero otherwise, $D^k_{i,0}$ is an indicator whether supplier i belongs to knowledge stock category k, S_o is the manufacturer-level regulatory stringency in 2020 as defined in equation (2), O is the set of all regulated car manufacturers relying on diesel cars for compliance with the CO_2 emission standard in 2015.[37] To quantify the effect in terms of additional supply chain links, I include a dummy to identify pre-existing supply chain links from the period 2010 - 2015 ($\mathbb{1}(J_{i,0} \cap J_{o,0})$). Finally, ϵ_{io} is the error term.

As before, the regulatory stringency S_o entering the model in (16) is endogenous since it reflects manufacturer o's product portfolio in 2020, which also drives the supplier network. I use the manufacturer-level reliance on diesel cars as a compliance tool as an instrument $IV^M_o = \frac{S^D_{o,2014} - S^{ND}_{o,2014}}{S^{ND}_{o,2014}}$.[38] The model in Equation (16) is estimated using a Probit Correlated Random Effects Control Function Approach (Papke and Wooldridge, 2008, Lin and Wooldridge, 2019). The residuals of first-stage regressions for the interaction between manufacturer-level regulatory stringency and the knowledge stock category $E_{i,o} = S_o \times D^k_{i,0}$ are included as regressors in Equation (16) to control for endogenous variation in S_o and the interaction term. The following first-stage regressions are estimated to obtain these residuals:

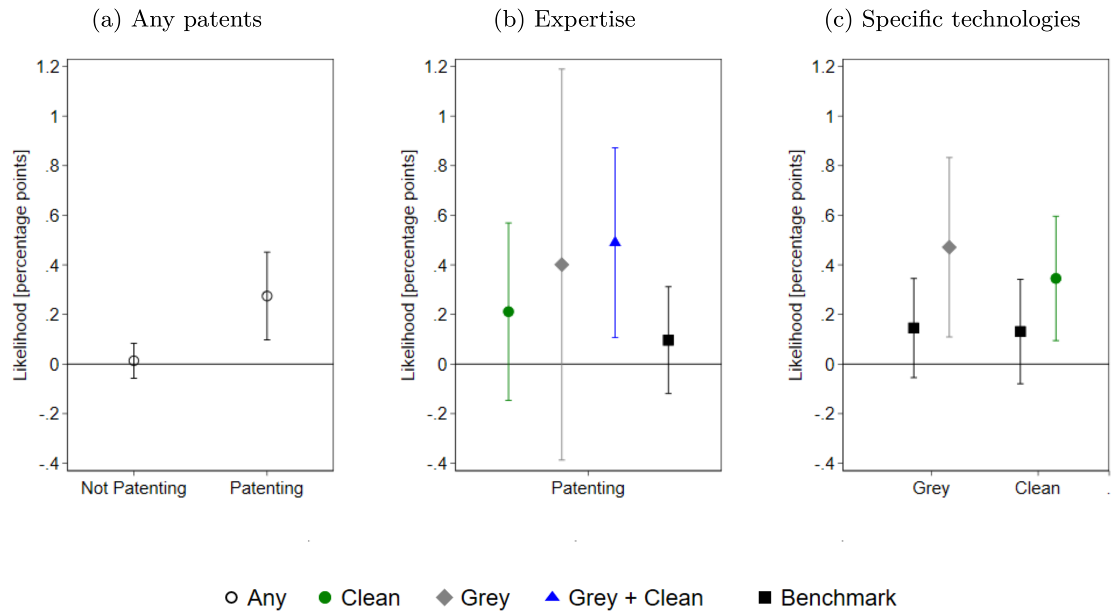
$$\begin{aligned}E_{i,o} =& \gamma_1 IV^M_o + \sum_{k \in K}\left(\gamma^k_1\left(D^k_{i,0} \times IV^M_o\right) + \gamma^k_2 D^k_{i,0}\right) + \gamma_3 \mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] \\ &+ \gamma_4 \frac{1}{|O|}\sum_{o \in O}\mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] + \xi_{io}\end{aligned} \tag{17}$$

[36] A robustness test estimating a slightly modified version of the model in Equation (16) using a linear probability fixed effects estimator can be found in Appendix D.

[37] For these car manufacturers, the emissions of the average diesel car exceed the emissions of the average vehicle in their remaining new vehicle sales. This implies that the 2015 Volkswagen diesel scandal should increase the stringency of the emission standard for these manufacturers.

[38] $S^D_{o,2014}$ is defined in equation (11). $S^{ND}_{o,2014}$ is defined analogously.

Figure 4: Effect of regulatory stringency on supply chain relationships to specific suppliers



Notes: Average partial effects (APE) of manufacturer-level regulatory stringency on the propensity of supply chain links materializing in 2020 - 2021. Based on the Probit Control Function Approach introduced in Equations (16) and (17). Panel (a) displays the APE for supply chain links to suppliers with and without knowledge stocks in any of the categories clean, grey, dirty, or benchmark in 2015 (908 suppliers, 23 car manufacturers). Panels (b) and (c) restrict the sample to pairs involving a supplier with patent stocks in those categories (224 suppliers, 23 car manufacturers). Panel (b) displays the APE for supply chain links to suppliers in mutually exclusive categories. Category Grey in Panel (b) includes only pairs with suppliers holding grey knowledge stocks and not holding clean knowledge stocks. Clean and Grey + Clean are defined analogously. Benchmark contains suppliers with neither clean nor grey knowledge stocks. Panel (c) combines the previous categories into Grey (Grey or Grey + Clean) / Benchmark (Benchmark or Clean) and Clean (Clean or Grey + Clean) / Benchmark (Benchmark or Grey). 95% confidence intervals based on bootstrapped standard errors (500 draws, clustered at the level of suppliers). Regression results are displayed in Appendix Table A5.

Using the results of this estimation, I calculate the Average Partial Effect (APE) of manufacturer-level regulatory stringency evaluated for suppliers with different pre-2015 knowledge stocks. The APEs are displayed in Figure 4. In panel (a), I compare the effect of regulatory stringency on the likelihood of forming of supply chain links to a supplier with versus without knowledge stocks in any of the technology categories clean, grey, dirty, or benchmark. A one-percentage-point increase in the manufacturers fleet-average emissions relative to the 2020 target of the standard (i.e., a one-percentage-point increase in the stringency measure) increases the likelihood that a supply chain link is formed by 0.27 percentage points for pairs involving a supplier with knowledge stocks. In contrast, I do not find evidence for an effect among suppliers without knowledge stocks in 2015. The estimated APEs imply that the increase in the stringency of the standard by 36.8 percentage points between 2015 and 2020 should have led to a 9.9 percentage point increase in the propensity that car manufacturers form additional supply chain links to innovative suppliers. In panels (b) and (c), I drop 684 suppliers without knowledge stocks to study how technology-specific expertise moderates the effect of regulatory stringency at the manufacturer level. I categorize suppliers as follows: suppliers with a knowledge stock of at least one for grey technologies but no knowledge stock for clean technologies are categorized as grey. Analogously, suppliers with clean but no grey knowledge stocks are categorized as clean. Suppliers with both grey and clean knowledge stocks are categorized analogously. Finally, innovating suppliers without knowledge stocks for both grey and clean technologies are categorized as benchmark. Panel (b) shows that the positive effect of regulatory stringency on the formation of supply chain links to innovative suppliers is driven by suppliers with both clean and grey knowledge stocks. In this category, a one-percentage-point increase in regulatory stringency increases the propensity of supply chain relationships materializing by 0.49 percentage points. This effect is 0.39 percentage points (significant at the 10%-level) higher than the effect among suppliers in the benchmark category. Extrapolating this effect to assess the impact of the increase in the stringency of the standard between 2015 and 2020, the estimated APEs imply an increase in the propensity to form links to suppliers innovating in clean or grey technologies by 18.2 percentage points. This is a substantial effect, given that the likelihood of the average supply chain link involving a supplier with clean and grey knowledge stocks in 2010 - 2015 was 22.4%. In contrast, the effect of regulatory stringency is not significant for suppliers with purely clean or grey knowledge stocks. However, the magnitude of the coefficient for suppliers with grey knowledge stocks is similar in magnitude to the effect among mixed suppliers. A direct test whether the effect among innovating suppliers is driven by clean or grey technology suppliers is inhibited by a large group of mixed suppliers. One can, however, assess differences between clean vs. non-clean and grey vs. non-grey suppliers to see for which technology category there is a larger difference in the response to regulatory stringency. The result of this exercise can be found in panel (c). Manufacturer-level regulatory stringency increases the likelihood of sourcing components from firms with expertise in either technology (+ 0.47 percentage points per percentage point increase in stringency for grey suppliers, + 0.35 percentage points for clean suppliers, both significant at the 5% - level). However, the difference between firms with and without knowledge stocks is more pronounced for grey technology (+0.33 percentage points, significant at the 10% -level, see Appendix Table A2). The response among suppliers with clean knowledge stocks is not significantly larger than the response among those without clean knowledge stocks (see Appendix Table A2).

4.4 Discussion

So far, the analysis in this paper yielded two main results: first, automotive suppliers exposed to car manufacturers with larger compliance gaps increase their innovation output for clean but not for grey and dirty technologies. Second, car manufacturers with larger compliance gaps are more likely to form additional supply chain links with suppliers that have expertise in both grey and clean technologies.

The first result is in line with the predictions of the theory of directed technological change for the effect of environmental regulation on innovation (Acemoglu et al., 2012). Environmental regulation increases the size of the market for clean technologies, thus increasing incentives for clean innovation. In the upstream market, exposure to a larger manufacturer-level compliance gap today implies exposure to a larger market share for clean technologies in future markets under the more stringent regulatory target. This is due to the fleet-average emission standard in Europe, which, at its post-2020 levels, acts like a quota for a certain share of EVs in a manufacturer's fleet.

At the same time, environmental regulation should reduce the size of the market and, therefore, incentives for innovation for dirty technologies. This paper does not find evidence for this effect. For grey technologies, the aforementioned market size effect is counteracted by a price effect. More stringent environmental regulation increases the returns of innovations that reduce CO_2 emissions of ICEVs, thus creating incentives to innovate in this technological field. This leaves the sign of the effect of environmental regulation on grey innovation undetermined. Unfortunately, the empirical analysis in this paper did not produce evidence for an effect on grey technologies either.

Observing strong effects on innovation in the upstream market one year after emission levels in the downstream market changed indicates a fast innovation response. The speed of this reaction is not surprising since existing research shows that there is a contemporaneous relationship between R&D expenditures and patent applications (Hall et al., 1984), indicating that patent applications are filed at the beginning of the innovation process. In addition, an immediate response after one year is possible if suppliers advance patent applications for existing innovation projects in response to more stringent regulation. This explanation is in line with the strong attenuation of the effects when controlling for the share of clean patent applications in the previous period.

Manufacturers for which compliance with environmental regulation during the period 2015 - 2019 is more difficult are more likely to form new supply chain links with automotive suppliers with knowledge stocks in both grey and clean technologies. While it is not possible to perfectly disentangle the effect on suppliers with clean and on suppliers with grey knowledge stocks, a comparison of the effect sizes in both groups suggests a stronger response among suppliers with grey knowledge stocks. Improving the CO_2 emissions of ICEV technologies still seems to be an important objective for manufacturers with large compliance gaps.

4.5 Robustness tests

I address the robustness of my results to several choices made regarding data assembly and sample restrictions.

In the main analysis, I summarize all entities held by a common global ultimate owner into one firm with common exposure to different car manufacturers. Columns (3) and (4) in Table 5 show that the magnitude of my result is robust to the omission of ownership links. Considering only entities observed in both the MarkLines and the patent data, I find that patent applications for clean technologies increase by 9.9% in response to exposure to higher regulatory stringency in the downstream market. However, the effect is only significant at the 10% level. The lower precision in the sample that does not consider indirect supply chain links could be driven by the omission of important innovators for which only indirect links are observed via their global ultimate owner. Especially for the larger firms in my sample, three groups of indirectly linked subsidiaries might be relevant for the innovation outcomes of the firm. First, several companies have separate entities in charge of the firm's R&D efforts. As an example, I observe supply chain links for UFI Filters S.P.A, a supplier of filter modules for automotive applications, but not for the UFI Innovation Center. Second, patents are often held by the holding of a firm, which often is not the entity observed in the MarkLines data (e.g., Kongsberg Automotive ASA and Kongsberg Automotive Holding). Third, by summarizing all commonly owned firms into one entity, I capture additional important suppliers for which I do not observe a direct supply chain link in the MarkLines data. For example, consider the German automotive supplier Robert Bosch. Although I observe a number of supply chain links for this supplier, I do not observe a supply chain link for the Robert Bosch Battery Systems GmbH, which is certainly relevant in the given setting. Aggregating firms to their global ultimate owner does, however, also lead to an overaggregation of firms in some instances. As an example, consider the German automotive supplier Continental AG, which also owns the automotive suppliers Schaeffler AG and Vitesco Automotive.

Table 5: Sensitivity analysis for the effect on clean innovation

	Baseline		No Ownership Links		No Outliers [99 perc]	
	Poisson	GMM (IV)	Poisson	GMM (IV)	Poisson	GMM (IV)
	(1)	(2)	(3)	(4)	(5)	(6)
Stringency_{t-1}	2.834	11.233**	3.151*	9.938*	-1.024	9.88***
	(2.022)	(4.588)	(1.891)	(6.025)	(1.614)	(3.806)
First Stage						
Instrument		-0.322***		-0.275***		-0.322***
		(0.048)		(0.040)		(0.048)
F (within)		68.041		53.215		67.238
Years	6	6	6	6	6	6
Firms	339	339	287	287	336	336
Firm FE		X		X		X
Controls	X		X		X	
Year FE	X	X	X	X	X	X

Notes: Models titled GMM (IV) estimate the specification in Equation 3 using the moment conditions in Equation 15. Models titled Poisson estimate the specification in Equation C.1. Baseline estimated on global owners holding at least 25% of a firm. No ownership links indicates regressions estimated on a sample that ignores these ownership links. No Outliers is estimated on global owners, but removing the 99th percentile of owners according to their annual patent counts for clean technology. Firms is the number of firms (companies or global owners) observed. Controls indicates that the logarithm (log(x+1)) of the pre-sample patent stock in the benchmark category ("clean" category) were included as controls. First-Stage F after within-transformation. Block-bootstrapped standard errors for GMM models (100 draws, clustered at the level of firms, using re-weighted bootstrapping procedure by Brown and Newey (2002)). Standard errors for non-instrumented regressions clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

To study the influence of firms with an exceptionally high number of annual patent applications, I reestimate the main analysis after removing suppliers with annual clean patent applications exceeding the 99th percentile in any year between 2016 and 2020 in columns

(5) and (6) of Table 5. Due to the high persistence in patent outcomes, only three firms fall into that category. Before the exclusion of "outliers", the largest annual patent count observed in the full sample was 942 patents, it is now limited to 416 patent applications. Although finding a positive and significant effect is robust to the exclusion of these firms, the visible change in the coefficient of exposure to regulatory stringency in the downstream market indicates that important innovators are, in fact, driving the results in this paper.

5 Threats to identification

In the following section, I address four main threats to the exclusion restriction. First, the 2015 Volkswagen diesel scandal was a disruptive event for the European car industry. Besides reshaping the car market in terms of vehicle technologies sold, it could also have affected the financial situation of many firms in the industry, including automotive suppliers. I provide evidence suggesting that changes in firm financial outcomes do not seem to explain the effects on innovation previously observed. Second, the change in the composition of the European car fleet affected both the compliance with the CO_2 emission standard for passenger cars and the average fuel price consumers in Europe face. Using additional variation in fuel prices between countries and over time, I show that this fuel price effect cannot explain my results. Third, I show that the results found for the increased innovation in clean technologies are not driven by preexisting trends. Fourth, I shed light on the role of preexisting differences in supplier exposure to EV technologies. My findings suggest that EV market size effects are not driving the results of my study. Instead, the effects observed are driven by suppliers with preexisting knowledge stocks for clean technologies.

Exposure to changes in regulatory stringency and firm financial outcomes:
Besides increasing the stringency of the CO_2 emission standard for a manufacturer, the demand shock implied by the diesel scandal might also directly affect patenting via reduced profits or credit constraints for some automotive suppliers.

A change in revenues, for example, a drop for a supplier providing components for diesel cars, could translate into changes in R&D budgets. A direct effect of the demand shock on R&D expenditures would violate the exclusion restriction. I obtain balance sheet data from Orbis for 125 out of the 339 supplier firms in my sample to address this concern. Using those data, I first check whether the instrument is correlated to firm financial outcomes in the pre-2015 period. Second, I test whether my instrument or changes in regulatory stringency directly affect firm financial outcomes, such as revenues, profits and R&D expenditures. Finally, I assess the robustness of my main regression to including firm revenues in period t as a control variable.

Panel B of Appendix Table A2 provides descriptive evidence on the correlations in the period 2012 - 2014 between a firm's financial outcomes and the instrument, controlling for firm and year fixed-effects. Reassuringly, the instrument is not correlated to firm R&D expenditures, revenues, profits, or assets held in cash or cash equivalents.

In Table 6, I test whether changes in the stringency of the European CO_2 emission perfor-

Table 6: Effects on firm financial outcomes

	R&D Expenditures			Revenues			Profits		
	RF	OLS	2SLS	RF	OLS	2SLS	RF	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Stringency		1.733	2.591		-0.834	-1.909		-0.202	0.917
		(2.673)	(6.643)		(0.550)	(2.485)		(0.754)	(3.181)
Instrument	-0.519			0.382			-0.184		
	(1.266)			(0.498)			(0.622)		
First Stage									
F			6.81			6.81			6.81
Firms	125	125	125	125	125	125	125	125	125
Periods	5	5	5	5	5	5	5	5	5
Firm FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X

Notes: Models titled 2SLS estimate the specification in Equation C.6 using a two-stage least squares estimator. Exposure to regulatory stringency is the endogeneous variable. Models titled OLS estimate the specification in Equation C.6 using an ordinary least squares estimator. Dependent variables are the logarithm of contemporaneous firm financial outcomes indicated in the top row. Instrument is the instrumental variable developed in 12. Firms is the number of firms observed (global ultimate owners holding more than 25 % of the subsidiary). Kleinbergen Paap F-statistic reported. Periods is the number of years. Standard errors clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

mance standard for cars directly affected the financial results of automotive suppliers. First, a reduced-form regression is estimated for the correlation between the instrumental variable and several financial outcomes. Reassuringly, the instrument is not correlated to changes in the financial outcomes of firms. Second, I estimate the effect of regulatory stringency on financial outcomes using a two-stage least squares (2SLS) approach. None of the effects is significant in neither the 2SLS nor the ordinary least squares (OLS) regressions.[39] Note, however, that the Kleinbergen-Paap F statistic indicates a weak instrument in the reduced sample of firms for which financial results are available.

Despite the small F statistic (KP = 6.81), the analysis is repeated in column (2) of Table 3 for the reduced sample of firms with financial outcomes available in Appendix Table A1. For the reduced sample, the effect in the main specification in column (1) is slightly larger than in the full sample (a 12% increase in the number of clean patent applications for a unit increase in the stringency of the standard) and becomes significant at the 1% level. A larger effect was anticipated since financial results are available primarily for larger firms with higher patenting activity. Furthermore, controlling for a firm's contemporaneous revenues reduces the size of the coefficient for regulatory stringency, but an economically and statistically significant increase by 7.1% remains.

Changes in fuel prices:

Besides affecting the stringency of the fleet-average emissions standard for cars, the change in the composition of the European car fleet away from diesel cars and towards a higher share

[39]Details on the empirical approach for the 2SLS and OLS regressions are provided in Appendix B.

of gasoline cars also changes the average fuel price perceived by European car buyers. This is due to higher excise taxes levied on gasoline than on diesel in most European countries. Previous research shows that fuel prices are, in fact, a strong driver of clean innovation (Aghion et al., 2016, Crabb and Johnson, 2010). Relying solely on changes in the composition of the car fleet, the effects of fuel prices and the CO_2 emission standard would not be separately identified. Additional inter-temporal and cross-country variation in fuel prices does, however, enable the identification of both effects. I obtain supplier-level exposure to fuel prices by aggregating national tax-inclusive fuel prices for diesel and gasoline first to the level of car manufacturers. To do so, I rely on data on energy prices and energy taxes in OECD countries (in US dollars) provided by the International Energy Agencies Energy Prices data service. I then use manufacturer-level registrations of diesel and gasoline-powered cars in a given EU member state to aggregate country-level fuel prices for both fuels to the manufacturer level. Next, I use the supplier exposure weights ω_{io} to aggregate these manufacturer-specific fuel prices to the supplier level. The construction of supplier exposure to average fuel prices over time combines time-constant exposure weights of suppliers to car manufacturers with time-varying manufacturer-level fuel prices. Since the supplier exposure weights are also used to construct the exposure to the CO_2 emission standard, I take the first difference of fuel prices to isolate variation in prices over time.[40]

Comparing columns (1) and (2) in Table 7, one can see that controlling for both supplier exposure to changes in fuel prices and supplier exposure to larger compliance gaps with the CO_2 emission standard does not change the magnitude of the effect of the standard. The results imply that persistent changes in the stringency of the performance standard have a much larger effect on clean innovation than short-term changes in average fuel prices.

Differential trends in patenting:
Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2024) point out that the assumptions made for formula instruments using the exposure of firms to shocks on a higher level impose a parallel trends assumption on the outcome variable. Following Goldsmith-Pinkham et al. (2020), I regress past and future outcomes on the instrument in the first post-shock period to assess this assumption. Note that the GMM estimator used in my study relies on a weaker sequential exogeneity assumption. Not rejecting the strict exogeneity assumption made by Goldsmith-Pinkham et al. (2020) implies not rejecting the sequential exogeneity assumption, but rejecting the strict exogeneity assumption does not imply rejecting sequential exogeneity.

Appendix Figures E.3 and E.4 show the results of event study regressions of patenting outcomes on a suppliers' exposure to manufacturers with lower emissions in their diesel fleet in 2014 times their reduction in diesel market share from 2015 to 2016, i.e., the first period after the diesel scandal. For the overall innovation outcomes of suppliers measured by patenting in the benchmark category and for the clean patenting of suppliers, pre-trends between firms differentially exposed to manufacturers relying on diesel technology are parallel (see Figure E.3), which corroborates the approach taken in this paper. Suppliers exposed to

[40] This implies that I cannot separately control for tax-exclusive fuel prices and fuel taxes since taxes observed in the data combine almost time-invariant excise taxes with time-varying value added taxes which are collinear to the variation in fuel prices.

Table 7: Effect of the CO_2 emission standard vs. effect of fuel prices

	GMM (IV)			Poisson		
	(1)	(2)	(3)	(4)	(5)	(6)
Stringency	11.233**	11.779***		2.834	2.965	
	(4.588)	(3.818)		(2.022)	(2.053)	
Δ Fuel Price		0.244	6.844***		4.955	3.889
		(1.966)	(2.030)		(5.849)	(5.711)
First Stage						
Instrument	-0.322***	-0.318***				
	(0.048)	(0.049)				
Δ Fuel Price		-0.045				
		(0.103)				
F (within)	68.041	34.236				
Periods	6	6	6	6	6	6
Firms	339	339	339	339	339	339
Firm FE	X	X	X			
Controls				X	X	X
Year FE	X	X	X	X	X	X

Notes: Models titled GMM (IV) estimate the specification in Equation 3 using the moment conditions in Equation 15. Models titled Poisson estimate the specification in Equation C.1. Controls indicates that the logarithm (log(x+1)) of the pre-sample patent stock in the benchmark category ("clean" category) were included as controls. Δ Fuel Price is the year-to-year change in the fuel price suppliers are exposed to. Note that the GMM estimator in column 3 does not use an excluded instrument and thus has no first stage regression. First-Stage F after within-transformation. Block-bootstrapped standard errors for GMM models (100 draws, clustered at the level of firms, using re-weighted bootstrapping procedure by Brown and Newey (2002)). Standard errors for non-instrumented regressions clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

car manufacturers relying more on diesel technology increases their overall patenting activity in the benchmark category in the years after 2015. I find no effect on patenting for clean technologies. For patenting in the grey and dirty patent categories, Appendix Figure E.4 does not indicate a clear pre-trend. However, some of the pre-treatment coefficients are significantly different from zero. Appendix Table A4 indicates that this does not translate into significant differences in pre-treatment outcomes, at least not at the 5%-level. Since the 2014 emissions gap between diesel and gasoline technologies used to calculate the treatment variable in these regressions is an outcome of the pre-2014 innovations in these categories, this pre-trend is not surprising. Expecting such effects is, in fact, the main reason for resorting to an estimator requiring only sequential exogeneity.

After the diesel scandal in 2015, suppliers more exposed to car manufacturers that use diesel cars as a compliance technology seem to first increase patenting in both the grey and dirty technological fields after 2015 before reducing it more quickly towards the end of the sample. This is in line with the affected downstream firms demanding technologies to reduce the emissions of cars with an internal combustion engine in the years immediately after 2015.

Electric vehicle market size effects:
To assess whether the innovation response to higher regulatory stringency is driven by an increase in the market size of EVs independently from the stringency of the CO_2 emission standard for passenger cars, I split the sample into firms that are exposed to above vs. below-median growth in the market shares of EVs between 2010 and 2014. The rationale for this split is that suppliers exposed to car manufacturers with ex-ante growing EV market shares might expect to sell EV technologies in the downstream market in the short- to medium-term. The median EV market share a supplier was exposed to in 2014 is 0.5% and virtually zero in 2010. Appendix Table A3 shows that the effect observed in the main analysis is not sustained in either sub-sample after the split.

Splitting the sample into suppliers with and without pre-existing knowledge stocks for clean technologies in Table 8 suggests an alternative explanation. I find that the effect is driven by firms with at least one patent for clean technologies in 2014. While exposure to more stringent regulation in the downstream market has virtually no effect on the innovation outcomes of suppliers without pre-existing knowledge stocks for clean technologies in column (2) of Table 8, the response among suppliers with at least one patent application for clean technologies is significant and slightly larger than the effect found in the main analysis. This is in line with results by Noailly and Smeets (2015) and Dugoua and Dumas (2023), showing that many firms specialize in one technological field and that innovation in the corresponding field is mostly driven by those specialized firms.

6 Conclusion

In this paper, I study how environmental regulation in the car industry affects the innovation outcomes of automotive suppliers and the formation of supply chain links. I create a novel data set linking administrative data on manufacturer compliance with the CO_2 emission stan-

Table 8: Effect on clean innovation for suppliers with different pre-existing knowledge stocks

	No Clean Knowledge Stock		Clean Knowledge Stock	
	Poisson (1)	GMM (IV) (2)	Poisson (3)	GMM (IV) (4)
Stringency	0.961 (2.775)	-0.032 (6.449)	2.862 (2.06)	12.698** (5.401)
First Stage				
Instrument		-0.368*** (0.091)		-0.293*** (0.056)
F (within)		25.056		44.489
Firms	129	129	210	210
Periods	6	6	6	6
Firm FE		X		X
Controls	X		X	
Time FE	X	X	X	X

Notes: Models titled GMM (IV) estimate the specification in Equation 3 using the moment conditions in Equation 15. Models titled Poisson estimate the specification in Equation C.1. Controls indicates that the logarithm (log(x+1)) of the pre-sample patent stock in the benchmark category ("clean" category) were included as controls. Suppliers in the no "clean" knowledge sample have filed no patents in the "clean" category before 2014. The "clean" knowledge sample is the complement. First-Stage F after within-transformation. Block-bootstrapped standard errors for GMM models (100 draws, clustered at the level of firms, using re-weighted bootstrapping procedure by Brown and Newey (2002)). Standard errors for non-instrumented regressions clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

dard for passenger cars in Europe to supplier patent data using information on automotive supply chains. Using an instrumental variable approach, I study the effect of changes in the stringency of environmental regulation imposed on downstream car manufacturers. I provide causal evidence for two knowledge spillovers to car manufacturers. First, suppliers exposed to manufacturers for which the environmental regulation becomes more stringent direct their innovation efforts towards clean vehicle technologies. Exposure to a one-percentage-point increase in the stringency of environmental regulation increases the number of patent applications for clean technologies among automotive suppliers by 11.23%. Second, an increase in the stringency of the environmental regulation increases the manufacturer's propensity to source from additional suppliers holding patents in technological fields relevant to the car industry. A one-percentage-point increase in the manufacturer-level stringency of the regulation increases the propensity of sourcing from an innovating supplier by 0.27 percentage points. The propensity of sourcing components from non-innovating suppliers, however, is not affected. The increased propensity to source from innovating suppliers is driven by suppliers with knowledge stocks in both clean and grey technologies, i.e. low-emission vehicle technologies and technologies improving the emission intensity of fossil-fuel propelled cars.

While studying the heterogeneous exposure to changes in the stringency of environmental regulation adds insights on the role of supply chains for the pass-through of innovation incentives to upstream firms, a limitation of this approach is that it ignores changes in the stringency of the regulation driven by anticipated regulatory updates. Linearly extrapolating the effects found in my study thus potentially exaggerates the innovation response to these aggregate changes. In this study, I consider only suppliers with preexisting supply chain relationships to at least one car manufacturer in 2010 - 2015, including only manufacturers that sell at least 10.000 cars in Europe in 2015. This implies that some prominent manufacturers specializing in electric vehicles, such as Tesla or BYD, are not included in my study.

Both the innovation response to more stringent downstream environmental regulation among exposed suppliers and the formation of supply chain links to additional manufacturers are driven by suppliers with pre-existing expertise in emission-reducing technologies. This suggests that regulated manufacturers can tap into the innovative potential of specialized upstream firms to comply with more stringent environmental regulation. The car industry provides an early example of an established industry with long-standing supply networks that transitions from fossil fuel-based technology to zero-emission technology. Governments designing policies to guide similar transitions in other industries should take into account potential spillovers of ambitious environmental regulations along supply chains.

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A Patent Search Strategy

Table A1: CPC patent codes for clean and dirty technology

CPC Codes	Description
Panel A: Patents for electric vehicle technologies	
Y02T 10/60	**Other road transportation technologies with climate change mitigation effect**
Y02T 10/62	- Hybrid vehicles
Y02T 10/64	- Electric machine technologies in electromobility
Y02T 10/70	- Energy storage systems for electromobility, e.g. batteries
Y02T 10/7072	- Electromobility specific charging systems or methods for batteries, ultracapacitors, supercapacitors or double-layer capacitors
Y02T 10/72	- Electric energy management in electromobility
Y02T 90/00	**Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation**
Y02T 90/10	- Technologies relating to charging of electric vehicles
Y02T 90/12	- Electric charging stations
Y02T 90/14	- Plug-in electric vehicles
Y02T 90/16	- Information or communication technologies improving the operation of electric vehicles
Y02T 90/40	- Application of hydrogen technology to transportation, e.g. using fuel cells
Y02E 60/10	- Energy storage using batteries
Y02E 60/30	- Hydrogen Technology
Y02E 60/50	- Fuel Cells
B60K 01	- Arrangement or mounting of electrical propulsion units
B60K 06	- Arrangement or mounting of plural diverse primemovers for mutual or common propulsion, e.g. hybrid propulsion systems comprising electric motors and internal combustion engines
B60K 16	- Arrangements in connection with power supply of propulsion units in vehicles from forces of nature, e.g. sun or wind
B60L	**Propulsion of electrically-propelled vehicles; Supplying electric power for auxiliary equipment for electrically-propelled vehicles; Electrodynamic brake systems for vehicles in general; Magnetic suspension or levitation for vehicles; Monitoring operating variables of electrically propelled vehicles; Electric safety devices for electrically-propelled vehicles.**
B60R 16/033	- Characterised by the use of electrical cells or batteries
B60R 16/04	- Arrangement of batteries
B60S 05/06	- Supplying batteries to, or removing batteries from, vehicles
B60W 10	- Conjoint control of vehicle sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle
B60W 20	- Control systems specially adapted for hybrid vehicles
H01M	**Processes or means, e.g. batteries, for the direct conversion of chemical energy to electrical energy**
Panel B: Patents for dirty technologies	
B60K 13	- Arrangement in connection with combustion air intake or gas exhaust of propulsion units
B60K 15	- Arrangement in connection with fuel supply of combustion engines
B60K 28	- Safety devices for propulsion-unit control, specially adapted for, or arranged in, vehicles, e.g. preventing fuel supply or ignition in the event of potentially dangerous conditions
F02B	**Internal combustion piston engines, combustion engines in general**
F02D	**Controlling combustion engines**
F02F	**Cylinders, pistons or casings, for combustion engines; arrangements of sealings in combustion engines**
F02M	**Supplying combustion engines in general with combustible mixtures or constituents thereof**
F02N	**Starting of combustion engines; Starting aids for such engines, not otherwise provided for**
F02P	**Ignition, other than compressing ignition, for internal combustion engines; Testing of ignition timing in compression-ignition engines**

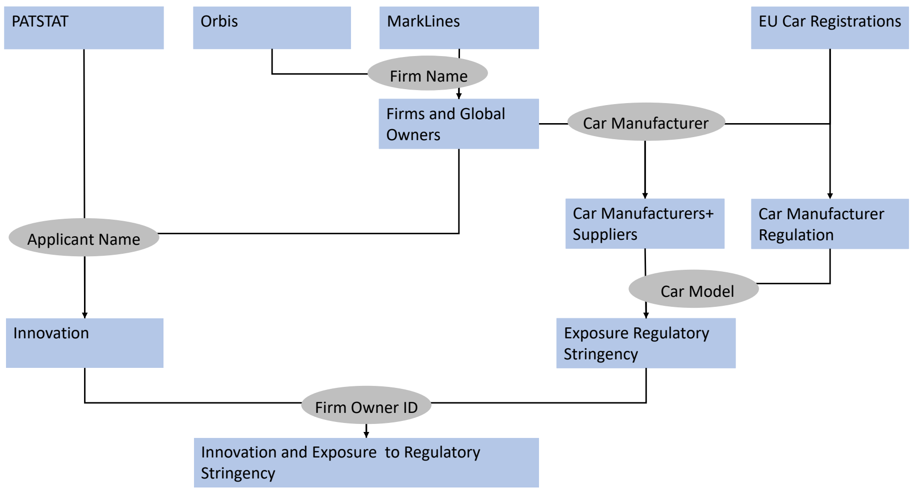
Table A2: CPC patent codes for grey and benchmark technologies

CPC Codes		Description
Panel C: Patents for grey technologies		
F02B 1/12	-	Engines characterised by fuel-air mixture compression ignition
F02B 11	-	Engines characterised by both fuel-air mixture compression and air compression, or characterised by both positive ignition and compression ignition, e.g. in different cylinders
F02B 13/02	-	Engines characterised by the introduction of liquid fuel into cylinders by use of auxiliary fluid; Compression ignition engines using air or gas for blowing fuel into compressed air in cylinder
F02B 3/06	-	Engines characterised by air compression and subsequent fuel addition; with compression ignition
F02B 7	-	Engines characterised by the fuel-air charge being ignited by compression ignition of an additional fuel
F02B 47/06	-	Methods operating engines involving adding nonfuel substances or antiknock agents to combustion air, fuel, or fuel-air mixtures of engines, the substances including nonairborne oxygen
F02B 49		**Methods of operating air-compressing compression-ignition engines involving introduction of small quantities of fuel in the form of a fine mist into the air in the engine's intake**
F02D 41		**Electrical control of supply of combustible mixture or its constituents**
F02M 23		**Apparatus for adding secondary air to fuel-air mixture**
F02M 25		**Engine-pertinent apparatus for adding nonfuel substances or small quantities of secondary fuel to cumbustion-air, main fuel or fuel-air mixture**
F02M 3		**Idling devices for carburetors preventing flow of idling fuel**
F02M 39-71	-	**Fuel-injection apparatus**
Y02T 10/10	-	Conventional vehicles (based on internal combustion engine)
Panel D: Patents in benchmark category		
B60		**Vehicles in general**
H01		**Electric elements**
F02		**Combustion engines, hot-gas or combustion engine plants**

B Data Merging Procedure

This appendix provides details on the data merging and harmonization procedures. It is organized in three steps: i) merging the patent data, manufacturer-supplier links and the European car registrations to Orbis, ii) merging the car registrations and manufacturer-supplier links and iii) merging the outcome of step ii) to the patent data. A graphical illustration of the merging procedure can be found in Figure B.1.

Figure B.1: Outline of the data merging procedure



Notes: Rectangles contain data sets, ellipses contain the variables the data sets are matched on. First row contains raw data, last row contains final data. Firm Owner ID abbreviates the identifier assigned in Orbis for the Global Ultimate Owner (GUO) of the company (owning more than 25% of the company).

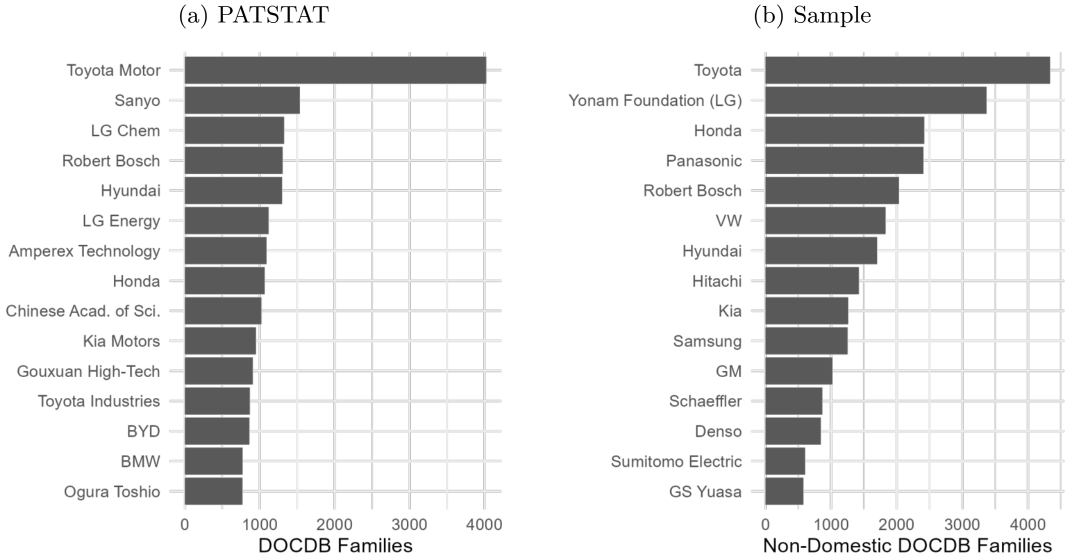
Step 1:

In a first step, I merge the EU car registrations, the patent data and the manufacturer-supplier links for the period 2010 - 2015 to ORBIS using the company names. I limit the data to the period 2010-2015 since the typical production period for a car model is six to eight years (Mueller et al., 2016), such that most model links observed are still relevant in 2019 (the last year for which I need the regulatory data). The car registration data contains 92 car manufacturers, which I match manually to ORBIS. For the merge of Orbis with PATSTAT and MarkLines Who Supplies Whom, I use a semi-automated matching procedure based on similarity scores for the company names. Before matching the company names, I clean the company names in the three datasets following the procedure outlined by Magerman et al. (2006). I remove punctuation and non-alphanumeric characters, set all characters to uppercase, harmonize special characters such as umlaute ä, ö, ü, and remove the legal forms of companies, as well as country names, the names of some bigger Chinese cities, as well as a list of common words for company names in the industry. I extract the 10 best matches based on string similarity scores. To do so, I use the token set ratios from the *fuzzywuzzy* package in python. Token set ratios assign a perfect similarity score as soon as two tokens (words) in both firm names are the same. This accounts for the fact that company names are different across the three datasets. If the cleaned company names are the same in both datasets (the strings being exactly equal, not in terms of the similarity score) I keep the pair as a match. For imperfect matches, I manually assign matches out of the 10 company names in Orbis with the highest string similarity score. In case of a tie, all companies with the same score are kept. I manually checked all matched pairs. In cases where the matched names before cleaning are not perfectly congruent, I check whether the two firms belong to the same global ultimate owner in ORBIS. In some cases, the ownership information in ORBIS does not seem accurate based on prior knowledge of the industries or based on information on company websites. In these cases, I trust the information available on the companies website.

To harmonize the set of subsidiaries selling automotive components to the subsidiaries in charge of R&D with the ones actually providing model components to manufacturers, I aggregate firms to the level of the global ultimate owner. As an example for an intended match, consider JOHNSON CONTROLS NEW ENERGY BATTERY RESEARCH AND DEVELOPMENT in PATSTAT and the Johnson Controls (China) Investment Co. Ltd. in MarkLines. However, this strategy will summarize firms more broadly. To determine the global ultimate owner of a company, I use historical firm ownership information for the year 2015 from ORBIS on the global ultimate owner (GUO) holding more than 25% of the company to each firm. There are ten entities in the MarkLines data for which the global ultimate owner is not unique based on the 25% ownership threshold. In these cases, I randomly assign one of the two firms as the global ultimate owner. Since I calculate supplier exposure shares based on pre-2015 manufacturer-supplier links, I ignore changes in the ownership of companies after 2015. For the GUOs, I create firm-level patent stocks by summing over all patent applications held by companies belonging to the GUO.

Step 2:
I link the manufacturers in the MarkLines Who Supplies Whom data to the car manufacturers in the EU car registrations data based on the manufacturer name (make) and the car model name in both datasets. I consider only 34 car manufacturers selling more than 10,000 vehicles in Europe in 2015. While all these firms are regulated by the standard, manufacturer pools selling less than 300,000 cars are eligible for a niche derogation, which implies that they have to comply with a manufacturer-specific standard that takes into account the structure of their product portfolio in the past. While the EU car registrations contain information on the vehicles type-variant-version code and the type-approval number of the vehicle type (broader than the commercial names of car models), which would in theory allow for a better merge, such information is not contained in MarkLines. Model names in the MarkLines data are relatively coarse, such that one model might span several type-variant-version combinations in the EU car registration data. As an example, the MarkLines data would list a Mercedes Benz C-Class as one model, while the registration data would list a Mercedes Benz C 180. To merge the MarkLines data with the European car registrations, I conduct a number of cleaning steps. First, I harmonize the model names in both datasets. To do so, I use information on the building series (Baureihe) in contained in a model catalogue by the Gen-

Figure B.2: Top 15 innovators for clean technologies, PATSTAT versus sample



Notes: PATSTAT: simple patent counts for patent applicants as listed in PATSTAT. Sample: fractional patent counts for applicants in the set of merged global ultimate owners (GUO) of the patent applicants observed in PATSTAT. Patent counts may be higher due to the aggregation to the GUO or lower due to the fractional count.

eral German Automobile Club[41] to assign model names with a granularity that is available in both data sets. Second, I merge the car registrations and the manufacturer-supplier links to obtain manufacturer-model-supplier observations over the period 2010 - 2015. I obtain a suppliers exposure share by aggregating the total model registrations for each manufacturer supplier pair over the full pre-period and dividing it by the total model registrations for the supplier. This way, I obtain sales-weighted exposure shares to the 34 regulated car manufacturers for all supplier companies. These first cleaning and harmonization steps reduce the size of the sample from 2172 supplier companies (number of company names after basic name harmonization, including subsidiaries later summarized into one global ultimate owner) to observing 1324 suppliers held by 542 global ultimate owners providing components for 494 car models sold by 34 car manufacturers. I include supplier links for all 30 car manufacturers, since 4 manufacturers did not sell any diesel cars in 2015. Thus, the instrumental variables approach does not work for these manufacturers.[42] I observe at least one component supplier for 80% of all new car registrations in Europe by these 30 manufacturers in Europe between 2010 and 2015.

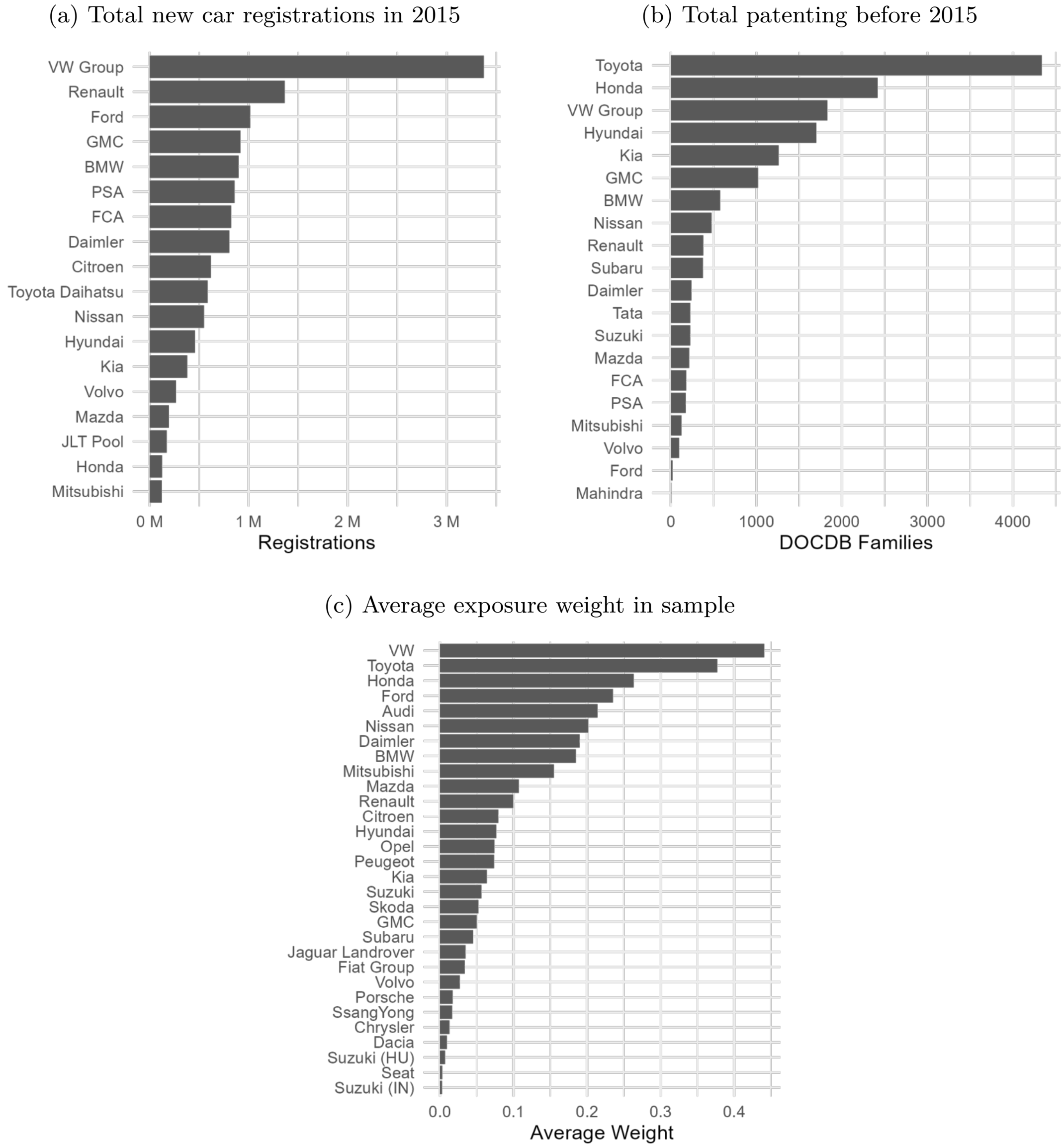
Nevertheless, I observe an incomplete set of automotive components. To see this, divide the total number of components procured by the 34 car manufacturers in 2015 (60024) by the number of car models (494). The implied number of components per model (121) is much lower than the industry average of 1500 (Mueller et al., 2016). To translate the regulatory outcomes (regulatory stringency, gap between the CO_2 emissions of the average diesel vs. non-diesel vehicle of a manufacturer, the manufacturers share of diesel vehicles among its

[41] ADAC Autokatalog, `https://www.adac.de/rund-ums-fahrzeug/autokatalog/`

[42] The brands excluded are Avtovaz, Bugatti, Rolls Royce and Tata Motors.

new car registrations) to the supplier level, I merge the supplier exposure data with the manufacturers regulatory data over the full period 2010 - 2020.

Figure B.3: Role of regulated car manufacturers in terms of car registrations, clean patenting and supplier exposure



(a) Total new car registrations in 2015

(b) Total patenting before 2015

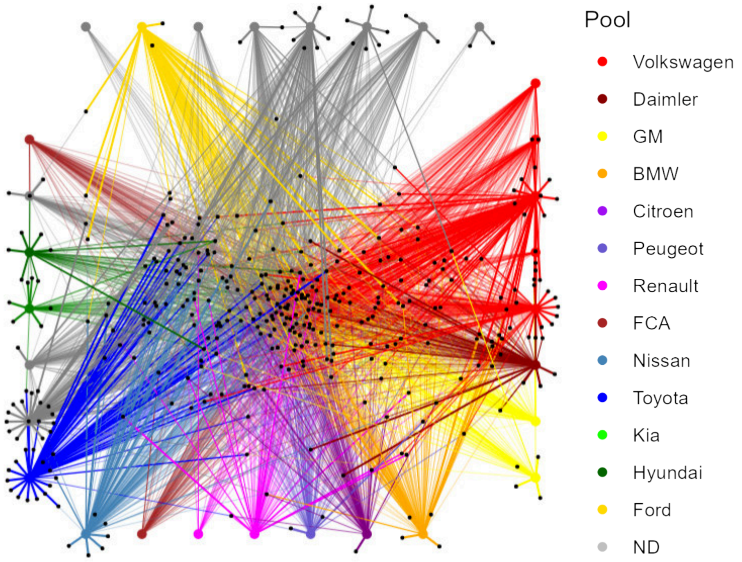
(c) Average exposure weight in sample

Notes: Registrations for the EU 28 + Norway and Iceland in 2015. Patents for the period 2010 - 2015 for the final sample, i.e. firms matched across the MarkLines, PATSTAT and ORBIS data. Exposure weights are suppliers exposure weights to manufacturers, measured as the share of the manufacturers model sales 2010 - 2015 for models for which supplier i provides a component.

Step 3:

I merge the PATSTAT data measuring innovative activity per year and the data measuring exposure to regulatory stringency on both the manufacturer and the supplier level using the GUOs ID in the ORBIS data. In the main sample, I keep only GUOs that applied for at least one patent for EV technologies in the period 2010 - 2020. This reduces the size of the final sample from 410 GUOs matched to the PATSTAT data to 339. This way, I obtain patent data for 1,737 patent applicants. In total, I merge 81,155 of 384,964 patent families for EV technologies with an earliest application date between 2015 and 2020 (21%). In my sample, 55% of these patents are held by supplier companies. This highlights the importance of supplier companies for innovation in the car industry in Europe. To assess the quality of the merge in terms of the outcome variable, Figure B.2 compares the top 15 innovators holding most patents for EV technology across the final sample and the initial PATSTAT data over the sample period 2015 - 2019. To further assess the quality of my data merging procedure, I draw a random sample of 50 firm names (not global ultimate owners) from the sample of firms in MarkLines that are linked to a manufacturer that is regulated in 2015 (sells more than 300,000 new cars in Europe). Manually matching these firms to patent applicants in PATSTAT, both directly and via their global ultimate owners, I find that the semi-algorthmic match I employ did not miss any company name in MarkLines for which there would have been a patent application (false negative rate = 0), and only assigned a patent applicant to one firm in PATSTAT that should not be found in the PATSTAT data, neither directly nor via its global ultimate owner (false positive rate = 2%). These statistics are silent on the number of patent applicants per firm, i.e. whether I match all potential patent applicants linked to a firm contained in MarkLines either directly or via common ownership. In addition, Figure B.3 compares the average exposure share for each car manufacturer in our sample to the manufacturers total new vehicle registrations in 2015 and its patent count over the period 2010 - 2015 to assess whether the exposure weights reflect the manufacturers importance in terms of market share and the role played in patenting for EV technologies in the pre-2015 period.

Figure B.4: Manufacturer-Supplier Network



Notes: Manufacturer-supplier network visualization. Black nodes are global ultimate owners of suppliers. Colored nodes are car manufacturer pools, as observed in 2015. Edges indicate supply chain relationships. Based on supply chain links between 2010 and 2015 for the final sample of 239 suppliers. ND summarizes a number of small manufacturer pools selling between 10,000 and 300,000 cars in Europe in 2015.

C Additional Regression Specifications

Besides the GMM estimator based on the moment conditions developed by Wooldridge (1991, 1997), Windmeijer (2000) used in the main analysis, the following models are estimated:

Poisson Quasi-Maximum Likelihood Estimator:
In the regressions not instrumenting for the exposure to more stringent environmental regulation, the following specification is estimated using a Poisson Quasi-Maximum Likelihood Estimator as implemented in the *fixest* package in R (Bergé, 2018)

$$PAT_{it} = exp(\gamma S_{i,t-1} + \beta X_{it} + \mu_t) + \eta_{it} \tag{C.1}$$

Here, PAT_{it} includes counts of patent applications for clean, dirty, grey and benchmark technologies (defined using CPC codes listed in Tables A1 and A2) and X_{it} includes the logarithm of knowledge stock of EV patents (log(x+1)) and patents in the benchmark category (log(x)) in 2014. This model is based on the control function approach developed by Blundell et al. (1999) to proxy out the firm fixed effect by controlling for pre-2015 knowledge stocks. Their estimator has been used in previous studies on the effect of environmental regulation on innovation outcomes, including Rozendaal and Vollebergh (2024) and a secondary specification in Aghion et al. (2016). Knowledge stocks are defined as in Equation (7):

$$K_{it}^{k} = \sum_{l=2005}^{t} (1-\delta)^{l} PAT_{it}^{k} \tag{C.2}$$

The knowledge stock K_{it}^{k} for technology k is calculated using the perpetual inventory method, (following Cockburn and Griliches, 1988, Peri, 2005) including patent applications dating back to 2005 and assuming a knowledge depreciation rate of $\delta = 0.2$, following Aghion et al. (2016).

Long Quasi-Differencing Estimator:
To quantify the effect of exposure to more stringent environmental regulation over the period 2016 - 2020 following the Volkswagen diesel scandal in 2015, I again rely on the moment conditions developed by Wooldridge (1991) and Windmeijer (2000). I quasi-difference the period 2016 - 2020 using patent counts aggregated over the period 2011 - 2015.

$$\mathbf{E}\left(Z_{i,Post}\left(\frac{y_{i,Post}}{\exp(X_{i,Post}\beta)} - \frac{exp(\mu_{Post})}{exp(\mu_{Pre})}\frac{y_{i,Pre}}{exp(X_{i,Pre}\beta)}\right)\right) = 0 \tag{C.3}$$

Here, $y_{i,t}$ is the count of patent applications for the technology of interest, accumulated over either the full period 2019 - 2020 (Post) or 2011 - 2015 (Pre). $X_{i,t}$ includes the exposure to regulatory stringency S_{it} defined in Equation (4) averaged over the periods 2010 - 2014 (Pre) and 2015 - 2019 (Post) and μ_t is a period fixed-effect. Notice that I again assume a one-year time-lag between changes in regulatory stringency and innovation responses in this specification.

In specifications controlling for lagged patenting outcomes, $X_{i,t}$ includes the share of clean knowledge stocks in the beginning of the corresponing period, i.e. in 2011 for the pre, and in 2014 for the post-period, defined by modifying Equation (6) to working with knowledge stocks K^k_{it-1} instead of within-period patent counts:

$$A_{it-1} = \frac{K^k_{it-1}}{K^b_{it-1}} \tag{C.4}$$

and Z_{it} comprises the included instrument A_{it} and the excluded instrument specified similar to Equation (12):

$$IV_{i,Post} = \sum_{o \in O} \omega_{io} \frac{S^D_{o,2014} - S^{ND}_{o,2014}}{S^{ND}_{o,2014}} \overline{\Delta\sigma}^D_{o,Post} \tag{C.5}$$

where $\overline{\Delta\sigma}^D_{o,Post}$ is the average across the change in the market share of diesel cars since 2014 for the years 2015 - 2019.

Two-Stage Least Squares Estimator:

For the financial outcomes of automotive suppliers, the following equations are estimated:

$$log(y_{it}) = \beta_1 S_{i,t} + \eta_i + \nu_t + \epsilon_{it} \tag{C.6}$$

where y_{it} includes the suppliers R&D expenditures, revenues and profits. These measures are obtained for the global ultimate owners observed in Bureau van Dijks ORBIS database, which retrieves the information from the annual reports of these firms. $S_{i,t}$ is the suppliers exposure to compliance gaps between manufacturer-level fleet average emissions in a given year and the 2020 emission target of the European CO_2 emission standard for passenger cars, as defined in Equation (4). The remaining terms are fixed effects and individual and time-specific error terms: η_i is a firm fixed-effect, ν_t is a year fixed-effect and ϵ_{it} the error term. This is the specification estimated in the Ordinary Least Squares (OLS) regressions. Since the exposure to regulatory stringency is potentially endogenous to a suppliers financial outcomes, e.g. due to demand shocks for certain components relevant only for diesel cars that might cut into a suppliers bottom line, I instrument for S_{it} using the instrumental variable specified in Equation (12) in the Two-Stage Least Squares Regressions (2SLS). Finally, to rule out a direct correlation between the instrument and the financial outcomes of firms, I estimate Equation (C.6) again, only replacing S_{it} by IV_{it}.

D Robustness: Formation of new supply chain links

To assess the robustness of the Probit model in Equation (D.1) to the inclusion of supplier and manufacturer fixed-effects[43] I estimate the following regression specification using a linear probability model model. I again study the effect of regulatory stringency at the level of car manufacturers on the propensity that additional supply chain links to suppliers with expertise in benchmark, clean, grey, and dirty technology are formed:

$$\mathbb{1}\left[J_i \cap J_o \neq \emptyset\right] = \sum_{k \in K} \beta_1 k \left(D_i^k \times S_o\right) + \beta_2 \mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] + \eta_i + \nu_o + \epsilon_{io} \tag{D.1}$$

As before, J_i is the set of car models for which supplier i provides at least one component in the period 2021 - 2022, J_o is the set of car models produced by manufacturer o in that period. The subscript 0 indicates that the corresponding variable is evaluated in 2015. In addition, $\mathbb{1}$ is an indicator function assuming the value one when the condition inside the brackets holds and zero otherwise, S_o is manufacturer o's regulatory stringency in 2020, $D_{i,0}^k$ is an indicator for supplier i belonging to knowledge stock category k, ϕ is the cumulative distribution function of a standard normal random variable, η_i and ν_o are supplier and manufacturer fixed effects, respectively. Finally ϵ_{io} is the error term. To quantify the effect in terms of additional supply chain links, I include a dummy to identify pre-existing supply chain links from the period 2010 - 2015 ($\mathbb{1}(J_{i,0} \cap J_{o,0})$).

For the endogenous regulatory stringency S_0, I again use the manufacturer-level reliance on diesel cars as a compliance tool as an instrument $IV_o^M = \frac{S_{o,2014}^D - S_{o,2014}^{ND}}{S_{o,2014}^{ND}}$.[44] Since I interact the measure of regulatory stringency with dummies for supplier-level knowledge stock categories, I need an instrument for each interaction term $E_{i,o} = S_o \times D_{i,0}^k$. I use the interaction between IV_o^M with the corresponding knowledge stock category as an instrument. The model in Equation (16) is estimated using a two-stage least squares estimator (2SLS), using the following first-stage regressions:

$$E_{i,o} = \gamma_1 \left(D_{i,0}^k \times IV_o^M\right) + \gamma_2 \mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] + \eta_i + \nu_o + \xi_{io} \tag{D.2}$$

As before, the exclusion restriction assumed for the exposure to diesel technology is that changes in the product portfolio of car manufacturers in the period 2015 - 2019 are exogenous to the manufacturers reliance on diesel cars in 2014.

The results of estimating the above specification can be found in Tables A1 and A2. Comparing the results of the Probit-model in columns (1), (2), (5) and(6) to the corresponding results of the linear probability model in columns (3), (4), (7) and (8), one can see that my findings are robust to the choice of estimator and the inclusion of manufacturer fixed-effects and supplier fixed-effects.

[43] Including a large set of fixed effects in Probit models leads to an incidental parameter problem. As the sample size grows, the number of fixed-effects grows too. In small samples, estimating a large number of fixed-effects leads to imprecision in Probit estimators.

[44] $S_{o,2014}^D$ is defined in equation (11). $S_{o,2014}^{ND}$ is defined analogously.

Table A1: Differences in effects on the formation of new supply chain links

	Any Patent				Expertise			
	CF	Probit	2SLS	OLS	CF	Probit	2SLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stringency	0.013	-0.011			0.096	-0.056		
	(0.036)	(0.023)			(0.110)	(0.063)		
Stringency × Patenting	0.261**	-0.004	0.244**	-0.023				
	(0.097)	(0.057)	(0.084)	(0.050)				
Stringency × Grey, Not Clean					0.305	0.051	0.328	0.049
					(0.418)	(0.237)	(0.356)	(0.187)
Stringency × Clean, Not Grey					0.115	0.125	0.091	0.100
					(0.211)	(0.132)	(0.167)	(0.107)
Stringency × Grey and Clean					0.393*	-0.030	0.421**	-0.053
					(0.221)	(0.124)	(0.191)	(0.116)
Existing Link_{10-15}	0.258**	0.256**	0.231**	0.231**	0.279**	0.273**	0.218**	0.218**
	(0.011)	(0.010)	(0.009)	(0.011)	(0.022)	(0.022)	(0.019)	(0.021)
First Stage								
F (Interaction 1)	79.154		9365323.481		52.996		8231050.199	
F (Interaction 2)	84.814				52.349		3189671.892	
F (Interaction 3)					56.018		4696137.022	
F (Interaction 4)					52.206			
Potential Links	20884	20884	20884	20884	5152	5152	5152	5152
Suppliers	908	908	908	908	224	224	224	224
Manufacturers	23	23	23	23	23	23	23	23
Supplier and Manufacturer FE			X	X			X	X
Controls	X	X			X	X		

Notes: The following effects are evaluated: *Stringency* is the Average Partial Effect (percent) of more stringent environmental regulation in the left-out category. *Stringency × Some Sample* shows the difference in the Average Partial Effect (percentage points) of more stringent environmental regulation between the subsample indicated and the left-out category. *Patenting* is the sample of supply chain links involving a supplier with knowledge stocks in any of the following categories in 2015: clean, grey, dirty, benchmark. *Grey, Not Clean* are suppliers in group Patenting which have knowledge stocks in the grey category but no knowledge stocks in the clean category. Categories *Clean, Not Grey / Grey and Clean* are defined analogously. Columns (1) - (4) include all possible supply chain links between 908 suppliers observed with at least one supply chain link in both the period 2010-2015 and 2021-2022 and 23 regulated car manufacturers relying on diesel cars as a compliance technology in 2014. For columns (5) - (8), the set of suppliers is reduced to 224 suppliers with at least one patent in the period 2005 - 2015 in any of the categories clean, grey, dirty, benchmark. Existing Links_{10-15} shows the average effect (percentage points) of supply chain links for firms with vs. firms without a pre-existing supply chain links. Stringency is the manufacturer-level stringency as defined in Equation 2 in 2020. Columns labeled Probit display the results of a probit model defined in Equation 16. CF displays results of the corresponding Probit Correlated Random Effects Control Function Approach defined in Equations 16 and 17. OLS displays results of a linear probability model, defined in Equation D.1. 2SLS displays results of the corresponding two-stage least squares approach, defined by Equations D.1 and D.2. Block-bootstrapped standard errors are indicated (500 draws, clustered at the level of suppliers). *p<0.1; **p<0.05; ***p<0.01.

Table A2: Differences in effects on the formation of new supply chain links: grey and clean technology

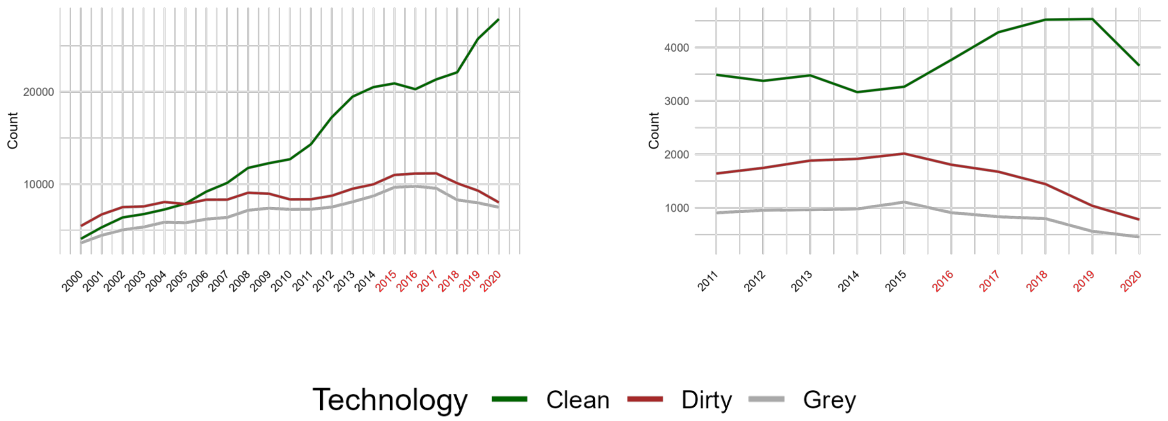
	Grey				Clean			
	CF	Probit	2SLS	OLS	CF	Probit	2SLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stringency	0.145	-0.001			0.131	-0.051		
	(0.102)	(0.062)			(0.108)	(0.062)		
Stringency ×	0.326*	-0.073	0.368**	-0.075	0.214	0.046	0.211	0.022
Knowledge Stock	(0.197)	(0.112)	(0.168)	(0.103)	(0.173)	(0.104)	(0.140)	(0.086)
Existing Link$_{10-15}$	0.274**	0.268**	0.218**	0.218**	0.278**	0.272**	0.218**	0.218**
	(0.022)	(0.022)	(0.019)	(0.021)	(0.022)	(0.022)	(0.019)	(0.021)
First Stage								
F (Interaction 1)	81.988		3136891.467		83.795		73297473.623	
F (Interaction 2)	77.798				52.349			
Potential Links	5152	5152	5152	5152	5152	5152	5152	5152
Suppliers	224	224	224	224	224	224	224	224
Manufacturers	23	23	23	23	23	23	23	23
Supplier and Manufacturer FE			X	X			X	X
Controls	X	X			X	X		

Notes: The following effects are evaluated: *Stringency* is the Average Partial Effect (percent) of more stringent environmental regulation in the left-out category. *Stringency* × *Knowledge Stock* shows the difference in the Average Partial Effect (percentage points) of more stringent environmental regulation between suppliers with and without a knowledge stock of at least one patent in the corresponding category (grey or clean) in 2015. The unit of observation are potential supply chain links between 23 car manufacturers 224 suppliers with at least one patent in the period 2005 - 2015 in any of the categories clean, grey, dirty, benchmark. Existing Links$_{10-15}$ shows the average effect (percentage points) of supply chain links for firms with vs. firms without a pre-existing supply chain links. Stringency is the manufacturer-level stringency as defined in Equation 2 in 2020. Columns labeled Probit display the results of a probit model defined in Equation 16. CF displays results of the corresponding Probit Correlated Random Effects Control Function Approach defined in Equations 16 and 17. OLS displays results of a linear probability model, defined in Equation D.1. 2SLS displays results of the corresponding two-stage least squares approach, defined by Equations D.1 and D.2. Block-bootstrapped standard errors are indicated (500 draws, clustered at the level of suppliers). *p<0.1; **p<0.05; ***p<0.01.

E Additional Graphs and Tables

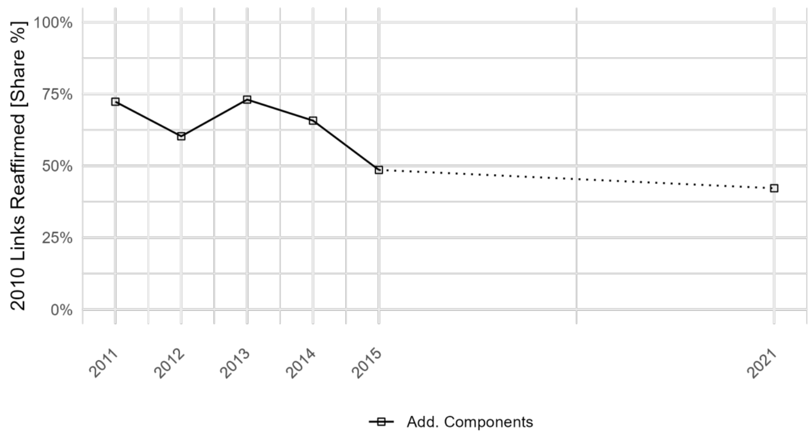
Figure E.1: Trends in fractional patent counts

(a) PATSTAT (b) Sample



Notes: PATSTAT includes all patents identified by the patent search outlined in Section 2.2. Only patents by applicants (psn_id in PATSTAT) with at least one patent in the benchmark category between 2005 and 2015 are included, which is consistent with the sample construction in the paper. Count of non-domestic DOCDB patent families per year. Sample includes only patents by applicants in the final sample. See Section 2.2 for details on the construction of the sample. Count of non-domestic DOCDB patent families per year (summation of fractional counts, equivalent to raw counts over the full sample). Red labels highlight years after the beginning of the 2015 Volkswagen Diesel Scandal.

Figure E.2: Persistence of links between car manufacturers and their Tier 1 suppliers



Notes: The share of reaffirmed links indicates the share of manufacturer-supplier pairs observed in 2010 for which an additional supply chain link (in the form of at least one additional component sourced from the supplier in the corresponding year) is observed.

Table A1: Effect of regulatory stringency on EV patenting, robustness to financial controls

	"Clean" Patents			
	Poisson	GMM (IV)	Poisson	GMM (IV)
	(1)	(2)	(3)	(4)
Stringency$_{t-1}$	-3.724	12.165***	-6.980***	7.188***
	(2.584)	(2.219)	(2.064)	(1.446)
Revenue$_t$			0.461***	−0.014
			(0.070)	(0.102)
First Stage				
Instrument$_{t-1}$		-0.200***		-0.200***
		(0.077)		(0.076)
Revenue$_t$				-0.002***
				(0.001)
F (within)		12.031		6.523
Firms	125	125	125	125
Periods	6	6	6	6
Firm FE	X	X	X	X
Year FE	X	X	X	X

Notes: Models titled GMM (IV) estimate the specification in Equation 3 using the moment conditions in Equation 15. Models titled Poisson estimate the specification in Equation C.1. Revenue is the logarithm of a firms revenue as reported in Orbis, measured at the level of global owners. F statistic calculated after within-transformation. Block-bootstrapped standard errors for GMM models (100 draws, clustered at the level of firms, using re-weighted bootstrapping procedure by Brown and Newey (2002)). Standard errors for non-instrumented regressions clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table A2: Correlation between the instrument and potential confounders before 2014

Variable	Instrument	Diesel Share	Stringency
Panel A: Patents and Market Shares			
EV Market Share	0	-0.013	0
	(0.023)	(0.008)	(0.013)
Clean Patents	1.74	0.379	-0.613
	(2.765)	(1.023)	(1.793)
Benchmark Patents	0.75	-0.22	-0.84
	(1.884)	(0.857)	(1.172)
Grey Patents	6.431*	-0.722	2.822
	(3.698)	(2.21)	(3.284)
Dirty Patents	0.307	-2.29	0.788
	(2.695)	(1.471)	(3.493)
Firms	339	339	339
Periods	3	3	3
Panel B: Firm Financials			
R&D Expenditures	5.521	-3.475	6.604
	(4.49)	(3.926)	(4.368)
Revenues	1.051	0.156	1.358***
	(1.909)	(0.765)	(0.478)
Asset: Cash	-0.926	0.635	1.711
	(4.199)	(1.572)	(1.278)
Profit	0.889	0.315	0.779
	(2.172)	(0.879)	(0.724)
Firms	140	140	140
Periods	3	3	3

Notes: This table reports estimates of the relationship between the instrument and time-varying firm characteristics in the period 2012- 2014, i.e. before the diesel scandal. Each row reports the coefficient of a regression of the instrument on the controls indicated in each row, controlling for firm and year fixed effects. Instrument is the IV from equation 12, Diesel Share is the first lag of the diesel share, Stringency is the first lag of the regulatory stringency measure in equation 2. Patent counts and logarithms of firm financial outcomes. Only suppliers included in all regressions. Standard errors are clustered by firm. *p<0.1; **p<0.05; ***p<0.01.

Table A3: Effect on electric vehicle patenting for firms exposed to an above vs. below median market share of electric vehicles

	Low EV Growth		High EV Growth	
	Poisson	GMM (IV)	Poisson	GMM (IV)
Stringency	2.595**	4.658	-0.118	3.673
	(1.238)	(3.921)	(2.775)	(4.498)
First Stage				
Instrument		-0.365***		-0.208***
		(0.068)		(0.062)
F (within)		42.084		16.235
		(df = 1 ; 663)		(df = 1; 683)
Obs	835	835	860	860
Firms	167	167	172	172
Firm FE		X		X
Controls	X		X	
Time FE	X	X	X	X

Notes: Models titled GMM (IV) estimate the specification in Equation 3 using the moment conditions in Equation 15. Models titled Poisson estimate the specification in Equation C.1. Controls indicates that the logarithm (log(x+1)) of the pre-sample patent stock in the benchmark category ("clean" category) were included as controls. Suppliers in the low EV growth sample are exposed to car manufacturers with below-median growth in EV market shares between 2010 and 2015. The high EV growth sample is the complement. First-Stage F after within-transformation. Block-bootstrapped standard errors for GMM models (100 draws, clustered at the level of firms, using re-weighted bootstrapping procedure by Brown and Newey (2002)). Standard errors for non-instrumented regressions clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01.

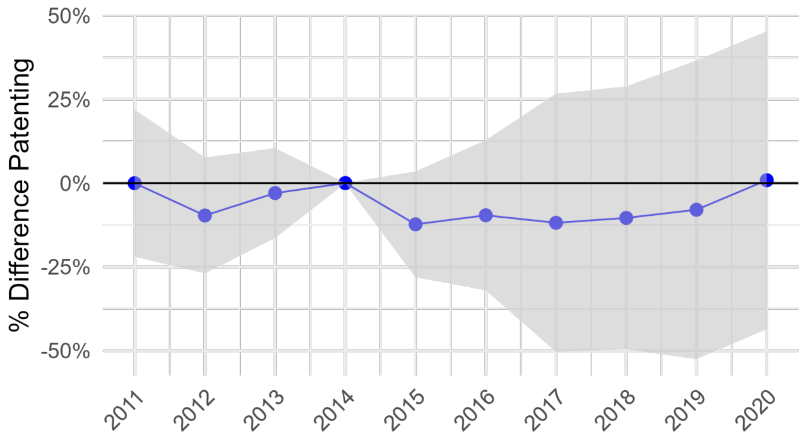
Table A4: Test for the joint significance of pre-trends

Statistic	Clean	Grey	Dirty	Benchmark
Wald	0.573	2.406*	2.434*	1.986
	p = 0.633	p = 0.065	p = 0.063	p = 0.114
Degrees of Freedom	(3, 3330)	(3, 3330)	(3, 3330)	(3, 3330)

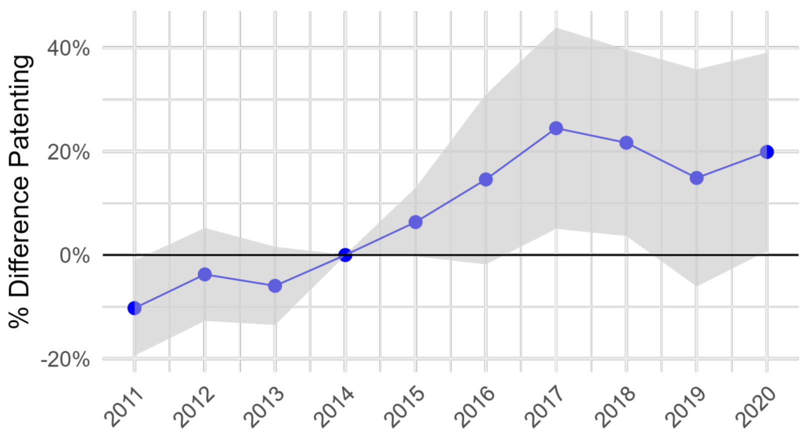
Notes: Wald-test for the joint significance of the pre-2014 coefficients of an event study regression (fixed-effects Poisson QMLE) of patent outcomes on supplier exposure to manufacturer-level reliance on diesel cars for compliance with the fleet-average emission standard in 2014 × manufacturer change in the market share of diesel cars between 2015 and 2016. Regressions interact the shift-share instrument in Equation 12 with a time dummy. Regressions include supplier and year fixed effects, but no other controls. Standard errors clustered at the firm level. *p<0.1; **p<0.05; ***p<0.01. Event study plots are provided in Tables E.3 and E.4 .

Figure E.3: Exposure to diesel as a compliance technology and trends in clean and benchmark patenting

(a) Pretrends in electric vehicle patenting



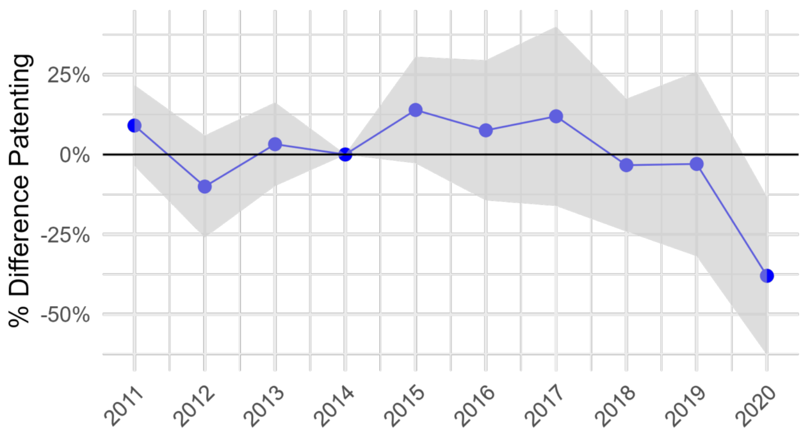
(b) Pretrends in patenting in the benchmark category



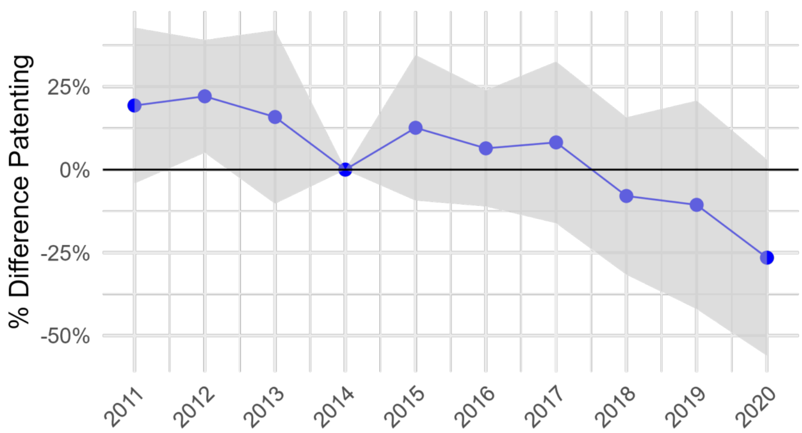
Notes: Event study regression (fixed-effects Poisson QMLE) of patent outcomes on supplier exposure to manufacturer-level reliance on diesel cars for compliance with the fleet-average emission standard in 2014 $\times$ manufacturer change in the market share of diesel cars between 2015 and 2016. Regressions interact the shift-share instrument in Equation (12) with a time dummy. Regressions include supplier and year fixed effects, but no other controls. Ribbons indicate 95% confidence intervals. Standard errors clustered at the firm level. Wald-tests for the joint significance of pre-treatment coefficients are provided in Table A4.

Figure E.4: Exposure to diesel as a compliance technology and trends in dirty and grey patenting

(a) Pretrends in patenting in the grey category



(b) Pretrends in patenting in the dirty category



Notes: Event study regression (fixed-effects Poisson QMLE) of patent outcomes on supplier exposure to manufacturer-level reliance on diesel cars for compliance with the fleet-average emission standard in 2014 $\times$ manufacturer change in the market share of diesel cars between 2015 and 2016. Regressions interact the shift-share instrument in Equation (12) with a time dummy. Regressions include supplier and year fixed effects, but no other controls. Ribbons indicate 95% confidence intervals. Standard errors clustered at the firm level. Wald-tests for the joint significance of pre-treatment coefficients are provided in Table A4.

Table A5: Effects on the formation of new supply chain links

	Any Patent		Expertise		Grey		Clean	
	CF	Probit	CF	Probit	CF	Probit	CF	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stringency × Not Patenting	0.013	-0.011						
	(0.036)	(0.023)						
Stringency × Patenting	0.274**	-0.014						
	(0.090)	(0.054)						
Stringency × Not Clean or Grey			0.096	-0.056				
			(0.110)	(0.063)				
Stringency × Grey, Not Clean			0.401	-0.006				
			(0.402)	(0.230)				
Stringency × Clean, Not Grey			0.211	0.068				
			(0.182)	(0.117)				
Stringency × Grey and Clean			0.489**	-0.086				
			(0.195)	(0.106)				
Stringency × No Knowledge Stock					0.145	-0.001	0.131	-0.051
					(0.102)	(0.062)	(0.108)	(0.062)
Stringency × Knowledge Stock					0.471**	-0.074	0.345**	-0.005
					(0.172)	(0.097)	(0.135)	(0.083)
Existing Link_{10-15}	0.258**	0.256**	0.279**	0.273**	0.274**	0.268**	0.278**	0.272**
	(0.011)	(0.010)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
First Stage								
F (Interaction 1)	79.154		52.996		81.988		83.795	
F (Interaction 2)	84.814		52.349		77.798		79.633	
F (Interaction 3)			56.018					
F (Interaction 4)			52.206					
Potential Links	20884	20884	5152	5152	5152	5152	5152	5152
Suppliers	908	908	224	224	224	224	224	224
Manufacturers	23	23	23	23	23	23	23	23
Supplier FE	X	X	X	X	X	X	X	X
Manufacturer FE	X	X	X	X	X	X	X	X

Notes: The following effects are evaluated: *Stringency × Some Sample* shows the Average Partial Effect (percent increase) of of more stringent environmental regulation in the subsample. *Not Patenting* is the sample of supply chain links involving a supplier without knowledge stocks in any of the following categories in 2015: clean, grey, dirty, benchmark. *Patenting* is the complement. *Not Clean or Grey* are suppliers in group Patenting which have no knowledge stocks in both the clean and grey category. Categories *Clean, Not Grey / Grey, Not Clean / Grey and Clean* are defined analogously. Categories *No Knowledge Stock* and *Knowledge Stock* combine the previous set of categories to distinguish firms with and without knowledge stocks in grey (columns 5-6) or clean technologies (columns 7 -8). Columns (1) and (2) include all possible supply chain links between 908 suppliers observed with at least one supply chain link in both the period 2010-2015 and 2021-2022 and 23 regulated car manufacturers relying on diesel cars as a compliance technology in 2014. For columns (3) - (8), the set of suppliers is reduced to 224 suppliers with at least one patent in the period 2005 - 2015 in any of the categories clean, grey, dirty, benchmark. Existing Links_{10-15} shows the average effect (percentage points) of supply chain links for firms with vs. firms without a pre-existing supply chain links. Stringency is the manufacturer-level stringency as defined in Equation 2 in 2020. Columns labeled Probit display the results of a probit model defined in Equation 16. Columns labeled CF display the results of the corresponding Probit Correlated Random Effects Control Function Approach defined in Equations 16 and 17. Block-bootstrapped standard errors are indicated (500 draws, clustered at the level of suppliers). *p<0.1; **p<0.05; ***p<0.01.