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

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March 19, 2026

Abstract

Suppliers of intermediate inputs can be important drivers of technological change. Nevertheless, regulation aiming to induce technological transformations, e.g. in the context of climate change mitigation, is often imposed only on final products. In this paper, I study the effect of a performance standard for a final product on the innovation outcomes of intermediate input suppliers. I construct a novel data set, linking patent applications by automotive suppliers to administrative data on their client's compliance with the European CO_2 emission standard for passenger cars. To identify the causal effect of changes in the stringency of the downstream emission standard, I leverage the heterogeneous exposure of suppliers, measured using proprietary data on supply chains in the car industry, to changes in the composition of the European car market. I find that being exposed to more stringent downstream environmental regulation increases innovation for zero-emission vehicle technologies among existing suppliers. Moreover, when car manufacturers face more stringent regulation, they are more likely to source from additional suppliers with expertise in emission-reducing technologies. These results suggest that environmental regulation induces technology spillovers from suppliers to the regulated downstream firms.

Keywords: environmental regulation, global value chains, innovation, fuel economy standards, directed technological change

JEL Classifications: O30, Q55, Q58

*I thank Ulrich Wagner, Bernhard Ganglmair, Arthur van Benthem and Laura Grigolon for their support and guidance. I am grateful for comments and suggestions by Andreas Gerster, Wolfgang Habla, Alex Rees-Jones, Mateus Souza, and Philipp Wangner. This research benefited from discussions at the EAERE 2024 Annual Conference, the Mannheim Conference on Energy and the Environment 2024, AURÖ Young Researchers Workshop 2024, the CRC TR224 Annual Meeting and Young Researchers Workshop 2024, and during seminars at the University of Mannheim, the University of Pennsylvania and the Yale School of the Environment.

Support by the German Research Foundation (DFG) through CRC TR 224 (Project B07) is gratefully acknowledged. This work was supported by a fellowship of the German Academic Exchange Service (DAAD). I acknowledge funding by the European Union (ERC, SPACETIME, grant n° 101077168). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them. Declarations of interest: none.

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1 Introduction

Governments around the globe have implemented environmental regulations that aim to speed up the transition towards technologies that mitigate global climate change. In many industries, this transition requires innovation in technologies on which incumbent firms lack expertise. Under such circumstances, technology spillovers from specialized suppliers can be a crucial driver of technological change (Dugoua and Dumas, 2024). However, suppliers of intermediate inputs are only indirectly affected by environmental regulations imposed on final products. Whether these regulations create incentives to induce sufficient upstream innovation is subject to an ongoing theoretical debate (Greaker, 2006, Heyes and Kapur, 2011, Dugoua and Dumas, 2021, Aghion et al., 2025). In this paper, I empirically investigate whether more stringent downstream environmental regulation affects the direction of technical change via upstream firms.

I study this question in the context of the European car industry, in which car manufacturers are subject to a carbon dioxide (CO_2) emission standard for passenger cars (Regulation EC 443/2009). This standard aims to reduce the amount of greenhouse gases the average car sold in Europe is allowed to emit per kilometer traveled. To quantify the effect of a more stringent standard on supplier innovation, I generate a novel firm-level dataset. The dataset combines supplier patent applications in the period 2016 - 2020 with their exposure to regulatory stringency in the downstream car market using product-level data on supply chain links in the automotive industry. To identify the causal effect of an increase in stringency exposure, I develop a Bartik-type instrument (Bartik, 1991), which 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. The results I find suggest that changes in the stringency of downstream environmental regulation affect the direction of technical change via suppliers: suppliers exposed to a one percentage point increase in stringency of the emission standard increase the number of patent applications for technologies relevant for zero- or low-emission vehicles by almost 13% in the following year. In addition, a one percentage point increase in regulatory stringency causes a 0.46 pp increase in the corresponding manufacturers likelihood to form supply chain links to firms with knowledge stocks on technologies relevant for low-emission vehicles or technologies reducing the emission intensity of internal combustion engine vehicles (ICEVs).

My paper makes three main contributions. First, it provides causal evidence for two spillover-effects of environmental performance standards imposed on a final product: a more stringent standard affects the direction of innovation among existing suppliers, as well as the formation of new supply chain links to ex-ante innovative firms. Second, it creates a new firm-level dataset to provide an measure of supplier-level exposure to downstream environmental regulation that does not rely on patent data. Third, it develops an instrumental variable approach to isolate the effect of a regional change in environmental policy on innovation in the globalized car industry.

I focus on the car industry to explore the effect of unilateral changes in environmental regulation on innovation outcomes along global supply chains. 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 provides an interesting setting to study directed technical change (Acemoglu, 1998) along a global supply chain, since 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, 2024). 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).

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.

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, "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.[2] Patents are sorted into these categories based on patent classes of the Cooperative Patent Classification (CPC) scheme, which are assigned by patent examiners.[3] 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 assess the formation of supply linkages between manufacturers and suppliers with expertise in different technologies using additional supply chain data for the years 2021 and 2022.

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

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

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

[3] For details how technology categories are assigned, see Section 3 and Appendix Tables A1 - A2.

is allowed to emit per kilometer (subsequently referred to as the manufacturer's fleet-average emissions). Emission targets are announced at least five years before they become binding. The 2015 target of the standard was 130 g CO_2 per km. The target was reduced to 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.[4] Automotive suppliers are exposed to regulatory stringency based on the manufacturers to which they have pre-existing and persistent supply chain relationships.

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 heterogeneity 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 used to be lower than the emissions of the average non-diesel car (see Figure 1), selling 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). This changed in the aftermath of the 2015 Volkswagen diesel scandal. 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. That damaged the reputation of diesel cars (Gross and Sonnberger, 2020), leading to substantial reductions in their market share. In Europe, the composition of the car market changed substantially over the following five years, as the market share of diesel cars fell from more than 50% in 2014 to 34% (for the set of car manufacturers studied in this paper) in 2019.

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, 1997) and Windmeijer (2000) to measure the effect on the innovation outcome. I estimate the effect of more stringent environmental regulation

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

[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).

on the propensity that a manufacturer-supplier pair forms a supply chain relationship using a Probit control function approach (Papke and Wooldridge, 2008).[6]

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 12.6% in the following year. This increase corresponds to 1.5 additional patents per year for the average supplier. At the same time, I do not find robust evidence that exposure to more stringent regulation changed patenting for dirty or grey technologies. If anything, suppliers seem to innovate less in grey technologies. 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. The spillover-effect of downstream environmental regulation on supplier innovation implies that persistent supply chain links in a vertically disintegrated industry shape the reaction of upstream firms to changes in downstream regulation.

The positive effect on clean innovation is consistent with theoretical predictions on directed technological change (Acemoglu et al., 2012, Aghion et al., 2016). A heterogeneity analysis shows that it is driven by suppliers with preexisting knowledge stocks. Furthermore, the effect is robust to controlling for the supplier's past clean patent share (significant at the 10%-level) in a regression using a long quasi-difference (Windmeijer, 2000) between the period 2011 - 2015 and the period 2016 - 2020, suggesting that path dependencies in supplier innovation are not sufficient to explain the observed effect. In conclusion, these results underscore the importance of specialized innovators established in previous studies (Noailly and Smeets, 2015, Dugoua and Dumas, 2024, Dugoua and Gerarden, 2025).

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, I show that my results are insensitive to an alternative data aggregation at the level of patent applicants instead of aggregating to the global owner of a firm and to the exclusion of suppliers with exceptionally high annual numbers of clean patent applications.

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 in 2019 has differential effects on the likelihood that a manufacturer sources components from suppliers with and without any prior patent applications. Manufacturers subject to a pp increase in standard stringency are 0.18 pp more likely to establish an additional supply chain link to a firm with prior expertise in any technology relevant for the car industry. Among these innovating suppliers, the effect

[6]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 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.

seems to be 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 pp. 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). Theoretical 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), finding spillover-effects on supplier innovation outcomes. My paper contributes to this literature by providing causal evidence for the importance of heterogeneous supply chain relationships for 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, 2025, 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 con-

trast 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. I provide causal evidence on the effect of changes in the stringency of environmental regulation using an instrumental variables approach. Finally, I study additional spillovers by including the effect of environmental regulation on the formation of supply chain links in my analysis.

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 introduces the context of the study. Section 3 introduces the data used. Section 4 presents the empirical strategy. Section 5 discusses the results. In Section 6, several empirical tests are conducted to rule out violations of the exclusion restriction. Section 7 concludes.

2 Policy Background

2.1 CO_2 Emission Standard for Cars in Europe

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[7] 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

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

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,[8] 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.[9] 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 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" (European Parliament and Council, 2009). 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 3.

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 (2025).

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

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, the weight adjustment factor and the 2020 emissions target. Ignored time-varying components include, for

[8] 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, the regulator converted these test results to NEDC-equivalent emissions using statistical software.

[9] In this study, only car manufacturers registering at least 10,000 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.

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 a_t and $M_{0,t}$ constant at their 2016 levels.

2.2 Volkswagen 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 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.

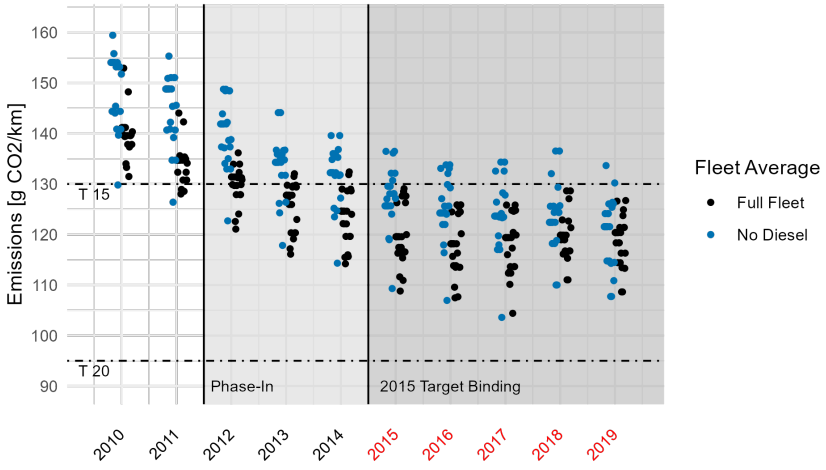
Governments in Europe historically promoted diesel cars as a means of reducing CO_2 emissions. They supported high market shares of diesel cars, for example, by charging lower excise taxes on diesel than on gasoline (Schipper et al., 2002). Thus, a high market share for diesel became a distinctive feature 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 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.[10] 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

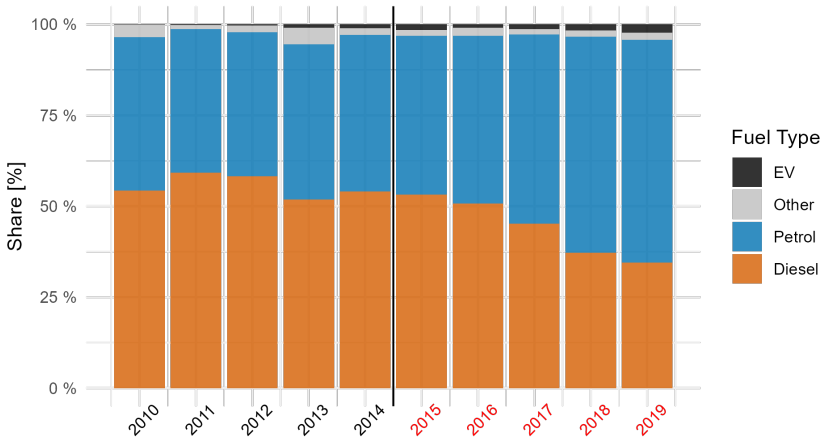
[10]This highlights an important feature of the diesel technology: while the weight-adjusted CO_2 emissions of diesel cars are lower than those of a comparable gasoline car, emissions of other air pollutants such as NO_x are higher.

Figure 1: Emissions and Market Share of Diesel Cars and Other Fuel Types

(a) Manufacturer Fleet-Average Emissions



(b) Market Share of Different Fuel Types



Notes: *Panel (a):* Points indicate weight-adjusted CO2 emissions per km for the average new passenger car registered by a manufacturer in a given year. No Diesel indicates that diesel-powered cars are omitted when calculating average emissions. 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. Based on 27 regulated car manufacturers not eligible for an exemption under Regulation (EC) 443/2009. *Panel (b):* Market share of different fuel types pooling vehicle registrations in the European Community. Based on 27 regulated car manufacturers not eligible for an exemption under Regulation (EC) 443/2009 and 7 manufacturers subject to a firm-specific emission target under a niche derogation (full set of manufacturers considered in this study). Years after the beginning of the diesel scandal highlighted in red.

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.[11] 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.

2.3 Manufacturer-Supplier Relationships in the 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 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. The extent to which these relationship-specific investments can shape the vertical relations between car manufacturers and suppliers has been discussed in a number of papers following Klein et al. (1978).

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.

3 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

[11] 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.

Appendix B.

3.1 Sources and Dataset Construction

Patent Data:

In this paper, I use patent data for 2000 - 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 (2024), 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.[12] 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.[13] To assess 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 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, weighting patents by the inverse of the number of applicants on a patent when counting patents at the firm-by-year level.[14] Second, I count patent families instead of patent applications. This

[12] 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.

[13] 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.

[14] 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.

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.[15] 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, 2025). 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)[16] 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 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

[15] 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.

[16] 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.

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.[17] 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 car models (nameplates) provided by 2,478 suppliers for 92 car makers globally over the period 2010 - 2015.[18] Combining this information with data on the number of registrations of car models in Europe, I obtain exposure weights that proxy for the share of components delivered from a supplier to a manufacturer (for details on the exposure weights, see Section 4). 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 innovative components 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 produc-

[17] 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).

[18] 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.

tion 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).[19][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 125 suppliers in my final sample for the period 2010 - 2020.

Merged Data 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, and Appendix Figure B.1 provides a graphical illustration.

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 (GUO) 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 manu-

[19] 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.

[20] Bureau van Dijk relies on different sources to determine the ownership of firms. Ownership information is available for firms that are, and firms that are not publicly traded. For exact information, see Bureau van Dijk (2022).

facturers 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. 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.[21] 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 date between 2015 and 2020 (21%).[22][23] 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. This highlights the importance of supplier companies for the technological transition towards clean technologies in the European car industry.

3.2 Descriptive Statistics

Table 1 provides descriptive statistics on the final sample of 339 automotive supplier companies. Panel A shows that the distribution of patent applications per year is positively skewed, with the median firm applying for 5 patents in a given year, compared to 49 patents by the average firm and a maximum of more than 1,600 patents per year. A similar pattern is also 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, less than 50% of the firms in my sample apply for either a clean or a dirty patent in a given year. The interested reader is referred to Appendix Figure B.2 for an illustration of the 15 largest

[21] 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.

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

[23] 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.

innovators by clean technology patents prior to 2015, including car manufacturers.

Table 1: Descriptive Statistics

Variable	Unit	Mean	Sd	Min	Pctile[25]	Pctile[50]	Pctile[75]	Max
Panel A: Annual supplier patenting between 2016 and 2020								
Benchmark Patents	Count	49	153	0	1	5	28	1674
thereof Clean Patents	Count	12	57	0	0	0	3	942
thereof Grey Patents	Count	1.9	14	0	0	0	0	284
thereof Dirty Patents	Count	3.6	19	0	0	0	1	344
Panel B: Manufacturer car market outcomes in 2015								
$Emissions^{15}$ - $Target^{20}$	gCO_2/km	23	11	0	17	24	33	41
$Target^{20}$	gCO_2/km	102	18	90	95	95	95	159
$(Emissions^{15} - Target^{20})/Target^{20}\times100$	% Target	24	12	0	18	23	34	45
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 Share	%	51	21	14	39	48	63	92
Panel C: Supplier exposure to car market outcomes in 2015								
$(Emissions^{15} - Target^{20})/Target^{20}\times100$	% Target	25	5.9	0	22	25	26	45
Diesel Emissions Disadvantage	gCO_2/km	-12	14	-67	-17	-14	-10	47
without weight-adjustment	gCO_2/km	0.78	14	-63	-4.9	-1.5	2.7	60
Diesel Share	%	47	13	14	39	50	56	92
Panel D: Change insupplier exposure to car market outcomes from 2015 to 2019								
$(\Delta$ Emissions$)/Target^{20}\times100$	%-points Target	0.13	5.2	-20	-2.3	0.63	2.4	30
Δ Diesel Share	%-points	-21	4.9	-48	-23	-20	-18	-14

Notes: Descriptive statistics on the final sample of 339 tier-1 automotive suppliers and 22 groups of commonly owned car manufacturers. Panel A displays supplier-level counts of annual patent applications in the corresponding technological fields. Patents classification based on CPC codes, see Tables A1 and A2. Panel B displays manufacturer-level regulatory outcomes in 2015. $Emissions^{15}$ are fleet-average CO2 emissions across all passenger cars registered by the manufacturer. $Target^{20}$ is the manufacturer's emissions target for 2020 set by the European CO_2 emission standard for passenger cars. Diesel Share is the share of diesel-powered vehicles registered. Diesel Emissions Disadvantage is the difference in weight-adjusted emissions between the average diesel and the average non-diesel car sold by the manufacturer. Panel C displays supplier exposure to manufacturer-level regulatory outcomes in 2015. Exposure is measured using past supply chain links, using the formula introduced in Equation (5). Panel D displays changes in supplier exposure to manufacturer-level outcomes from 2015 to 2019. Δ denotes the difference between the corresponding supplier-level variable in 2015 and in 2019.

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 set the standard after 2020. There are, however, car manufacturers (SsangYong), for whom the 2020 target is not binding already in 2015.[24] The emission targets set by the standard vary between manufacturers. Most car manufacturers in my sample belong to a pool selling more than 300.000 cars in Europe. Thus, the regulation prescribes that their fleet-average CO_2 emissions may not exceed 95 g in 2020. Some smaller manufacturers in my sample receive a derogation. Their fleet-average emissions are subject to an emissions target that can be higher or lower than 95 g, depending on their historical emissions intensity. For almost all manufacturers, the average diesel car sold has lower weight-adjusted CO_2 emissions per km than the average

[24]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.

non-diesel car sold. For the average manufacturer, the weight-adjusted emissions of the fleet of diesel cars sold is 14 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. Finally, diesel cars make up a substantial share of new vehicle sales for all manufacturers in 2015, ranging between 14 and 92% (51% 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.[25] Second, we see that there is heterogeneity 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.[26]

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 0.13 g CO_2 per km for the average supplier. On the other hand, for more than 25% of the sample, exposure to compliance gaps dropped by at least 2.3 g CO_2/km. The market share of diesel cars sold by the manufacturers a supplier is exposed to, however, dropped for all suppliers. Reductions range between 14 and 48 pp.

4 Research Design

4.1 Empirical Model

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:

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

where PAT_{it} is supplier i's number of technology-specific patent applications in year t, X_{it-1} are control variables, η_i is a supplier fixed-effect, μ_t is a year fixed-effect and u_{it} is the error term. In the main specification, $X_{i,t-1}$ incudes only $S_{i,t-1}$, which is the suppliers exposure to regulatory stringency of the EU CO_2 emission standard for cars in the previous year. $S_{i,t-1}$

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

[26] A graph illustrating the network between car manufacturers and their suppliers is provided in Appendix Figure B.4.

will be introduced in the next paragraph. In alternative specifications, $X_{i,t-1}$ will also contain lags of supplier exposure to country-level fuel prices, or supplier revenues. In contrast to other papers working with patent data (e.g. Aghion et al., 2016, Rozendaal and Vollebergh, 2025), 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.

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 manufacturer o in year $t-1$ defined in Equation (2).

After counting new vehicle registrations $q_{j,2010-2015}$ for all car models j 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 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 exposure weights are pre-determined over the sample period.

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.

The context of a globalized 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. These concerns imply that an estimator relying on the assumption that the exposure to downstream environmental regulation is exogenous to supplier innovation would produce biased results.

4.2 Instrumental Variables Approach

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 assumptions 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:

$$S_{it-1} = \sum_{o \in O} \omega_{io} \underbrace{\frac{\sum_{j \in J_o} \sigma_{ojt-1} \left(e_{ojt-1} - a_t(M_{ojt-1} - M_{0t-1})\right) - Target_T}{Target_T}}_{S_{ot-1}} \tag{6}$$

All components are defined exactly as in Equations (4) and (2). 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.

$$S_{it-1} = \sum_{o \in O} \omega_{io} \left(\sigma^D_{ot-1} S^D_{ot-1} + (1 - \sigma^D_{ot-1}) S^{ND}_{ot-1}\right) \tag{7}$$

$$= \sum_{o \in O} \omega_{io} \left(S^{ND}_{ot-1} \left(1 + \sigma^D_{ot-1} \frac{S^D_{ot-1} - S^{ND}_{ot-1}}{S^{ND}_{ot-1}} \right) \right) \tag{8}$$

where $\sigma^D_{ot} = \sum_{j \in J_{o|D}} \sigma_{ojt}$ 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,

$$S^D_{ot-1} = \frac{\sum_{j \in J_{o|D}} \sigma_{ojt-1} \left(e_{ojt-1} - a_t(M_{ojt-1} - M_{0t-1})\right) - Target_T}{Target_T} \tag{9}$$

is the stringency measure evaluated on manufacturer o's fleet of diesel cars sold, and S^{ND}_{ot-1}, defined analogously, is the corresponding measure for a manufacturer's fleet of non-diesel passenger cars.

Equation (8) 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 (8) should provide a relevant, time-varying instrument for the stringency of the European CO_2 emission standard for passenger cars.[27] To gain precision, I focus on changes in the manufacturer-share of diesel cars relative to 2014: $\Delta\sigma^D_{ot-1} = \sigma^D_{ot-1} - \sigma^D_{o,2014}$.

$$IV_{it-1} = \sum_{o \in O} \omega_{io} \frac{S^D_{o,2014} - S^{ND}_{o,2014}}{S^{ND}_{o,2014}} \Delta\sigma^D_{ot-1} \tag{10}$$

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

Exclusion Restriction The instrumental variable addresses three previously raised concerns for identification. First, 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 shocks. The exposure is correlated to future changes in the exposure to regulatory stringency, but plausibly exogenous to confounding future shocks to supplier innovation. Second, 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. Third, 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 exclusion restriction:

$$\mathbb{E}\left(\sum_{o \in O} \omega_{io} \frac{S^D_{o,2014} - S^{ND}_{o,2014}}{S^{ND}_{o,2014}} \Delta\sigma_{o,t-2}(u_{i,t} - u_{i,t-1})\right) = 0 \tag{11}$$

where u_{it} is the error term of Equation (3).

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).[28] This assumption implies that the pre-2015 exposure to car

[27] 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.

[28] Borusyak et al. (2022) show that exogeneity in the "shift" component of shift-share instruments can also

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 pp (see Figure 1), in contrast to a reduction of 19.6 pp 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, Panel A of Appendix Table A4 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 may not be 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 fleet-average 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 CO_2 emission technologies. EV subsidies, on the other hand, are known to incentivize innovation for EV technologies (Barwick et al., 2024). 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 (see Appendix Table A4). Nevertheless, I include a robustness test comparing effects among suppliers exposed to manufacturers selling more EVs before 2015 (see Table 3), which suggesting that my results are not driven by the effect of unobserved EV subsidies.

Estimator With the instrument at hand, I proceed to estimate the specification in Equation (3) using a GMM quasi-differencing estimator developed by Wooldridge (1991, 1997) and Windmeijer (2000) and suggested by Jochmans (2022) for fixed-effects count data models with

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.

endogenous regressors. This estimator relies on sequential moment restrictions

$$\mathbf{E}(u_{it}|\eta_i,\ \mu_t,\ \omega_{io},\ S^D_{o,2014},\ S^{ND}_{o,2014},\ PAT_{i,1},\dots PAT_{i,t-1}) = 1 \tag{12}$$

which imply the exclusion restriction in Equation (11) and a sequential exogeneity assumption for PAT_{it}, implying that past patent outcomes may be correlated with future error terms $u_{ir}, r > t$.[29] 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:

$$\mathbf{E}\left(Z_{it}\left(\frac{y_{it}}{\exp(X_{it}\beta)} - \frac{exp(\mu_t)}{exp(\mu_{t-1})}\frac{y_{i,t-1}}{exp(X_{i,t-1}\beta)}\right)\right) = 0 \tag{13}$$

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).[30]

5 Results

The following section presents the main results of the paper. Section 5.1 provides evidence for the effects of exposure to downstream regulatory stringency on the innovation outcomes of suppliers. Section 5.2 presents the results on the formation of supply linkages between car manufacturers and suppliers with expertise in different technological fields. Sections 5.3 and Section 5.4 provide a discussion of these results and robustness tests, respectively.

5.1 Innovation Output of Suppliers

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 technology in 2014. This comparison sheds light on correlation between the share-component of my instrumental variable and the patent outcomes of automotive suppliers. I measure the exposure to manufacturers relying on diesel cars for compliance with the standard using the following formula, where all components have been introduced in the description of Equation (10):

$$E_i = -\sum_{o \in O} \omega_{io} \frac{S^D_{o,2014} - S^{ND}_{o,2014}}{S^{ND}_{o,2014}} \tag{14}$$

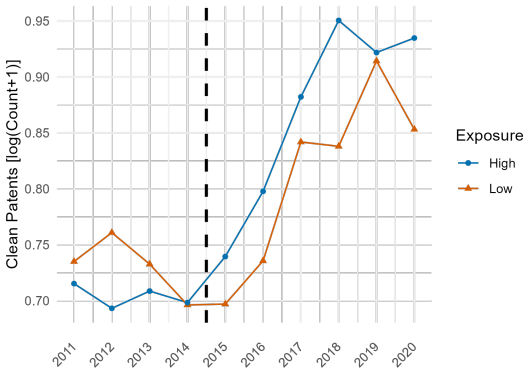
Figure 2 shows that patent applications for clean, dirty and benchmark technology seem to evolve mostly in parallel for suppliers with a high vs. a low exposure to diesel technology in the period before 2015. Across both groups, two changes in trends are are visible in the period after 2015. First, panels (a) and (b) show that suppliers increases the number of patent applications

[29] 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.

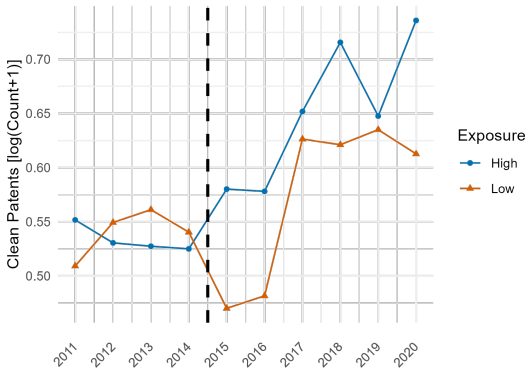
[30] I implement the GMM estimation in R, using matrix algebra and the *gmm* package in R for the optimization procedure (Chausse, 2010).

Figure 2: Exposure to Diesel Emission Advantages and Trends in Innovation Output

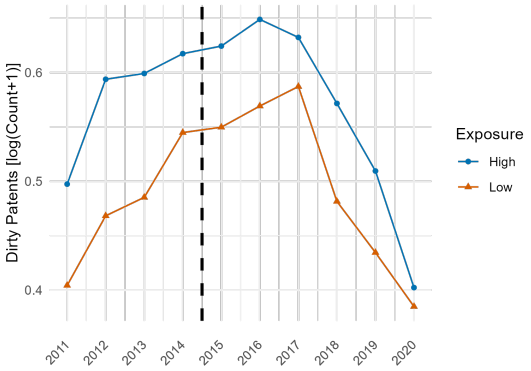
(a) Clean Innovation, Median Split



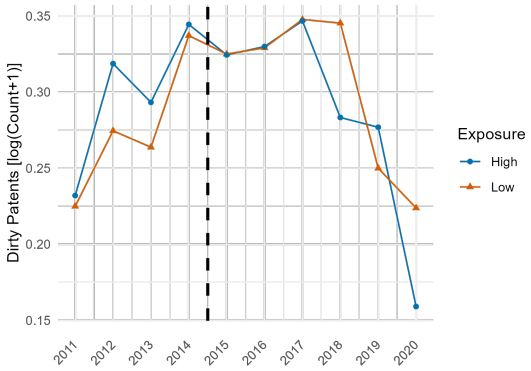
(b) Clean Innovation, Q1 vs. Q4



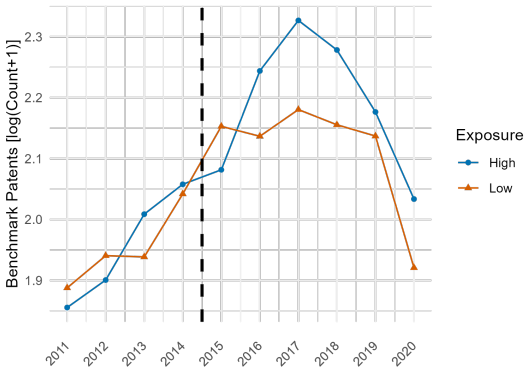
(c) Dirty Innovation, Median Split



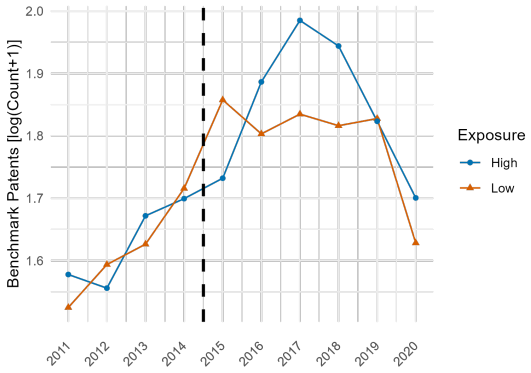
(d) Dirty Innovation, Q1 vs. Q4



(e) Benchmark Innovation, Median Split



(f) Benchmark Innovation, Q1 vs. Q4



Notes: Average annual count of patent applications of suppliers. Average across the logarithm of the patent cound + 1. Exposure to diesel emission advantages is defined in Equation (14). Panels (a), (c), and (e) compare patent outcomes for suppliers with above vs. below median exposure. Panels (b), (d) and (f) compare suppliers in the lowest vs. the highest quartile of the exposure variable. For the latter distinction to work, I drop suppliers with an exposure outcome in q2 and q3. Patent applications are classified as pertaining to benchmark, clean, or dirty technologies based on the selection of CPC codes in Tables A1 and A2.

for clean technologies around 2015. Second, roughly two years later, panels (c) - (f) show that suppliers reduce the number of patent applications for dirty technologies, as well as their overall innovation activity.

Comparing companies with high versus low exposure to manufacturers using diesel cars as a compliance technology, Figure 2 shows that if anyithing, the increase in clean innovation is more pronounced among suppliers with a high exposure to diesel technology. This is particularly visible in the first two years after 2015. In 2017, suppliers with a lower exposure seem to catch up again, but the pattern after 2017 differs between panel (a) and panel (b). At the same time, the change in dirty innovation does not seem to differ much between suppliers with a high vs. a low exposure to diesel technology, as can be seen in panels (c) and (d). The number of patents in the benchmark category serves as a proxy for the total innovation activity that is relevant to the car industry. Panels (e) and (f) show that suppliers with high exposure to diesel cars seem to increase their overall patenting activity between 2016 and 2018 beyond the patent activity in the low-exposure group. However, this is counteracted by a stronger reduction in the number of patent applications in the benchmark category in 2019 and 2020.

In summary, contemporaneous to a change in the composition of the European car market away from diesel cars, suppliers exposed to manufacturers relying on these cars for compliance with the European CO_2 emission standard for cars seem to increase clean innovation, and potentially their overall innovation efforts more strongly than suppliers exposed to manufacturers less reliant on diesel cars. The next two sections incorporate this variation into an instrumental variables approach to test whether an increase in the stringency of downstream environmental regulation affects supplier innovation outcomes.

First Stage The GMM approach depends on a non-zero correlation between the shift-share instrument developed in Section 4 and supplier exposure to regulatory stringency at the manufacturer-level. While the GMM approach does not require a separatly estimated first stage, I estimate the following first-stage regression to assess the relevance of my instrument:

$$S_{i,t-1} = \gamma IV_{i,t-1} + \nu_i + \lambda_{t-1} + \varepsilon_{i,t-1} \tag{15}$$

where $S_{i,t-1}$ and $IV_{i,t-1}$ have been defined in Section 4 and ν_i, λ_{t-1}, and $\varepsilon_{i,t-1}$ are a supplier fixed-effect, a time fixed-effect, and an error term, respectively. The second panel of Table 2 shows the result of two first-stage regression for the main specification. Based on the large effective F-statistic (Montiel Olea and Pflueger, 2013), which is robust to clustering standard errors at the level of suppliers, I can reject the hypothesis that my instrument is irrelevant.

Given the formula for exposure to regulatory stringency in Equation (8), one would expect a positive correlation between the instrument and supplier exposure to regulatory stringency. This initial conjecture is not confirmed in the first stage regressions. The following considerations rationalize the negative sign of the coefficient on the excluded instrument in the first-stage regression for Table 2. Appendix Table A1 provides supporting empirical evidence. Suppliers exposed to car manufacturers relying on diesel cars for compliance in 2015 are exposed to an increase in downstream regulatory stringency after 2015. Suppliers exposed to manufacturers selling diesel cars with lower average emissions in 2015 are exposed to higher downstream regu-

latory stringency after 2015 (see columns 1 and 2 of Appendix Table A1). The same is true for suppliers exposed to manufacturers selling a larger share of diesel cars in 2015 (see column 4). Given the assumption about persistent supply chain relationships, suppliers are exposed to a constant set of manufacturers over time. Among these manufacturers, those facing higher regulatory stringency could 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 is reflected in a positive correlation between the exposure to higher shares of diesel cars sold post-2015 and exposure to downstream regulatory stringency in column 5. This positive correlation translates into a negative correlation between my instrumental variable and exposure to regulatory stringency in the downstream car market (see Table 2).

Note that the exclusion restriction assumed in this paper is that the suppliers time-constant exposure to manufacturers relying on diesel cars for compliance with the regulation is exogenous to future shocks to supplier innovation. Thus, the potential endogeneity of supplier exposure to changing diesel sales shares does not violate the exclusion restriction.

Table 2: Effect of Downstream Environmental Regulation on Supplier Innovation

	Clean		*Grey*		*Dirty*		*Benchmark*	
	GMM (IV) (1)	GMM (2)	GMM (IV) (3)	GMM (4)	GMM (IV) (5)	GMM (6)	GMM (IV) (7)	GMM (8)
Stringency$_{t-1}$	12.576***	2.526	−9.232*	−3.440	−3.850	1.106	1.027	1.412
	(4.869)	(4.563)	(5.568)	(5.652)	(4.204)	(3.516)	(4.230)	(2.927)
First Stage								
Instrument$_{t-1}$	-0.322***		-0.322***		-0.322***		-0.322***	
	(0.048)		(0.048)		(0.048)		(0.048)	
F	44.388		44.388		44.388		44.388	
Years	6	6	6	6	6	6	6	6
Suppliers	339	339	339	339	339	339	339	339
Supplier FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X

Notes: Outcome variables are non-domestic patent counts in the technological fields indicated in the top row. The upper panel displays the result estimating Equation (3) using the moment conditions in Equation (13). Stringency is the supplier exposure to downstream regulatory stringency, defined in Equation (4). GMM indicates that exposure to regulatory stringency was assumed to be sequentially exogeneous, and thus contained in the matrix of instruments Z_{it}. GMM (IV) indicates that Z_{it} contains the instrument developed in Equation (10) instead. Results of the first-stage regression defined in Equation (15) in the lower panel. Effective F-statistic following Montiel Olea and Pflueger (2013), clustering standard errors at the supplier level. Suppliers is the number of suppliers observed. Years is the number of years used in the quasi-differencing approach. Coefficients transformed to reflect percentage changes in the outcome in response to a percentage-point increase in stringency. Block-bootstrapped standard errors (250 draws, clustered at the level of suppliers, using re-weighted bootstrapping procedure by Brown and Newey (2002)). *p<0.1; **p<0.05; ***p<0.01.

Effects on Technology-Specific Innovation Table 2 shows the effect of exposure to a more stringent CO_2 emission standard for passenger cars on the number of patent applications

by automotive suppliers across four technological fields. I estimate the model introduced in Equation (3) using the GMM-estimator based on the moment conditions introduced in Equation (13). In columns labeled GMM (IV), the instrument set Z_{it} contains the instrument $IV_{i,t-1}$ developed in Equation (10), while columns labeled GMM use S_{it-1} as the instrumental variable, assuming that the exposure to regulatory stringency S_{it-1} is itself sequentially exogenous. The coefficients are transformed to reflect percentage changes in the number of patent applications in response to being exposed to a one percentage point increase in the stringency of downstream regulation.[31] For car manufacturers who are not eligible for an exemption from the CO_2 emission standard, a one percentage-point increase in regulatory stringency corresponds to widening the gap between their current fleet-average emissions and the target level of the future standard by 0.95 g CO_2 per km. Between 2015 and 2019, the median supplier was exposed to a change in downstream compliance gaps by 0.82 g CO_2 per km (see Table 1).

Column (1) of Table 2 shows that an increase in regulatory stringency for downstream firms causes an increase in the number of clean patents filed among exposed suppliers. The number of applications for clean patents increases by 12.6% in response to a percentage point increase in the stringency of downstream environmental regulation. For supplier innovation output for grey technologies, column (3) suggests that, if anything, the effect of more stringent downstream environmental regulation is negative. However, since the implied reduction by 9.2% per pp increase in downstream regulatory stringency is statistically significant only at the 10%-level, I refrain from a causal interpretation. I do not find evidence for a significant change in dirty innovation in response to more stringent downstream environmental regulation in column (5). To assess whether the observed increase in patenting for clean technologies is partially explained by an overall increase in supplier innovation outcomes, I estimate the effect of exposure to regulatory stringency on patent applications in the benchmark category in column (7). I do not find evidence for a change in the the overall innovation outcomes of supplier firms.

Comparing the effects estimated in the instrumented GMM specifications to the non-instrumented estimates in columns (2), (4), (6), and (8), it stands out that almost all coefficients in the non-instrumented regressions are much smaller than their instrumented counterparts. This is in line with a reverse causality between exposure to manufacturers lowering their fleet-average emissions and suppliers dircting their innovation efforts away from dirty and towards clean technologies, which would attenuate the effects on technology-specific innovation outputs (clean, grey and dirty) in the non-instrumented regressions.

Since only the effect on clean innovation was statistically significant at the 5%-level, I will focus on clean innovation as an outcome variable in the analysis of heterogeneous effects across different supplier groups and in subsequent robustness tests.

Heterogeneity Across Suppliers To assess potential drivers of the observed change in clean innovation, I next re-estimate the instrumented GMM specification in column (1) of Table 2 for different subsets of the sample of automotive suppliers.

First, I assess whether the positive effect on clean innovation is driven by suppliers exposed

[31] Since the estimating Equation (3) is an exponential function, the effect of a one percentage-point increase in the measure of regulatory stringency in terms of a percentage change in the outcome variable can be calculated as $(\exp(0.01\beta) - 1) \times 100$, where β is the estimated coefficient for the exposure to regulatory stringency.

Table 3: Effect on Clean Innovation in Different Groups of Suppliers

	EV Exposure		*Clean Expertise*		*Region*	
	High	Low	No Expertise	Expertise	European	Asian
	(1)	(2)	(3)	(4)	(5)	(6)
Stringency$_{t-1}$	5.031	4.28	-0.032	13.54**	0.063	12.171**
	(4.238)	(4.559)	(6.238)	(5.592)	(6.916)	(5.506)
First Stage						
Instrument$_{t-1}$	-0.368***	-0.199***	-0.368***	-0.293***	-0.012	-0.355***
	(0.069)	(0.061)	(0.091)	(0.056)	(0.126)	(0.058)
F	28.682	10.594	16.367	27.953	0.009	37.913
Suppliers	167	172	129	210	107	171
Years	6	6	6	6	6	6
Supplier FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Notes: Outcome variable is the count of non-domestic patent applications for clean technologies. Sample splits indicated in the top row. EV Exposure splits suppliers exposed to an above vs. below median (= 0.5%) electric vehicle sales share in 2014. Clean expertise splits suppliers with and without at least one application for a clean patent before 2015. Region splits suppliers registered in Europe or in Asia (leaving out suppliers registered elsewhere). The upper panel displays the result estimating Equation (3) using the moment conditions in Equation (13). Stringency is the supplier exposure to downstream regulatory stringency, defined in Equation (4). GMM indicates that exposure to regulatory stringency was assumed to be sequentially exogeneous, and thus contained in the matrix of instruments Z_{it}. GMM (IV) indicates that Z_{it} contains the instrument developed in Equation (10) instead. Results of the first-stage regression in Equation (15) in the lower panel. Effective F-statistic following Montiel Olea and Pflueger (2013), clustering standard errors at the supplier level. Suppliers is the number of suppliers observed. Years is the number of years used in the quasi-differencing approach. Coefficients transformed to reflect percentage changes in the outcome in response to a percentage-point increase in stringency. Block-bootstrapped standard errors (250 draws, clustered at the level of suppliers, using re-weighted bootstrapping procedure by Brown and Newey (2002)). *p<0.1; **p<0.05; ***p<0.01.

to an above-median growth of electric vehicle sales shares between 2010 and 2014. The median share of EVs among a manufacturers new car registrations that suppliers were exposed to in 2014 is 0.5% and virtually zero in 2010. The rationale for this split is that suppliers exposed to car manufacturers with ex-ante growing EV sales shares could have an incentive to innovate in clean EV technologies, independent of environmental regulation. Heterogeneous effects of more stringent environmental regulation depending on the ex-ante size of the market for EVs would indicate a potential violation of the exclusion restriction. Columns (1) and (2) of Table 3 show that the effect observed in the main analysis is not sustained in either sub-sample, alleviating this concern.

Second, prior literature on directed technical change found that specialized entities tend to be important drivers of technical change (Noailly and Smeets, 2015, Dugoua and Gerarden, 2025). To assess whether firms with prior knowledge on clean technologies drive the innovation response to more stringent downstream environmental regulation, I split the sample accordingly in columns (3) and (4) of Table 3. I find that the innovation response is driven by firms with prior knowledge stocks for clean technologies, having applied for at least one patent for clean technologies in the period 2005 - 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 (3) of Table 3, 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.

Third, firms registered in Europe should presumably be more responsive, since they are more directly affected by the European CO_2 emission standard for passenger cars. To assess this conjecture, I separately consider the sample of companies registered in a member state of the European Union, or in Norway, Iceland or Great Britain. The first stage regression in column (5) suggests that the instrumental variable constructed in Equation (10) is not relevant among European suppliers. This implies that, unfortunately, the instrumental variables approach is not informative about the innovation response to more stringent environmental regulation among European firms. In contrast, the first stage is relevant for the subset of suppliers owned by firms registered in Asian countries.[32] The observed increase in clean innovation among Asian firms suggests that the estimates observed in Table 2 represent a Local Average Treatment Effect among Asian automotive suppliers. Appendix Table A2 shows that the average exposure to downstream regulatory stringency, both for the entire vehicle fleet and limited to diesel cars, are similar between Asian and European suppliers. However, Asian firms are exposed to slightly cleaner non-diesel cars and slightly lower manufacturer-level sales shares of diesel cars on average. As outlined in the discussion of first stage results in this section, there is more variation in diesel shares over time among manufacturers less reliant on diesel cars. This gives rise to a stronger first-stage relationship for Asian suppliers.

Reassuringly, none of the first stage estimates indicates a violation of the monotonicity assumption for the correlation between the instrument and the endogenous variable.

5.2 Formation of Supply Linkages

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 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 924 suppliers and 24 car manufacturers in the years 2021 and 2022, i.e. the first two years in which the lower emissions target of 95 g CO_2 per km was fully binding.[33] After constructing a cross-section of all potential manufacturer-supplier

[32] Including China, Japan, India, Korea, Pakistan, Singapore, and Taiwan.

[33] There are 34 regulated car manufacturers in 2015. For the formation of supply linkages, I summarize Chrysler and Fiat Group and exclude the Magyar Suzuki Corporation Ltd. Chrysler and Fiat show up in the regulatory data as FCA US and FCA Italy. Each unit of FCA registers models of the other unit, so I did not disentangle both manufacturers in merge at using model-level information. Magyar Suzuki is not inlcuded as a separate entity in the MarkLines data. As before, I remove 8 manufacturers for whom the instrument based on diesel cars does not work. Four of them were not selling any diesel cars in 2015 (Rolls Royce, Avtovaz, Bugatti, Tata), four were selling diesel cars that caused higher emissions than the remainder of the fleet (Toyota, Mitsubishi, Volvo, SsangYong).

pairs, I estimate the following probit model:[34]

$$\mathbb{E}\left(\mathbb{1}\left[J_i \cap J_o \neq \emptyset\right] | S_o, J_{i,0}, J_{o,0}, D^k_{i,0}, X_{io}\right) = \phi\left(\beta_0 S_o + \sum_{k\in K}\left(\beta^k_1\left(D^k_{i,0} \times S_o\right) + \beta^k_2 D^k_{i,0}\right)\right.$$
$$\left. + \beta_3 \mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] + \beta_4 \frac{1}{|O|}\sum_{o\in O}\mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] + \beta_5 X_{io}\right) \tag{16}$$

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 has prior expertise in technology k, where expertise is defined as having applied for at least one non-domestic patent in the period 2005 - 2015. The stringency of the regulation S_o is measured at the level of car manufacturers in 2019, the last year before the stricter CO_2 emission standard of 95 g CO_2 per km was phased in in 2020. S_o was 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. 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 ($\mathbb{1}(J_{i,0} \cap J_{o,0})$). X_{io} denotes additional control variables, namely an indicator whether a supplier and a manufacturer are registered in the same country and whether a car manufacturer is owned by a European firm.

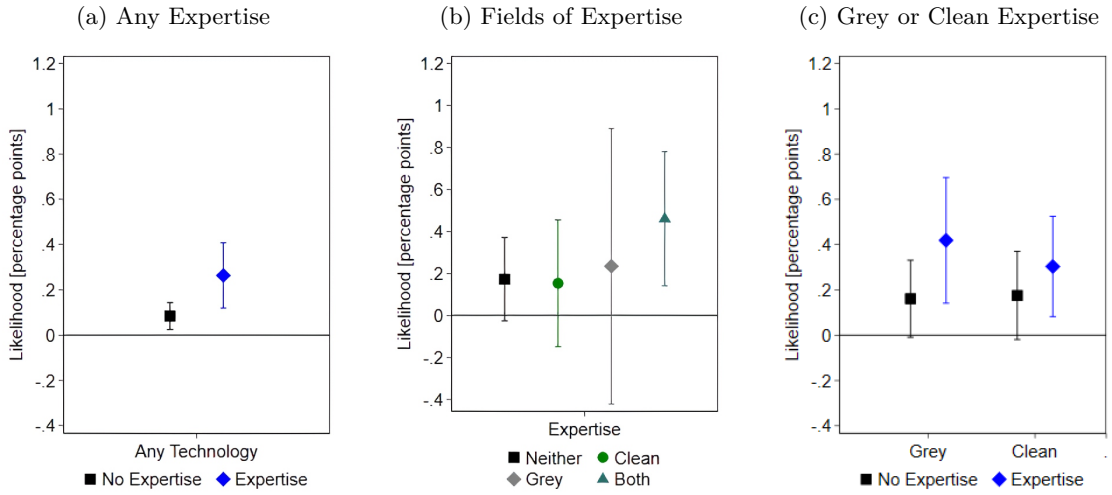
As before, the regulatory stringency S_o entering the model in (16) is endogenous since it reflects manufacturer o's product portfolio in 2019, which also drives the supplier network. I use the manufacturer-level reliance on diesel cars as a compliance tool as an instrument $IV^M_o = \frac{S^D_{o,2014} - S^{ND}_{o,2014}}{S^{ND}_{o,2014}}$.[35] 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 the following first-stage regression of manufacturer-level regulatory stringency on the instrumental variable and their interaction with the knowledge stock dummies $D^k_{i,0}$ are included as regressors in Equation (16) to control for endogenous variation in S_o and the interaction term with supplier knowledge stocks. Panel 2 of Appendix Table A6 shows that the effective F-statistic (Montiel Olea and Pflueger, 2013) for this regression ranges between 10.97 and 11.40, when standard errors are clustered at the level of car manufacturers.

$$\begin{aligned} S_o =& \gamma_1 IV^M_o + \sum_{k\in K}\gamma^k_2 D^k_{i,0} + \gamma_3 \mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] \\ &+ \gamma_4 \frac{1}{|O|}\sum_{o\in O}\mathbb{1}\left[J_{i,0} \cap J_{o,0} \neq \emptyset\right] + \gamma_5 X_{io} + \xi_{io} \end{aligned} \tag{17}$$

Using the results of this estimation, I calculate the Average Marginal Effect (AME) of manufacturer-level regulatory stringency evaluated for suppliers with different pre-2015 expertise. The AMEs are displayed in Figure 3. 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

[34] Implemented using the probit command in Stata (StataCorp, 2023).
[35] $S^D_{o,2014}$ is defined in Equation (9). $S^{ND}_{o,2014}$ is the analog for non-diesel cars.

Figure 3: Effect on the Formation of Supply Linkages



Notes: Average marginal effects (AME) of manufacturer-level regulatory stringency on the propensity of additional supply chain links forming in 2020 - 2021. Based on the Probit Control Function Approach introduced in Equations (16) and (17). Panel (a) displays the AME on sourcing from suppliers with and without expertise in any of the categories clean, grey, dirty, or benchmark in 2015 (924 suppliers, 24 car manufacturers). Panels (b) and (c) restrict the sample to pairs involving a supplier with any expertise (224 suppliers, 23 car manufacturers). Panel (b) displays the AME on sourcing from suppliers in mutually exclusive categories. Category Grey in Panel (b) includes only suppliers with expertise in grey no expertise in clean technology. Category Clean is defined analogously. Category Both (Neither) include suppliers with expertise in both (neither) technologies. Panel (c) combines the previous categories to distinguish pairs involving suppliers with and without expertise in the corresponding technological field. 95% confidence intervals based on bootstrapped standard errors (250 draws, clustered at the level of suppliers). Regression results are displayed in Appendix Table A6.

expertise 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 0.26 percentage points (pp) for pairs involving a supplier with any expertise. Among suppliers without expertise, the same increase in regulatory stringency increases the likelihood of an additional link by 8.4 pp. The difference between both effects is significant at the 5%-level (see Appendix Table A1).

In panels (b) and (c), I keep 224 suppliers who have expertise in any of the fields clean, grey, dirty or benchmark to study how technology-specific expertise moderates the effect of regulatory stringency at the manufacturer level. 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 expertise in both clean and grey technologies. In this category, a one pp increase in regulatory stringency increases the propensity of a supply chain relationship materializing by 0.46 pp.

In contrast, the effect of regulatory stringency is not significant for suppliers with purely clean or grey knowledge stocks. A direct test whether the effect among innovating suppliers is driven by clean or grey technology suppliers is inhibited by the 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 (+ 0.41 pp per pp increase in stringency for grey suppliers, + 0.30 pp 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 (+0.26 pp, see Appendix Table A2). This difference is significant in an alternative 2SLS specification, but not in the probit-model discussed in this section. 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).

5.3 Discussion

So far, the analysis in this paper yields three main results. First, downstream environmental regulation changes the direction of technical change among automotive suppliers exposed to car manufacturers with growing compliance gaps. Theory on directed technological change predicts that environmental regulation directs technological change towards clean and away from dirty technologies (Acemoglu et al., 2012), while leaving the sign of the effect on grey technologies undetermined (Aghion et al., 2016). In addition, the "weak" Porter Hypothesis suggests that environmental regulation should increase total innovation output (Porter, 1996). For suppliers of a regulated industry, the empirical results in this paper only support the positive effect on clean innovation. The observed increase in clean patenting by 12.6% in response to a pp increase in downstream regulatory stringency corresponds to 1.5 additional clean patents per year for the average supplier. Extrapolating the average annual reduction in the target level of the standard between 2015 and 2020 (-5.4 pp), I find that the number of clean patents should grow by 89% per year. This exceeds the observed increase in the average number of clean patents in Appendix Figure E.1, which might be due to heterogeneous effects across suppliers and to the anticipation of the increase in stringency since the adoption of the regulation in 2009.

The effect on clean innovation is much larger in magnitude than the effects found by studies that ignore supply chain relationships and instead study the effect of environmental regulation in countries in which firms previously patented (Aghion et al., 2016, Rozendaal and Vollebergh, 2025). The paper by Srinivasan (2017), which also studies the effect of downstream environmental regulation on supplier innovation, finds effects that are contained in my 95% confidence intervals. The causal evidence added by my study suggests that innovation incentives are passed-through to the direct suppliers of car manufacturers. Their innovation response seems to exceed the innovation response among the broader population of innovators that produce technologies related to passenger cars. Since the suppliers in my sample have direct supply chain links to at least one regulated car manufacturer, the innovation response is not surprising.

Second, there is substantial heterogeneity in the effect of exposure to changes in downstream regulation among different groups of suppliers. Given that the automotive suppliers in my sample supply a vast array of components, ranging from tires to EV batteries, heterogeneous effects are in line with expectations. The evidence for heterogeneous effects dictates that the instrumental variable results should only be interpreted as Local Average Treatment Effects (LATE) of exposure to more stringent downstream environmental regulation. The LATE is

potentially not representative for the broader population, but limited to firms for which the instrumental variable reduces exposure to regulatory stringency (the so-called compliers). I find evidence that this complier population is limited to Asian firms.

Third, more stringent environmental regulation induces manufacturers to source from firms with prior expertise in clean or grey technologies. While the effect on the innovation outcomes of existing firms is observed in the first year after the increase in regulatory stringency, the formation of new supply chain links takes time. It is observed in 2021 - 2022, which is when a new target level of the CO_2 emission standard becomes binding, but not immediately after the diesel scandal in 2016 - 2017, as Appendix Table A7 shows.

In combination, these results suggest two potential spillover effects of environmental regulation that could facilitate future compliance for car manufacturers. Manufacturers seem to gain access to additional clean technologies developed by their existing suppliers in the short term, and to existing clean and grey expertise from additional suppliers in the medium term. That manufacturers source additional components from suppliers with expertise in grey technologies suggests that improving the fuel efficiency of conventional cars still is an important objective after the introduction of the more stringent standard in 2020. This demand for expertise in grey technologies is not reflected in the suppliers innovation response to more stringent downstream regulation. If anything, suppliers seem to reduce their innovation output for grey technologies, hinting at a potential misalignment between manufacturer technology demand and supplier innovation.

5.4 Robustness Tests

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

First, I assess the effect of exposure to more stringent downstream environmental regulation at a higher temporal aggregation. Observing strong effects on innovation in the upstream market one year after regulatory stringency in the downstream market changed indicates a fast innovation response. The speed of this reaction is not too surprising, since a contemporaneous relationship between R&D expenditures and patent applications is established in the literature since Hall et al. (1984). In addition, an immediate response after one year is possible if suppliers advance patent applications for existing projects in response to more stringent regulation.

As a robustness test, I estimate a long quasi-difference to assess the innovation response to more stringent environmental regulation over a longer time horizon. I compare clean innovation in the period 2016 - 2020 to the period 2011 - 2015, i.e., the five years after the scandal to the five years before.[36]

Column (1) of Table 4 shows the effect in the main specification, instrumenting for regulatory stringency using a shift-share instrumental variable analogous to the main specification (for details, see Equation (C.5)). An increase in the average regulatory stringency in the period 2015 - 2019 by 1 pp causes an increase in clean patenting by 16.3 % (significant at the 5%-level). To assess whether path-dependencies in a suppliers innovation strategy could explain the observed

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

Table 4: Effect on Clean Innovation, Long Quasi-Difference

	Shift-Share IV		Diesel Emission IV		Exogenous Stringency	
	(1)	(2)	(3)	(4)	(5)	(6)
Stringency$_{t-1}$	16.305**	14.335*	13.014**	8.893*	6.930**	6.153**
	(7.422)	(7.735)	(5.362)	(4.730)	(2.954)	(2.837)
Clean Share$_{t-1}$		0.648		1.086		1.196**
		(0.840)		(0.761)		(0.595)
First Stage						
Instrument$_{t-1}$	0.998***	1.006***				
	(0.122)	(0.125)				
Diesel Emissions$_{t-1}$			-0.130***	-0.131***		
			(0.025)	(0.026)		
Clean Share$_{t-2}$		-0.006		-0.006		
		(0.009)		(0.009)		
F	66.658	64.901	26.118	25.341		
Periods	2	2	2	2	2	2
Suppliers	339	339	339	339	339	339
Supplier FE	X	X	X	X	X	X
Period FE	X	X	X	X	X	X

Notes: Outcome variable is the count of non-domestic patent applications for clean technologies in the period 2016 - 2020. The top row indicates the instrumental variable used in the corresponding regressions. Shift-share IV indicates that the instrument in Equation (C.5) combining (i) the suppliers pre-2015 exposure to manufacturers selling diesel cars with lower average emissions than their remaining fleet × (ii) changes in the share of diesel cars they sell is used. Diesel Emission IV indicates that only component (i) is used as an instrument. Exogenous stringency indicates that the suppliers exposure to downstream regulatory stringency is itself used as an instrument. The upper panel displays the result estimating Equation (3) using the moment conditions in Equation (C.1). Stringency is the period-average across the annual supplier exposure to downstream regulatory stringency, defined in Equation (4). Clean Share is the supplier share of clean patent applications relative to patent applications in the benchmark category. Results of the cross-sectional first-stage regression in Equation (C.2) in the lower panel. Kleinbergen-Paap F-statistic using heteroskedasticity-robust standard errors. Suppliers is the number of suppliers observed. Periods is the number of periods used in the quasi-differencing approach. Coefficients transformed to reflect percentage changes in the outcome in response to a percentage-point increase in the regressor. Block-bootstrapped standard errors (250 draws, clustered at the level of suppliers, using re-weighted bootstrapping procedure by Brown and Newey (2002)). *p<0.1; **p<0.05; ***p<0.01.

effect, I control for the suppliers' share of clean patents in the period 2011 -2015 in column (2).[37] The coefficient on stringency exposure does not change much and remains significant at the 10%-level, suggesting that more stringent downstream environmental regulation in fact induces an innovation response. Note that the sign of the coefficient for the instrument in the first stage changed in comparison to Table 2. This is due to the omission of supplier fixed-effects in the first-stage regression, which is estimated on cross-sectional data for the period 2016 - 2020. In columns (3) and (4), instead of using the shift-share instrument, I use the suppliers pre-2015 exposure to manufacturers relying on diesel cars as an instrument. This robustness test leverages only cross-sectional variation in supplier exposure to manufacturers using diesel cars to reduce their fleet-average emissions before 2015. It constitutes an alternative combination of the share-components of my shift-share instrument, which is a robustness test suggested by Borusyak et al. (2025b) to assess the validity of assuming an exclusion restriction that is based on the exogeneity of the share component. My results are robust under the alternative specification, indicating no violation of the exogeneous shares assumption. Finally, columns (5) and (6) show the results of GMM regressions assuming that the suppliers exposure to regulatory stringency is sequentially exogenous. While the magnitude of the estimated coefficients is again smaller than in the instrumented specifications, the positive effect on clean innovation remains significant at the 5%-level.

Second, I assess the robustness of my results when ignoring firm ownership structures. 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 (1) and (2) 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 10.4% 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. For several companies, separate subsidiaries are charge of the firm's R&D efforts. In other firms, patents are owned by a holding, which is typically not the entity observed in the MarkLines data. And finally, 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.

Third, I study the influence of firms with an exceptionally high number of annual patent applications. I re-estimate the main analysis after removing suppliers with annual clean patent applications exceeding the 99th percentile in any year between 2016 and 2020 in columns (4) and (5) of Table 5. Due to the high persistence in patent outcomes, only three firms fall into that category. The positive effect on clean patent applications (+10.4%, significant at the 1%-level) is robust both in terms of magnitude and significance.

For the formation of supply chain links, Appendix D contains a robustness test comparing the

[37] Due to the quasi-differencing approach (see Equation (C.1)), I need to instrument for the share of clean patents in $t-1$ using the second lag.

Table 5: Sensitivity Analysis for the Effect on Clean Innovation

	No Ownership Links		No Outliers [99 perc]	
	GMM (IV)	GMM	GMM (IV)	GMM
	(1)	(2)	(3)	(4)
Stringency$_{t-1}$	10.449*	0.097	10.385***	1.056
	(5.666)	(3.821)	(3.648)	(2.498)
First Stage				
Instrument$_{t-1}$	-0.275***		-0.322***	
	(0.040)		(0.048)	
F	47.274		44.223	
Years	6	6	6	6
Suppliers	287	287	336	336
Supplier FE	X	X	X	X
Year FE	X	X	X	X

Notes: Outcome variable is the count of non-domestic patent applications for clean technologies. Alternative specifications indicated in the top row. No ownership links indicates that supplier-level outcomes are not aggregated to the global owner owning at least a 25% share of the supplier. No Outliers aggregates to global owners, but removes the 99th percentile of owners according to their annual patent counts for clean technology. The upper panel displays the result estimating Equation (3) using the moment conditions in Equation (13). Stringency is the supplier exposure to downstream regulatory stringency, defined in Equation (4). GMM indicates that exposure to regulatory stringency was assumed to be sequentially exogeneous, and thus contained in the matrix of instruments Z_{it}. GMM (IV) indicates that Z_{it} contains the instrument developed in Equation (10) instead. Results of the first-stage regression in Equation (15) in the lower panel. Effective F-statistic following Montiel Olea and Pflueger (2013), clustering standard errors at the supplier level. Suppliers is the number of suppliers observed. Years is the number of years used in the quasi-differencing approach. Coefficients transformed to reflect percentage changes in the outcome in response to a percentage-point increase in stringency. Block-bootstrapped standard errors (250 draws, clustered at the level of suppliers, using re-weighted bootstrapping procedure by Brown and Newey (2002)). *p<0.1; **p<0.05; ***p<0.01.

Probit-specification estimated in Section 5.2 and an alternative 2SLS Linear Probability Model that incorporates manufacturer and supplier fixed-effects. The results found using the Linear Probability Model confirm the results in the Probit-specification. If anything, the evidence supporting the take-aways from Section 5.2 is stronger in the linear probability model.

6 Threats to Identification

I address three 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 a placebo-test showing that the scandal did not directly affect firm financial outcomes in my sample. Second, the change in the composition of the European car fleet affected both the compliance with the CO_2 emission stan-

dard for passenger cars and the average fuel price consumers in Europe face, since tax-inclusive fuel prices are higher for gasoline than diesel. Using additional variation in fuel prices between countries and over time, I show that this fuel price effect does not explain my results. Third, I show that the results found for the increased innovation in clean technologies are not driven by preexisting trends.

Direct Effects on Supplier 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 reduction 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. To address this concern, I obtain balance sheet data from Orbis for 125 out of the 339 supplier firms in my sample.

Using those data, I first assess whether the instrument is correlated to firm financial outcomes in the pre-2015 period. Panel B of Appendix Table A4 provides descriptive evidence that neither the instrument nor the suppliers exposure to manufacturer-level changes in the share of diesel cars sold is correlated to supplier financial outcomes (R&D expenditures, revenues, profits, or assets held in cash or cash equivalents) in the period 2012 - 2014, controlling for firm and year fixed-effects.

Second, I test whether the instrument or changes in regulatory stringency directly affect firm financial outcomes. The results can be found in Table 6. First, I estimate a reduced-form regression to assess the correlation between the instrumental variable and several financial outcomes in columns (1), (4) and (7). 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. In columns (2), (5), and (8), I estimate the correlation between supplier exposure to more stringent downstream regulation using ordinary least squares (OLS) regressions. In columns (3), (6) , and (9), I instrument for the exposure to regulatory stringency two-stage least squares (2SLS) approach. Note that the first stage in this substantially smaller sample is weak (F = 6.87), which manifests itself in large standard errors in the 2SLS specifications. Nevertheless, the absence of significant effects across all specifications is interpreted as absence of evidence for a relationship between firm financial outcomes. [38]

Third, I assess the robustness of my main regression to including firm revenues in period $t-1$ as a control variable. Given the weak first stage in the reduced sample of suppliers for which financial outcomes are available, this analysis is relegated to in Appendix Table A3. I find that controlling for a firm's revenues in the previous year reduces the size of the coefficient of exposure to regulatory stringency, but an economically and statistically significant increase in the number of clean patent applications by 6.7% per pp increase in stringency exposure remains.

Effect of 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

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

Table 6: Effects on Supplier 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_t		0.617	6.038		-0.834	-1.909		-0.203	0.927
		(1.337)	(8.406)		(0.550)	(2.485)		(0.754)	(3.183)
Instrument_t	0.179			0.277			-0.219		
	(1.489)			(0.732)			(0.832)		
First Stage									
Instrument_t			-0.200**			-0.200**			-0.200**
			(0.077)			(0.077)			(0.077)
F			6.87			6.87			6.87
Suppliers	125	125	125	125	125	125	125	125	125
Years	5	5	5	5	5	5	5	5	5
Supplier FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X

Notes: Outcome variables are the supplier financial outcomes indicated in the top row. Sample reduced to 125 suppliers for which financial results were reported in the period 2015 - 2020. The upper panel displays the result of Reduced Form (RF), Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS) regressions specified in Equation (C.6). Independent variables are the suppliers exposure to downstream regulatory stringency developed in Equation (4) or the instrumental variable in Equation (10). Results of the corresponding first-stage regression in the lower panel. Effective F-statistic following Montiel Olea and Pflueger (2013), clustering standard errors at the supplier level. Suppliers is the number of suppliers observed. Years is the number of years in the panel. Asymptotic standard errors, clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01.

towards a higher share of gasoline cars also changes the average fuel price for new passenger cars sold in Europe. This is mainly 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, Rozendaal and Vollebergh, 2025). 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 Interational 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} developed in Equation (5) 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.

Table 7 provides results for the effect on clean innovation using the moment conditions in Equation (13) when additionally en controlling for supplier exposure to (the logarithm of) tax-inclusive fuel prices. Comparing the coefficient on regulatory stringency exposure in columns (1) and (2), one can see that controlling for both supplier exposure to changes in fuel prices and

Table 7: Robustness to Controlling for Exposure to Tax-Inclusive Fuel Prices

	GMM(IV) (1)	GMM (2)	GMM(IV) (3)	GMM (4)	GMM (5)
Stringency$_{t-1}$	12.576***	2.526	9.141**	−0.257	
	(4.869)	(4.563)	(4.596)	(3.640)	
Fuel Price$_{t-1}$			2.647	2.326	−0.962
			(2.613)	(2.317)	(3.716)
First Stage					
Instrument$_{t-1}$	-0.322***		-0.287***		
	(0.048)		(0.053)		
Fuel Price$_{t-2}$			0.572**		
			(0.248)		
F	44.388		29.654		
Periods	6	6	6	6	6
Suppliers	339	339	339	339	339
Supplier FE	X	X	X	X	X
Year FE	X	X	X	X	X

Notes: Outcome variable is the count of non-domestic patent applications for clean technologies. The upper panel displays the result estimating Equation (3) using the moment conditions in Equation (13). Stringency is the supplier exposure to downstream regulatory stringency, defined in Equation (4). Fuel price is the supplier exposure to tax-inclusive average fuel prices, as defined in the text. GMM indicates that exposure to regulatory stringency was assumed to be sequentially exogeneous. In these specifications, Z_{it} contains either the stringency exposure developed in Equation (4), the lagged fuel price, or both. GMM (IV) indicates that stringency exposure is replaced in Z_{it} by instrument developed in Equation (10). Z_{it} contains either the instrument developed in Equation (10), the lagged fuel price, or both. Results of the first-stage regression in Equation (15) in the lower panel. Effective F-statistic following Montiel Olea and Pflueger (2013), clustering standard errors at the supplier level. Suppliers is the number of suppliers observed. Years is the number of years used in the quasi-differencing approach. Coefficients transformed to reflect percentage changes in the outcome in response to a percentage-point increase in stringency. Block-bootstrapped standard errors (250 draws, clustered at the level of suppliers, using re-weighted bootstrapping procedure by Brown and Newey (2002)). *p<0.1; **p<0.05; ***p<0.01.

supplier exposure to larger compliance gaps with the CO_2 emission standard changes magnitude of the effect of more stringent downstream regulation slightly.[39] However, the coefficient on the stringency of the standard remains significant at the 5%-level and of the same magnitude, while the effect of exposure to higher tax-inclusive fuel prices remains insignificant both in column (2) and (3). This result stands in contrast to previous findings by Rozendaal and Vollebergh (2025), who show that exposure to both higher country-level fuel taxes and fuel economy standards have a positive impact on clean innovation in the car industry. The quasi-differencing approach employed in my study should purge tax-inclusive fuel prices from almost time-constant differences in country-level fuel taxes, which is the identifying variation used in the study by Rozendaal and Vollebergh (2025). In congruence with that interpretation, they find no effect of fuel prices before taxes on clean innovation, too. The results imply that persistent changes in the stringency of the performance standard have a much larger effect on clean innovation than

[39]Since the fuel price in $t-1$ could be correlated to innovation in $t-1$, I use fuel prices in $t-2$ as an instrument in the quasi-differencing approach (see Equation (13).

short-term changes in average fuel prices.

Differential Trends in Patenting Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2025a) 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 sequential exogeneity assumption while the 2SLS estimator discussed by Goldsmith-Pinkham et al. (2020) requires a strict exogeneity assumption. Finding no violation in the parallel trends assumption in the following exercise is sufficient, but not necessary for a sequential exogeneity assumption.

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 2014 to 2015, i.e., the year of the diesel scandal.[40] In this section, I refer to this variable as exposure to the "diesel shock".

Across all four technological fields, clean, grey, dirty and benchmark, the event study regressions provide no evidence for a violation of parallel pre-trends in the period 2011 - 2014, which corroborates the approach taken in this paper. Appendix Table A5 indicates that the pre-2015 coefficients are not jointly significant at the 5%-level across all patent outcomes. However, the coefficients for pre-2015 effects on grey patenting and patenting in the benchmark category are significantly different from zero (10%-level). Inspecting the pre-2015 coefficients in Figures E.3 and E.4, this seems to be due to strong differences in 2012, rather than a clear pre-trend.

Post-2015, the following patterns emerge: higher exposure to the "diesel shock" reduces supplier innovation for clean technologies in the following four years (Panel A of Appendix Figure E.3. Exposure to the "diesel shock" does not seem to change the overall innovation activity for innovation in the dirty and the benchmark technology (Panel B of Appendix Figure E.3 and Panel B of Appendix Figure E.4). For grey technologies, I find evidence for a negative innovation response in 2020, which is five years after the diesel scandal began. At the same time, the negative effect on clean innovation observed in 2016- 2019 vanishes. These changes in innovation outcomes coincide with the introduction of the more stringent emission standard of 95 g CO_2 per km in 2020. This response is consistent with suppliers exposed to less stringent environmental regulation in 2016 - 2019 (see the first-stage results in Section 5, higher exposure to the "diesel shock" implies reduced exposure to downstream regulatory stringency) lagging behind their peers in terms of clean innovation output. The increase in the stringency of the downstream regulation in 2020 could have required these suppliers to re-direct their innovation efforts from grey to clean technologies.

Direct Effect on Supply Linkages The analysis in Section 5.2 uses a cross-section of manufacturer-supplier links in 2021 and 2022 to assess the impact of a more stringent standard on the formation of supply chain links. In so doing, it relies on the manufacturer-level emissions

[40] Details on the Poisson Quasi-Maximum Likelihood Estimation employed to estimate these event studies can be found in Appendix C.

gap between diesel cars and the remaining fleet in 2014 as an instrumental variable. This instrument could be correlated to changes in the composition of manufacturer supply networks as a direct consequence of the 2015 diesel scandal. For example, manufacturers could establish links to suppliers of grey technologies for gasoline vehicles as an immediate consequence of the diesel scandal. To assess this potential violation of the exclusion restriction, I re-estimate the Probit control function approach introduced in Equations (16) and (17) for a cross-section of manufacturer-supplier links in 2016 - 2017. The results can be found in Appendix Table A7. Reassuringly, I do not find evidence that would support a violation of the exclusion restriction. In the immediate aftermath of the 2015 diesel scandal, the formation of supply chain links to innovating suppliers is not affected. Beyond that, manufacturers subject to higher regulatory stringency are less likely to source from additional suppliers without any patent applications prior to 2015 (significant at the 10%-level), which is in line with expectations about the short-term effects of higher regulatory stringency on the formation of supply chain relationships.

7 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 standard for passenger cars in Europe to supplier patent data using information on automotive supply chains. Using an instrumental variable approach, I provide causal evidence for two spillover-effects. 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 12.6%. 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. The positive effect of a one percentage point increase in the manufacturer-level stringency of the regulation is significantly larger (+0.18 pp) among suppliers who innovated in the past. Both the innovation response to more stringent downstream environmental regulation among exposed suppliers and the formation of additional supply chain links 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 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 sectors should take potential spillovers of ambitious environmental regulations along supply chains into account.

Variation in the exposure of upstream firms to an unanticipated shock to the composition of the downstream car market allows me to identify the effect of environmental performance standards on the innovation outcomes of firms that are not themselves subject to the regulation. The magnitude of these indirect effects has been subject to debate in recent theoretical

contributions (Dugoua and Dumas, 2021). My paper shows that innovation incentives imposed by environmental regulation are passed-through along supply chains, giving rise to substantial changes in the innovation outcomes of upstream firms.

The approach taken in this paper has several limitations. Most importantly, I focus on suppliers of incumbent car manufacturers selling at least 10,000 cars in Europe in 2015. While this restriction is necessary to study spillover-effects along pre-existing supply chains, it implies that supply chain links to manufacturers specializing in electric vehicles, such as Tesla or BYD, are not included in my study. Since the CO_2 emission standard is not binding for these manufacturers, this does not threaten the internal validity of my results. Additionally, the study focuses on independent suppliers, who are not owned by a car manufacturer. The empirical evaluation of a potential mediating effect of vertical integration for the pass-through of innovation incentives along supply chains is left for future research.

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Appendix

A Patent Search Strategy

Table A1: CPC Patent Codes for Clean and Dirty Technologies

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**

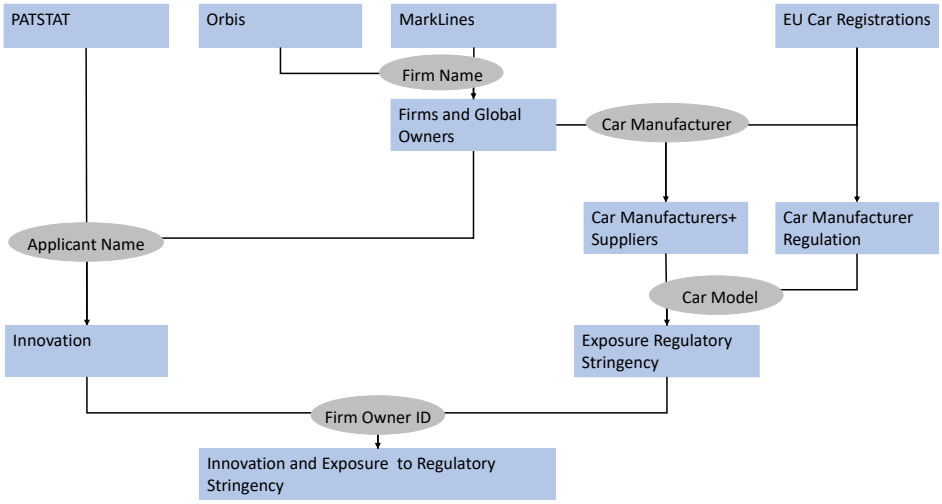
B Data Merging Procedure

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.

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

Figure B.1: Data Merging Procedure



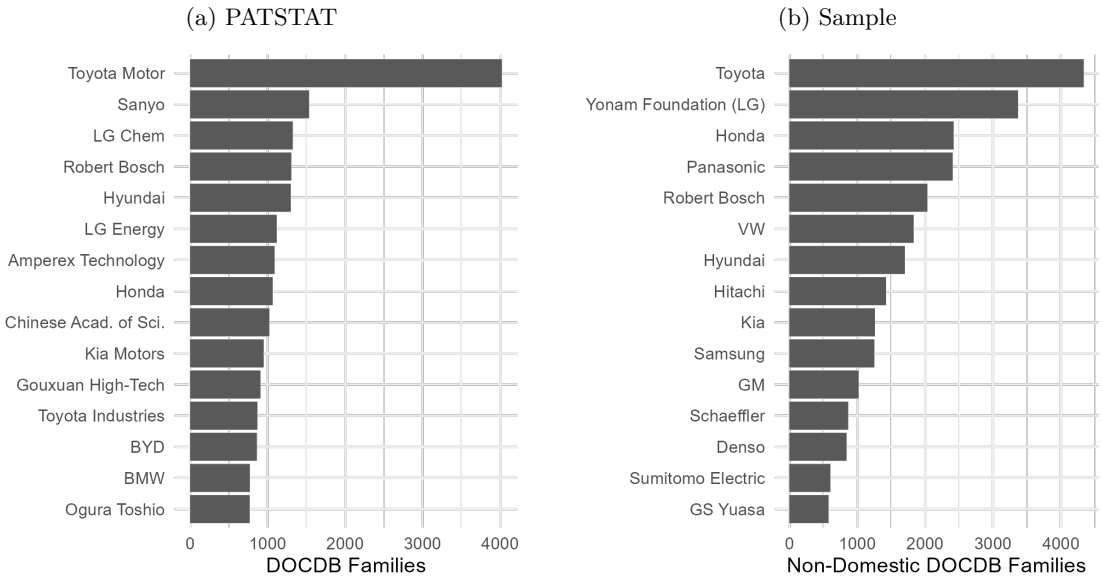
Notes: Rectangles contain data sets, ellipses contain the variables the data sets are matched on. First row contains raw data, last row contains final data. Firm Owner ID abbreviates the identifier assigned in Orbis for the Global Ultimate Owner (GUO) of the company (owning more than 25% of the company).

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.

Figure B.2: Top 15 Innovators for Clean Technologies



Notes: Patent counts in the period 2015 - 2020. 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.

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, 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 General German Automobile Club[41] to assign model names with a granularity that is available in both data sets. This model specification not only ignores model trims but also different model face-lifts produced over time. 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.

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. Figure B.3 compares the average weight assigned to each car manufacturer across the suppliers in my sample to the importance of these manufacturers in terms of the number of cars registered in Europe and the number of patents for benchmark technologies they filed prior to 2015. The manufacturer weights in my sample seem to reflect a mix between the manufacturers importance in terms of vehicle sales and in terms of their benchmark patent outcomes. Given the sample construction, this is not surprising.

Despite observing supply relationships for the majority of car models sold in Europe, 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 new car registrations) to the supplier level, I merge the supplier exposure data with the manufacturers regulatory data over the full period 2010 - 2020.

Step 3:

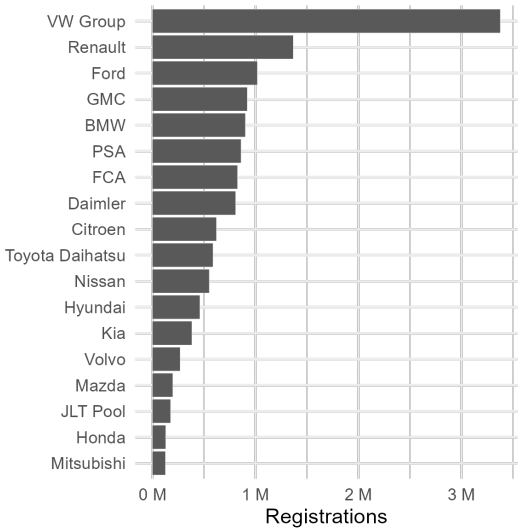
I merge the PATSTAT data measuring innovative activity per year and the data measuring exposure to regulatory stringency on both the manufacturer and the supplier level using the GUOs ID in the ORBIS data. In the main sample, I keep only GUOs that applied for at least one patent for EV technologies in the period 2010 - 2020. This reduces the size of the final sample

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

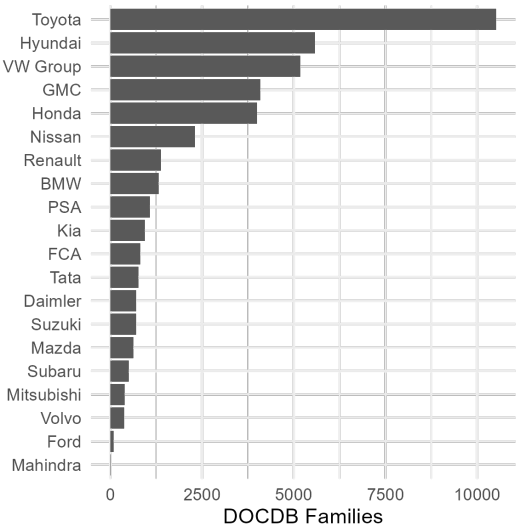
[42] The brands excluded are Avtovaz, Bugatti, Rolls Royce and Tata Motors.

Figure B.3: Importance of Different Car Manufacturers in the Sample

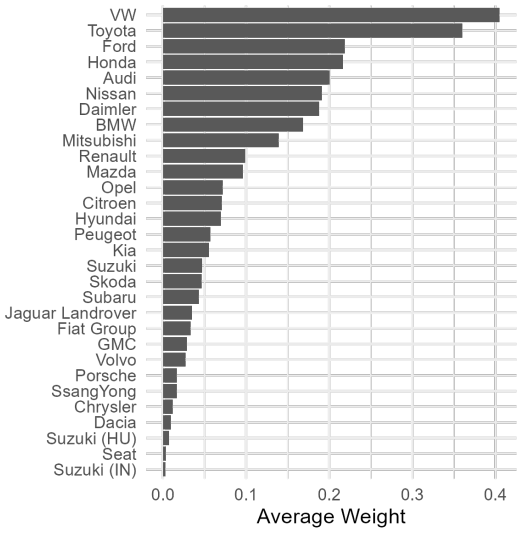
(a) Total New Car Registrations in 2015



(b) Total Benchmark Patenting Before 2015



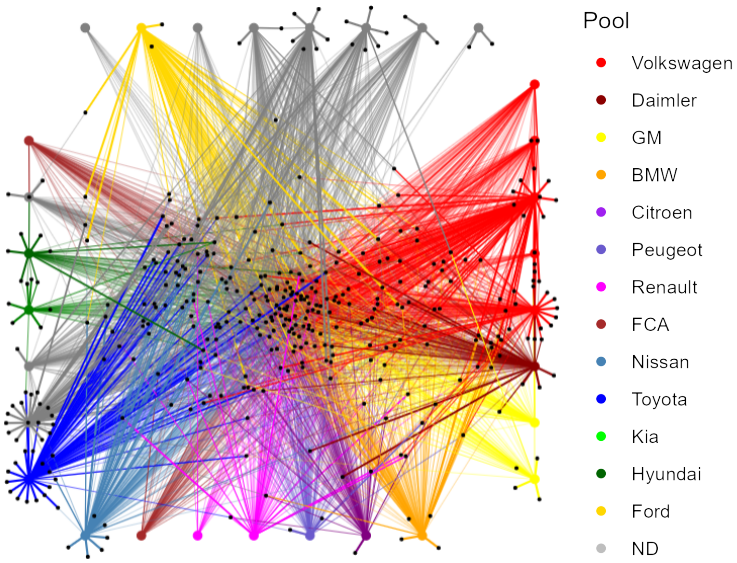
(c) Average Exposure Weight in Sample



Notes: New vehicle registrations for the EU 28 + Norway and Iceland in 2015. Panels (a) and (b) show outcomes for manufacturer pools. Panel (c) shows weights for individual manufacturers. Patents for the period 2010 - 2015 for the final sample, i.e. firms matched across the MarkLines, PATSTAT and ORBIS data. Exposure weights are the manufacturer-level averages across 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, Equation (5).

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.

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:

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.

$$\mathbf{E}\left(Z_{i,Post}\left(\frac{y_{i,Post}}{\exp(X_{i,Post}\beta)}-\frac{exp(\mu_{Post})}{exp(\mu_{Pre})}\frac{y_{i,Pre}}{exp(X_{i,Pre}\beta)}\right)\right)=0 \tag{C.1}$$

Here, $y_{i,t}$ is the count of patent applications for the technology of interest, accumulated over either the full period 2016 - 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 assume a time-lag of at least one year between changes in regulatory stringency and innovation responses, but that effects of changes in regulatory stringency in earlier years can now accumulate over time.

To assess the relevance of the instrument in the long quasi-difference, the following first-stage regression is estimated:

$$S_{i,Post}=\gamma Z_{i,Post}+\varepsilon_{i,Post} \tag{C.2}$$

In specifications controlling for lagged patenting outcomes, $X_{i,t}$ and $Z_{i,Post}$ include 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. To define this share, I first define supplier i's knowledge stock K_{it}^k for technology k. It 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):[43]

$$K_{it}^k=\sum_{l=2005}^{t}(1-\delta)^l PAT_{it}^k \tag{C.3}$$

Then, the share of clean knowledge stocks is simply defined as the ratio of the knowledge stock in clean technologies, K_{it-1}^c over the knowledge stocks in benchmark technologies, K_{it-1}^b.

$$A_{it-1}=\frac{K_{it-1}^c}{K_{it-1}^b} \tag{C.4}$$

Z_{it} comprises the included instrument A_{it} and the excluded instrument specified similar to

[43] 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 3.

Equation (10):

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

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 and Ordinary Least Squares:
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 (10) in two-stage least squares regression. 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}.

Event Studies Using a Poisson Quasi-Maximum Likelihood Estimator:
The event studies in Figures E.3 and E.4 rely on the following specification, which is estimated using a Poisson Quasi-Maximum Likelihood Estimator as implemented in the *fixest* package in R (Bergé, 2018)

$$\text{PAT}_{it} = exp\left(\sum_{t' \neq 2015} \gamma \left(\text{IV}_{i,2015} \times \mathbb{1}(t' = t) \right) + \eta_i + \mu_t \right) + \varepsilon_{it} \tag{C.7}$$

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 $\text{IV}_{i,2015}$ is the instrumental variable for supplier i in year 2015 as developed in Equation (10). The sum in Equation (C.7) interacts the instrument in 2015 with dummies for all years in 2011 - 2020, except for 2015. Thus, effects on patent outcomes are evaluated relative to the last year in which patenting is not affected by the diesel scandal, given the assumed lag structure. The remaining components are a supplier fixed-effect η_i, a year fixed-effect μ_t and an additive error term ϵ_{it}. Standard

errors are clustered at the firm-level.

D Robustness: Formation of Supply Linkages

To assess the robustness of the Probit model in Equation (D.1) to the inclusion of supplier and manufacturer fixed-effects[44] 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 $IV_o^M = \frac{S_{o,2014}^D - S_{o,2014}^{ND}}{S_{o,2014}^{ND}}$.[45] 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 following the specification in Equation (16) in columns (1), (2), (5) and(6) to the corresponding results of the linear probability model in columns (3),

[44] 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.

[45] $S_{o,2014}^D$ is defined in Equation (9). $S_{o,2014}^{ND}$ is defined analogously.

Table A1: Formation of Supply Linkages, Sensitivity to Functional Form Assumptions

	All Suppliers				*Innovating Suppliers*			
	CF	Probit	2SLS	OLS	CF	Probit	2SLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stringency	0.084**	0.010			0.172*	-0.066		
	(0.031)	(0.019)			(0.101)	(0.055)		
Stringency × Patenting	0.180**	-0.110**	0.152**	-0.083*				
	(0.079)	(0.049)	(0.073)	(0.042)				
Stringency × Grey, Not Clean					0.062	-0.091	0.224	-0.077
					(0.342)	(0.197)	(0.282)	(0.204)
Stringency × Clean, Not Grey					-0.019	-0.035	0.034	-0.018
					(0.184)	(0.109)	(0.151)	(0.088)
Stringency × Grey and Clean					0.289	-0.099	0.338**	-0.071
					(0.192)	(0.118)	(0.161)	(0.095)
Existing Link_{10-15}	0.205**	0.199**	0.192**	0.232**	0.208**	0.196**	0.161**	0.218**
	(0.010)	(0.010)	(0.009)	(0.011)	(0.020)	(0.019)	(0.018)	(0.021)
First Stage								
F Statistic	10.969		11.388		11.395		11.806	
Potential Links	22176	22176	22176	22176	5376	5376	5376	5376
Suppliers	924	924	924	924	224	224	224	224
Manufacturers	24	24	24	24	24	24	24	24
Supplier and Manufacturer FE			X	X			X	X
Controls	X	X			X	X		

Notes: Average marginal effects (AME) on the propensity of additional supply chain links forming in 2020 - 2021. The top row indicates the sample of manufacturer-supplier links used. Columns labeled *All Suppliers* include all potential manufacturer-supplier pairs. Columns labeled *Innovating Suppliers* contain only pairs involving a supplier who filed at least one patent in the categories clean, grey, dirty or benchmark in the period 2005 - 2015. *Stringency* indicates the AME (percent) of exposure to more stringent environmental regulation in 2019, defined in Equation (2). *Stringency* × *Some Sample* shows the difference in the AMEs (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 expertise in any of the following categories in 2015: clean, grey, dirty, benchmark. *Grey, Not Clean* are suppliers with expertise in the grey but not in clean technologies. Categories *Clean, Not Grey* / *Grey and Clean* are defined analogously. Existing Links_{10-15} shows the average partial effect (percentage points) of a pre-existing supply chain link (2010 - 2015) on the propensity to form a link in 2021-2022. 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 (250 draws, clustered at the level of suppliers). Effective F-statistic (Montiel Olea and Pflueger, 2013) of the first-stage regression in Equation (17), standard errors clustered at the level of manufacturers. *p<0.1; **p<0.05; ***p<0.01.

Table A2: Formation of Supply Linkages to Suppliers with Grey and Clean Expertise

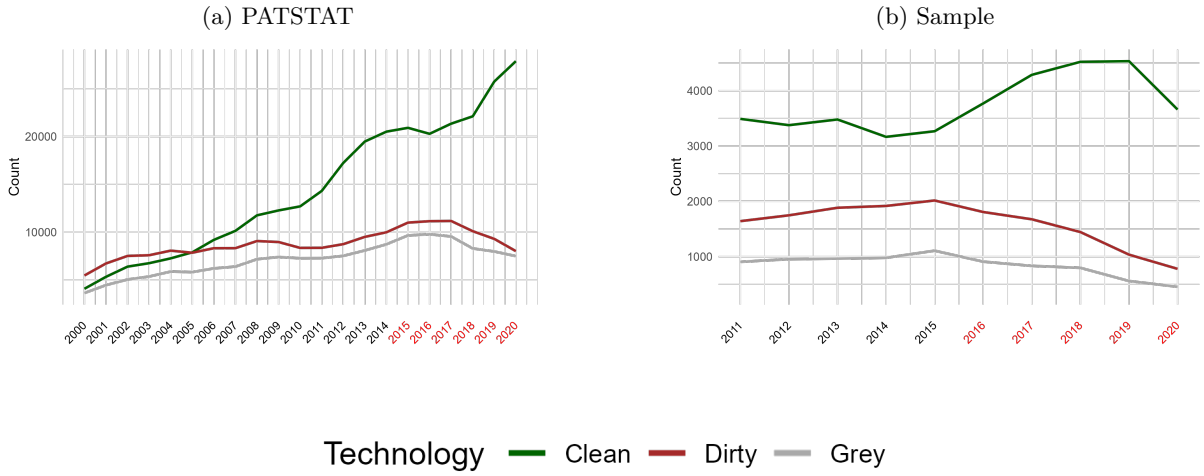
	Grey Expertise				*Clean Expertise*			
	CF	Probit	2SLS	OLS	CF	Probit	2SLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stringency	0.161*	-0.081			0.175*	-0.077		
	(0.087)	(0.050)			(0.099)	(0.053)		
Stringency ×	0.258	-0.084	0.304**	-0.065	0.128	-0.053	0.153	-0.035
Expertise	(0.164)	(0.101)	(0.144)	(0.088)	(0.152)	(0.091)	(0.117)	(0.072)
Existing Link_{10-15}	0.201**	0.189**	0.161**	0.218**	0.208**	0.196**	0.161**	0.218**
	(0.020)	(0.019)	(0.018)	(0.021)	(0.020)	(0.019)	(0.018)	(0.021)
First Stage								
F Statistic	11.396		11.806		11.398		11.806	
Potential Links	5376	5376	5376	5376	5376	5376	5376	5376
Suppliers	224	224	224	224	224	224	224	224
Manufacturers	24	24	24	24	24	24	24	24
Supplier and Manufacturer FE			X	X			X	X
Controls	X	X			X	X		

Notes: Average marginal effects (AME) on the propensity of additional supply chain links forming in 2020 - 2021. The top row indicates the technological fields used to split the sample into suppliers with different pre-existing expertise. Columns labeled *Grey Expertise* split the sample manufacturer-supplier pairs into pairs involving suppliers with and without at least one grey patent application in the period 2005-2015. Columns labeled *Clean Expertise* split the sample analogously along pre-existing patents for clean technology. *Stringency* is the AME (percent) of exposure to more stringent environmental regulation in 2019, defined in Equation (2). *Stringency* × *Knowledge Stock* shows the difference in the AMEs (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. Existing Links_{10-15} shows the average partial effect (percentage points) of a pre-existing supply chain link (2010 - 2015) on the propensity to form a link in 2021-2022. 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 (250 draws, clustered at the level of suppliers). Effective F-statistic (Montiel Olea and Pflueger, 2013) of the first-stage regression in Equation (17), standard errors clustered at the level of manufacturers. *p<0.1; **p<0.05; ***p<0.01.

(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.

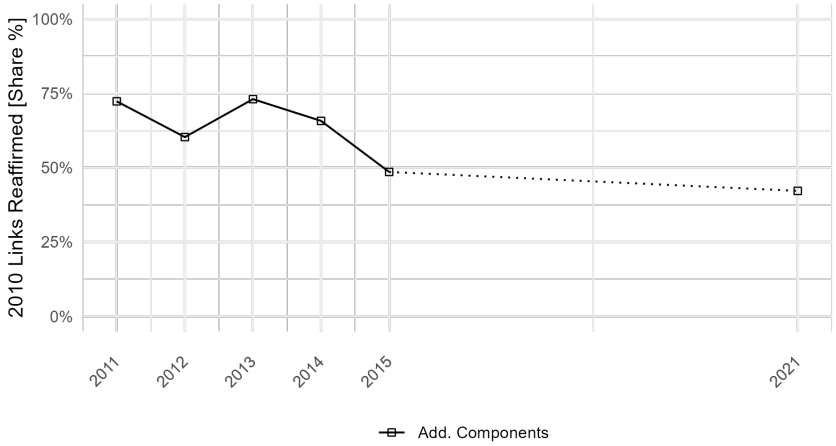
E Additional Graphs and Tables

Figure E.1: Trends in Fractional Patent Counts



Notes: PATSTAT includes all patents identified by the patent search outlined in Section 3. 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 3 for details on the construction of the sample. Count of non-domestic DOCDB patent families per year (summation of fractional counts, assigning equal weight to each applicant on the patent). 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 in the MarkLines data.

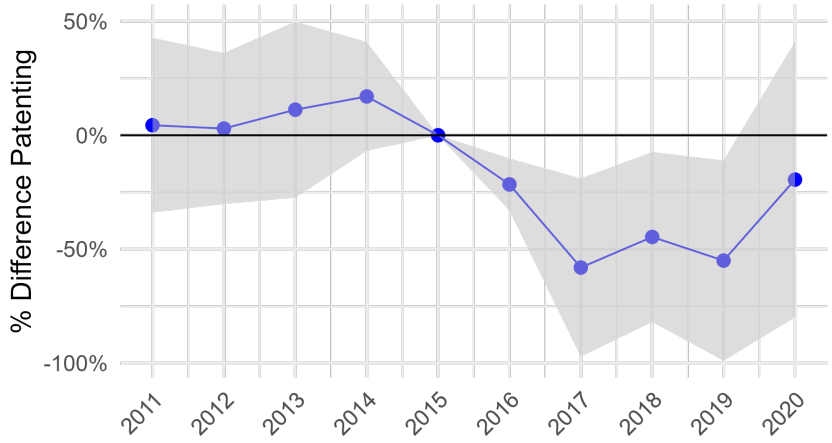
Table A1: Regulatory Stringency Post-2015 and Components of the Instrument

	(1)	(2)	(3)	(4)	(5)
Post Diesel Emission Advantage$_{2015}$	0.064***				
	(0.014)				
Post Stringency Diesel$_{2015}$		-0.188***			
		(0.065)			
Post Stringency Non-Diesel$_{2015}$			0.056		
			(0.048)		
Post Diesel Share$_{2015}$				0.064***	
				(0.024)	
Diesel Share$_t$					-0.035
					(0.061)
Post Diesel Share$_t$					0.072***
					(0.024)
Observations	3390	3390	3390	3390	3390
Suppliers	339	339	339	339	339
Years	10	10	10	10	10
R^2	0.914	0.915	0.913	0.914	0.914

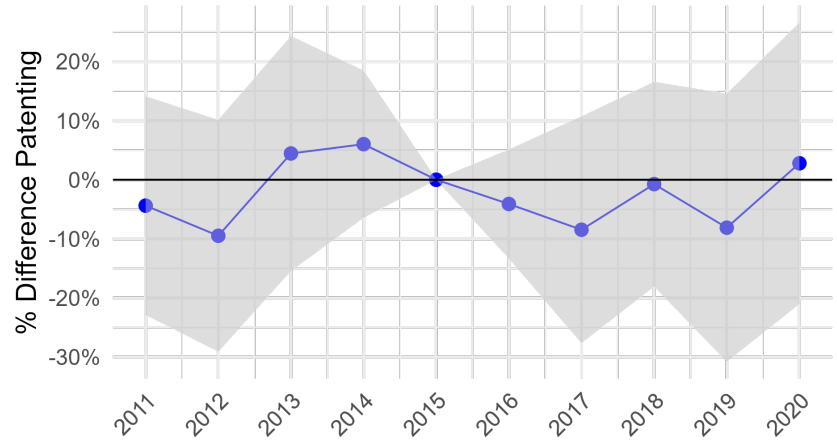
Notes: Regressions of exposure to downstream regulatory stringency as defined in Equation (4) on the indicated variables, controlling for supplier and year fixed-effects. Post is an indicator taking the value 1 for years after 2015. Diesel Emission Advantage$_{2015}$ is the difference between Stringency Non-Diesel$_2$015 and Stringency Diesel$_{2015}$. Stringency Diesel$_{2015}$ is the suppliers exposure to manufacturer-level differences between the weight-adjusted average emissions of all diesel cars sold by a manufacturer in 2015 and the emissions target of the standard in 2020, as defined in Equation (9), divided by the emissions target in 2020. Stringency Non-Diesel$_{2015}$ is the analogous outcome based on non-diesel cars. Diesel Share$_{2015}$ is the supplier exposure to the share of diesel cars sold at the manufacturer-level in 2015. Diesel Share$_t$ is the same outcome in year t. Standard errors clustered by suppliers. *p<0.1; **p<0.05; ***p<0.01.

Figure E.3: Testing Parallel Pretrends in Clean and Benchmark Innovation

(a) Pretrends in Clean Innovation



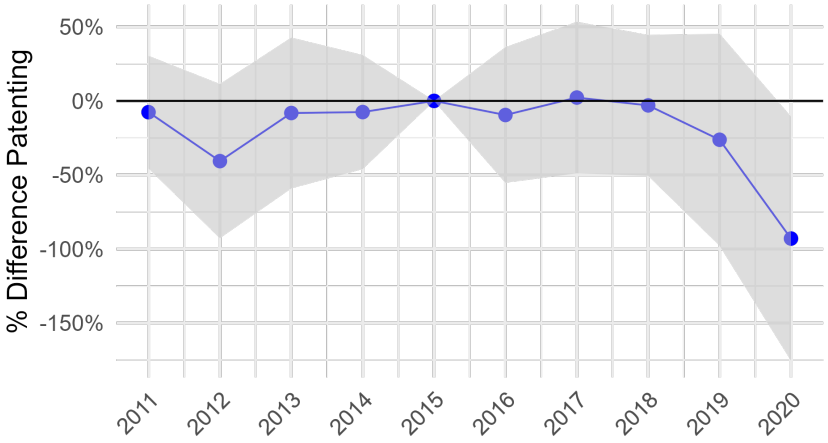
(b) Pretrends in Benchmark Innovation



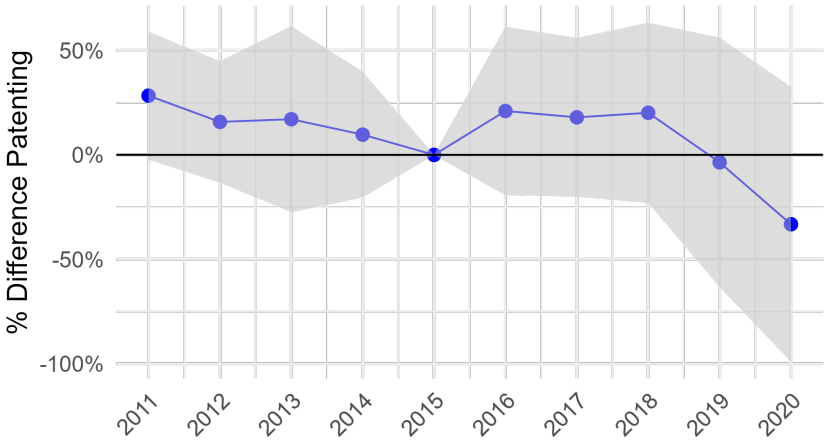
Notes: Event study regression (fixed-effects Poisson QMLE) of patent outcomes on supplier exposure to manufacturer-level reliance on diesel cars for compliance with the fleet-average emission standard in 2014 × manufacturer change in the market share of diesel cars between 2015 and 2016, as specified in Equation (C.7). 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 A5.

Figure E.4: Testing Parallel Pretrends in Dirty and Grey Innovation

(a) Pretrends in Grey Innovation



(b) Pretrends in Dirty Innovation



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 × manufacturer change in the market share of diesel cars between 2015 and 2016, as specified in Equation (C.7). 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 A5.

Table A2: Supplier Averages Across Different Outcomes, by Region (2014)

	Unit	Asia (1)	Europe (2)	Other (3)
Benchmark Patents	Count	59.34	40.21	23.54
Clean Patents	Count	13.71	6.5	2.01
Grey Patents	Count	2.39	5.06	0.44
Dirty Patents	Count	4.68	8.43	3.5
Stringency Exposure	%-points 2020 Target	0.28	0.29	0.29
only Non-Diesel	%-points 2020 Target	0.33	0.38	0.39
only Diesel	%-points 2020 Target	0.24	0.23	0.23
Diesel Share	%	42.19	56.81	54.49
EV Share	%	2.5	1.21	1.04

Notes: Average outcomes in 2014, for 339 tier-1 automotive suppliers registered in different regions. Patent outcomes reflect supplier-level counts of annual patent applications in the corresponding technological fields. Patents classification based on CPC codes, see Tables A1 and A2.Stringency Exposure displays the average stringency exposure, calculated according to Equation (4). only Diesel/Non-Diesel indicates that only passenger cars with the corresponding fuel type are considered when calculating the manufacturer fleet-average emissions, Equation (2). Diesel Share reflects the average supplier exposure to manufacturer-level shares of diesel-cars among all vehicle registrations. EV Share reflects the average supplier exposure to manufacturer-level shares of electric vehicles among all vehicle registrations.

Table A3: Robustness to Controlling for Supplier Revenues

	GMM (IV) (1)	GMM (2)	GMM (IV) (3)	GMM (4)
Stringency_{t-1}	12.936***	6.868	6.671**	7.425***
	(4.883)	(4.577)	(2.986)	(2.251)
$\log(\text{Revenue}_{t-1})$			−0.126	0.053
			(0.228)	(0.246)
First Stage				
Instrument_{t-1}	-0.136**		-0.136**	
	(0.059)		(0.060)	
$\log(\text{Revenue}_{t-1})$			-0.002	
			(0.001)	
F	5.242		5.218	
Suppliers	125	125	125	125
Periods	6	6	6	6
Supplier FE	X	X	X	X
Year FE	X	X	X	X

Notes: Outcome variable is the count of non-domestic patent applications for clean technologies. The upper panel displays the result estimating Equation (3) using the moment conditions in Equation (13). Stringency is the supplier exposure to downstream regulatory stringency, defined in Equation (4). Revenue is the annual revenue of a supplier (as observed in Orbis). GMM indicates that exposure to regulatory stringency was assumed to be sequentially exogeneous, and thus contained in the matrix of instruments Z_{it}. GMM (IV) indicates that Z_{it} contains the instrument developed in Equation (10) instead. Z_{it} also contains supplier revenues, as indicated for the specifications in columns (1) - (4). Results of the first-stage regression in Equation (15) in the lower panel. Effective F-statistic following Montiel Olea and Pflueger (2013), clustering standard errors at the supplier level. Suppliers is the number of suppliers observed. Years is the number of years used in the quasi-differencing approach. Coefficient transformed to reflect percentage changes in the outcome in response to a percentage-point increase in stringency. Block-bootstrapped standard errors (250 draws, clustered at the level of suppliers, using re-weighted bootstrapping procedure by Brown and Newey (2002)). *p<0.1; **p<0.05; ***p<0.01.

Table A4: Correlation with Potential Confounders Before 2015

Variable	Instrument$_{t-1}$	Diesel Share$_{t-1}$	Stringency$_{t-1}$
Panel A: Patents and Market Shares			
EV Market Share$_{t-1}$	0	-0.013	0
	(0.023)	(0.008)	(0.013)
Clean Patents$_t$	1.74	0.379	-0.613
	(2.765)	(1.023)	(1.793)
Benchmark Patents$_t$	0.75	-0.22	-0.84
	(1.884)	(0.857)	(1.172)
Grey Patents$_t$	6.431*	-0.722	2.822
	(3.698)	(2.21)	(3.284)
Dirty Patents$_t$	0.307	-2.29	0.788
	(2.695)	(1.471)	(3.493)
Firms	339	339	339
Periods	3	3	3
Panel B: Supplier Financials			
R&D Expenditures$_{t-1}$	5.521	-3.475	6.604
	(4.49)	(3.926)	(4.368)
Revenues$_{t-1}$	1.051	0.156	1.358***
	(1.909)	(0.765)	(0.478)
Asset: Cash$_{t-1}$	-0.926	0.635	1.711
	(4.199)	(1.572)	(1.278)
Profit$_{t-1}$	0.889	0.315	0.779
	(2.172)	(0.879)	(0.724)
Suppliers	140	140	140
Periods	3	3	3

Notes: This table reports estimates of the relationship between the instrument and time-varying supplier characteristics in the period 2012- 2014, i.e. before the diesel scandal. Each row reports the coefficient of a regression of the outcome variable indicated for the column on the regressor indicated in the corresponding row, controlling for supplier and year fixed effects. Instrument is the instrumental variable developed in Equation (10), Diesel Share is the suppliers exposure to manufacturer-level shares of diesel cars sold in the previus year, where the exposure is defined according to Equation (5), Stringency is the first lag of the suppliers exposure regulatory stringency defined in Equation (4). Patent counts and logarithms of supplier financial outcomes. Only suppliers included in all regressions. Standard errors are clustered by supplier. *p<0.1; **p<0.05; ***p<0.01.

Table A5: Evaluation of the Joint Significance of Pre-2015 Event Study Coefficients

Statistic	Clean	Grey	Dirty	Benchmark
Wald	1.051 p = 0.379	2.092 p = 0.079	0.852 p = 0.492	1.964 p = 0.097
Degrees of Freedom	(4, 3033)	(4, 3033)	(4, 3033)	(4, 3033)

Notes: Wald-test for the joint significance of the pre-2015 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 2014 and 2015, as specified in Equation (C.7). Standard errors clustered at the supplier level. *p<0.1; **p<0.05; ***p<0.01. The corresponding event study plots are provided in Figures E.3 and E.4 .

Table A6: Differential Effects on the Formation of Supply Linkages

	Any Expertise		Field of Expertise		Grey Expertise		Clean Expertise	
	CF	Probit	CF	Probit	CF	Probit	CF	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stringency × Not Patenting	0.084**	0.010						
	(0.031)	(0.019)						
Stringency × Patenting	0.264**	-0.100**						
	(0.074)	(0.043)						
Stringency × Not Clean or Grey			0.172*	-0.066				
			(0.101)	(0.055)				
Stringency × Grey, Not Clean			0.234	-0.157				
			(0.335)	(0.189)				
Stringency × Clean, Not Grey			0.153	-0.100				
			(0.154)	(0.094)				
Stringency × Grey and Clean			0.460**	-0.165				
			(0.163)	(0.101)				
Stringency × No Knowledge Stock					0.161*	-0.081	0.175*	-0.077
					(0.087)	(0.050)	(0.099)	(0.053)
Stringency × Knowledge Stock					0.419**	-0.165*	0.303**	-0.130*
					(0.142)	(0.091)	(0.113)	(0.073)
Existing Link_{10-15}	0.205**	0.199**	0.208**	0.196**	0.201**	0.189**	0.208**	0.196**
	(0.010)	(0.010)	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)
First Stage								
F	10.969		11.395		11.396		11.398	
Potential Links	22176	22176	5376	5376	5376	5376	5376	5376
Suppliers	924	924	224	224	224	224	224	224
Manufacturers	24	24	24	24	24	24	24	24

Notes: Average marginal effects (AME) on the propensity of additional supply chain links forming in 2020 - 2021. The top row indicates the specification used in the corresponding columns. Columns labeled *Any Expertise* evaluates AMEs among suppliers with and without patent applications in in the clean, grey, dirty or benchmark category in the period 2005 - 2015. Columns labeled *Field Of Expertise*,*Grey Expertise*, and *Clean Expertise* focus on manufacturer-supplier pairs involving suppliers with any expertise and study AMEs among suppliers with different technology-specific expertise. Stringency is the manufacturer-level stringency as defined in Equation 2 in 2019. *Stringency* × *Some Sample* shows the AME (percent increase) of of more stringent environmental regulation in the corresponding 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). Existing Links_{10-15} shows the average effect (percentage points) of a pre-existing supply chain link in the period 2010 - 2015. 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 (250 draws, clustered at the level of suppliers). Effective F-statistic (Montiel Olea and Pflueger, 2013) of the first-stage regression in Equation (17). For the first-stage regression, standard errors clustered at the level of manufacturers. *p<0.1; **p<0.05; ***p<0.01.

Table A7: Differential Effects on the Formation of Supply Linkages, 2016 - 2017

	Any Expertise		Field of Expertise		Grey Expertise		Clean Expertise	
	CF	Probit	CF	Probit	CF	Probit	CF	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stringency × Not Patenting	-0.058*	-0.038*						
	(0.035)	(0.022)						
Stringency × Patenting	-0.012	-0.067						
	(0.068)	(0.046)						
Stringency × Not Clean or Grey			-0.053	-0.050				
			(0.092)	(0.063)				
Stringency × Grey, Not Clean			0.053	-0.279				
			(0.264)	(0.195)				
Stringency × Clean, Not Grey			-0.006	-0.043				
			(0.135)	(0.091)				
Stringency × Grey and Clean			0.095	-0.060				
			(0.150)	(0.109)				
Stringency × No Knowledge Stock					-0.039	-0.052	-0.045	-0.078
					(0.083)	(0.053)	(0.088)	(0.058)
Stringency × Knowledge Stock					0.087	-0.097	0.043	-0.052
					(0.136)	(0.098)	(0.110)	(0.074)
Existing Link_{10-15}	0.319**	0.319**	0.354**	0.354**	0.349**	0.347**	0.353**	0.351**
	(0.011)	(0.011)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
First Stage								
F	8.375		8.485		8.486		8.488	
Potential Links	22176	22176	5376	5376	5376	5376	5376	5376
Suppliers	924	924	224	224	224	224	224	224
Manufacturers	24	24	24	24	24	24	24	24

Notes: Average marginal effects (AME) on the propensity of additional supply chain links forming in 2016 - 2017. The top row indicates the specification used in the corresponding columns. Columns labeled *Any Expertise* evaluates AMEs among suppliers with and without patent applications in in the clean, grey, dirty or benchmark category in the period 2005 - 2015. Columns labeled *Field Of Expertise*, *Grey Expertise*, and *Clean Expertise* focus on manufacturer-supplier pairs involving suppliers with any expertise and study AMEs among suppliers with different technology-specific expertise. Stringency is the manufacturer-level stringency as defined in Equation 2 in 2015. *Stringency* × *Some Sample* shows the AME (percent increase) of of more stringent environmental regulation in the corresponding 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). Existing Links_{10-15} shows the average effect (percentage points) of a pre-existing supply chain link in the period 2010 - 2015. 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 (250 draws, clustered at the level of suppliers). Effective F-statistic (Montiel Olea and Pflueger, 2013) of the first-stage regression in Equation (17). For the first-stage regression, standard errors clustered at the level of manufacturers. *p<0.1; **p<0.05; ***p<0.01.