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THINKING THE GREEN TRANSITION:
EVIDENCE FROM THE AUTOMOTIVE INDUSTRY

by Andrea Orame* and Daniele Pianeselli*

Abstract

We study the European automotive industry in the 2013-2018 period. Volkswagen's *Dieselgate* scandal and the Paris Agreement, both in 2015, substantially caused a technological shock prompting firms to produce low-emissions cars. By using patent and mergers and acquisitions (M&A) data, we test how firms reacted to that shock. We provide evidence that Italian firms intensified their internal R&D activity but, unlike the rest of Europe, they did not increase their M&A activity. This can potentially reduce the speed of the green transition of Italian firms to the advantage of their competitors.

JEL Classification: G34, L62, O14, O3.
Keywords: automotive, green transition, technical change, mergers and acquisitions, innovation, patents, electric car.
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Contents

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1. Introduction[1]

The automotive industry is one of the most important industries in the manufacturing sector. Eurostat (2021) indicates that in 2015, the European[2] automotive industry generated more than 10 per cent of the value added of the manufacturing sector. However, transport vehicles are also major contributors to air pollution. In 2015, road transportation accounted for 24 per cent of the carbon dioxide (CO_2) emitted in the atmosphere (EEA, 2017), which is the main responsible for global warming and its adverse effects on human activity.[3]

In 2015, within three months, two events generated one of the largest industry-wide shock in the history of the automotive sector. The Volkswagen's *Dieselgate* scandal essentially determined the phasing-out of the dominant technology in Europe: the diesel engine. Meanwhile, the Paris Agreement strengthened the overall global response to the threat of climate change, *de facto* transforming the not yet fully mature technology of the electric car in the only viable alternative to the diesel powertrain. However, corporate internal control systems have usually failed to deal with such type of fundamental shocks (Jensen, 1993). For instance, looking at the reaction of the automotive industry to the oil shock of the 1970's, empirical evidence shows that American firms in the automotive sector reacted with different speed according to their engineering capabilities (Bresnahan and Ramey, 1993).

European firms could have responded to the 2015 technological shock either by intensifying their internal research and development (R&D) activity or by diversifying their technological portfolio via mergers and acquisitions (M&A). Despite the literature provides no clear guidance, M&A activity could be a superior strategy in reaction to industry-wide shocks by helping to bridge the technological gap with competences and technologies that would otherwise be difficult to develop internally. In fact, Mitchell and Mulherin (1996) and Andrade and Stafford (2004) find that mergers and acquisitions cluster in specific times, in reaction to changes in the industry of the acquirer. Additionally, M&A may speed up the technological transition of a company, potentially at the expense of its competitors. However, extant literature also identifies several factors that can prevent firms from accessing this strategy: the presence of an innovation gap can be one of such factors. Indeed, firms may lack the skills to recognize and absorb the competences from the market or such

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[2] EU27 and United Kingdom.

[3] Passenger cars are responsible for the largest share in CO_2 emissions in road transportation.

competences may be less developed in their home market.[4] In this work, we combine patent and M&A data to document the innovation and M&A activity of Italian vis-à-vis the other European automotive firms (motor vehicles and components producers) covering three years before and after 2015.[5] We then test for any difference in their strategic behaviour, interpreting the results in light of the extensive literature to which we aim to contribute with new empirical evidence.

The analysis shows that Italian firms in the automotive industry intensified their internal R&D activity after the 2015 shock more than other European firms in the sector. However, their M&A activity remained subdued, casting doubts on the ability of the Italian firms to timely convert their production towards low-emissions cars. The paper is organized as follows. Section 2 provides background information on the car market and a review of the literature. Section 3 introduces the multi-sourced dataset used in this paper and Section 4 tests the main hypotheses using different econometric models. Section 5 discusses the results and concludes, outlining lines for future research.

2. Background and research framework

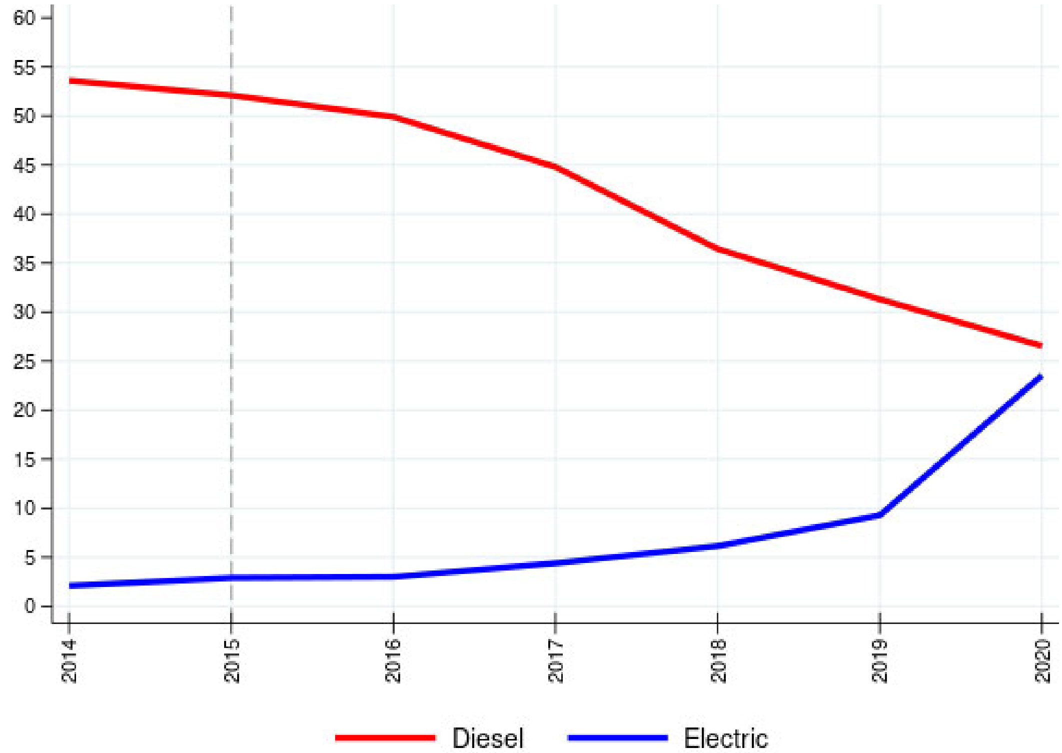
2.1. The car market

In 2015 –according to the International Organization of Motor Vehicle Manufacturers– passenger cars world production was considerably higher than in 2000. However, the increase was significantly weaker in the European Union (EU27 and United Kingdom), including also major German carmakers. In some countries, most notably Italy and France, production was even below the levels reached in 2000. In addition, more than 50 per cent of new passenger cars sold in the European Union in 2015 were powered by a diesel engine (Figure 1).

[4] The innovation lag in Italy vis-à-vis the other main European countries is well documented in the literature. See, for example, Parisi et al. (2006), Bugamelli et al. (2012), Bonaccorsi and Perani (2014) and Benvenuti et al. (2014).

[5] Due to patent data availability, this study ends in 2018. However, the analysis highlights clear-cut trends before and after the year 2015, which are likely to be persistent also over a longer horizon.

Figure 1: Passenger cars, market share in Europe



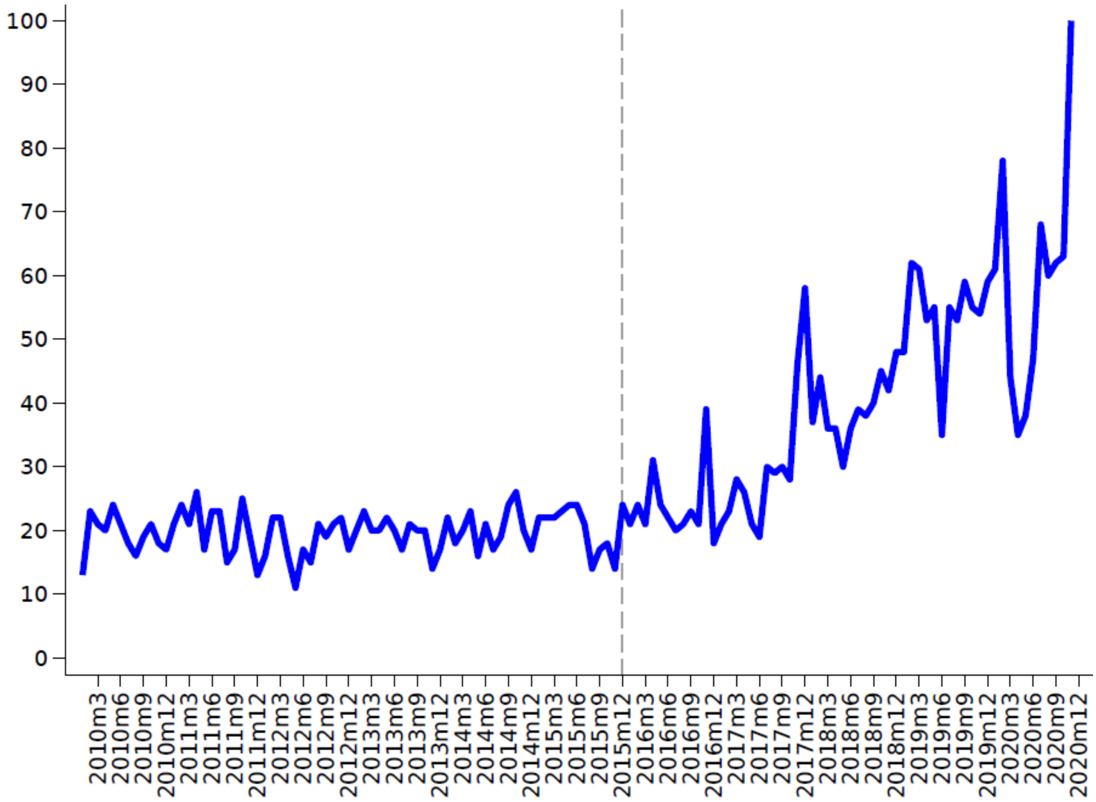
Source: Own elaborations on data from the European Automobile Manufacturers' Association.
Notes: EU15. Share over total passenger cars sold in each year. Electric motorization includes fully electric and hybrid cars.

In 2015 the Volkswagen's *Dieselgate* dramatically changed the course of the events, with one of the biggest environmental scandal of the automotive sector. On September 18, the U.S. Environmental Protection Agency (EPA) sent a note of violation to Volkswagen AG, Audi AG, and Volkswagen Group of America: EPA determined that their diesel light-duty vehicles were equipped with a defeat device that reduced air pollutant emissions under test conditions. On the road, the device turned off emission control and air pollutants rose above EPA emission standards. Three months later, on December 12, the Paris Agreement set new environment standards in terms of greenhouse gas emissions as part of a global response to the threat of climate change. The European Union signed the agreement.

Since then, the diesel engine has been considered a polluting technology, emitting in the atmosphere an amount of nitrogen oxides (NO_x) not compatible with the new European environmental standards. At the same time, electric and hybrid cars (henceforth, in the text, electric cars) attracted progressively more attention as the main alternative to the internal combustion engine. Although electric cars were far from being a mature technology, their market share increased substantially since 2017 (see Figure 1). Internet data confirm the discontinuity marked by the year

2015 in the car market. Figure 2 shows monthly Google searches at world level for the term *“electric car”* between 2010 and 2020, as a proxy of consumers’ interest. The magnitude of the general public attention towards the electric car, after being roughly stable in the first part of the decade, gained momentum after the events of 2015, and constantly increased over-time.

Figure 2: Google searches for the term “electric car” at world level



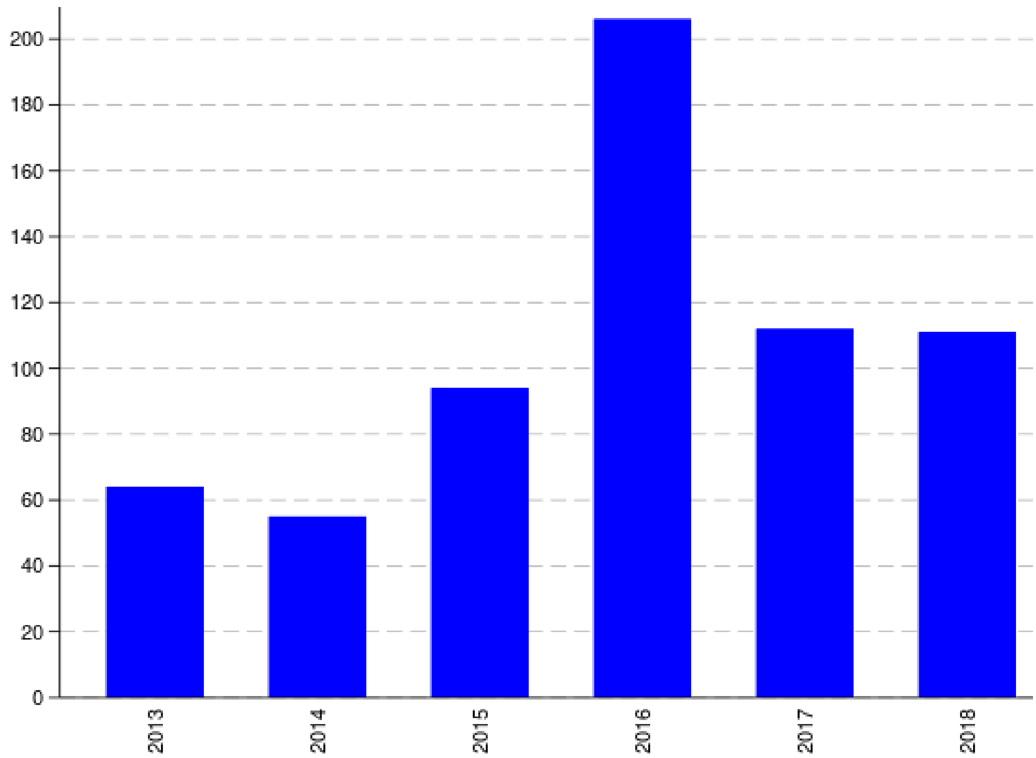
Source: Google Trends data: monthly data. Data normalized to 100 at the maximum search interest between 2010 and 2020. Search term: “electric car”. Geographical area: “world”.

As shown in Figure 3, in 2015 world car manufactures had already registered several electric vehicles in the European market. The number of new electric models peaked in 2016 and remained high between 2017 and 2018. Yet, Figure 4 displays a substantial heterogeneity between major European manufacturers. The most important Italian car manufacturer, at the time the Fiat Chrysler Automobiles group (FCA), did not register any electric car model in the European market between 2013 and 2018, signalling a potential weakness of the main Italian player.

In 2019, according to the European Environment Agency, the average emission level for new passenger cars was 122.3 g CO_2/km. In the same year, the European Union introduced for the 2020-

2024 period an annual fleet-wide cap of 95g CO_2/km, with a 2020-2022 super-credit system for cars emitting less than 50g CO_2/km.[6] Only electric cars –mainly battery, plug-in hybrid and fuel cell vehicles– could meet that standard, granting this technology an essential role also for law compliance.

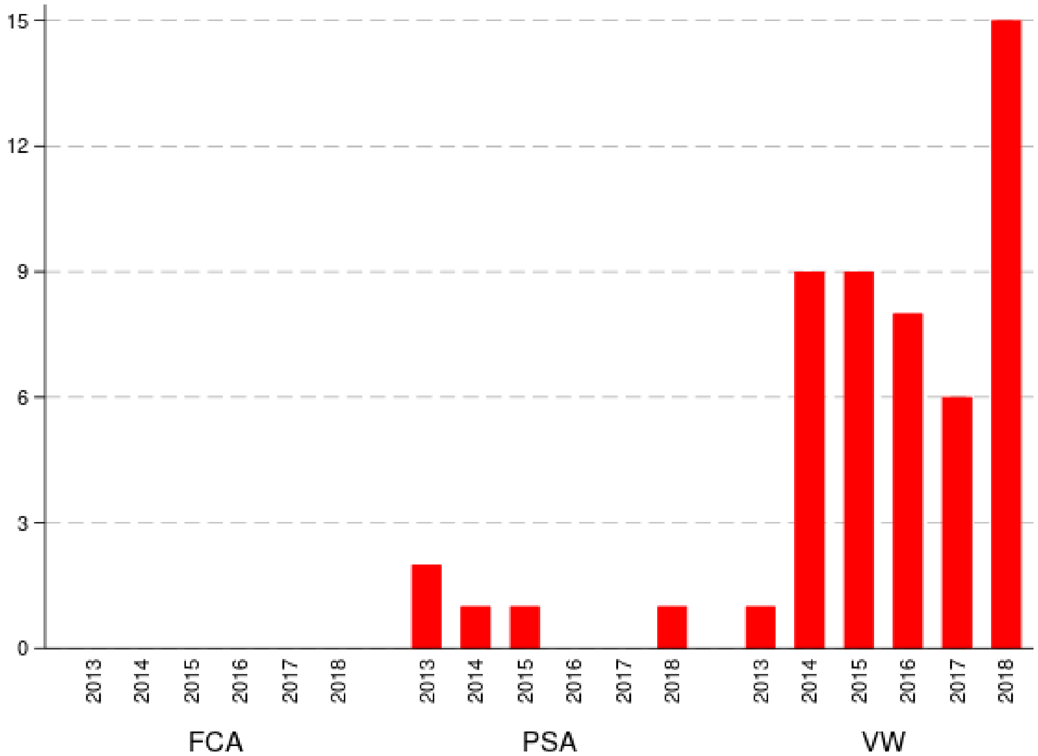
Figure 3: Registrations of new electric passenger car models in the European market



Own elaborations on data from the European Environment Agency.
Notes: Registrations of new model by world car manufacturers in the EU27 and United Kingdom. Data report the year in which the model is first registered in any of the country of the European Union (EU27 and United Kingdom) according to the CO2 monitoring database of the European Environment Agency.

[6] Regulation 2019/63. Stricter targets will apply from 2025. Light commercial vehicles are subject to different targets.

Figure 4: Electric passenger models in the European market, selected manufacturers



Own elaborations on data from the European Environment Agency.
Notes: EU27 and United Kingdom. Data report the year in which the model is first registered in any of the country of the European Union (EU27 and United Kingdom) according to the CO2 monitoring database of the European Environment Agency.

2.2. Decarbonisation strategies

After the events in 2015, the European automotive sector had to redirect production away from polluting to green technology. The latter can be considered a complex knowledge that stems from spillovers between industries and involves the application of novel know-how to a core technology (Zeppini and van Den Berg, 2011). Orsatti et al. (2020) shows that green technologies are more likely to be generated by teams that creatively recombine existing knowledge into original outcomes. Crucially, also the transition of the automotive industry from internal combustion engines to electric propulsion systems requires mastering intrinsically complex knowledge.[7]

In this work, we investigate how the European automotive firms diversified their technological portfolio in order to keep the pace with the green transition, and whether any difference exists between

[7] A Financial Times article titled "The race to train a new cohort of electric vehicle mechanics" reported that "fixing a faulty [electric] car will require a skillset more akin to that of a software engineer than someone adept wielding a wrench". The article also reported that "a modern car contains around 100 million lines of code. To put that into context, a top-spec airliner has 14 million lines" (https://www.ft.com/content/cc6e39c9-d83c-47f4-a419-cdbee40c1c92).

Italian firms and their European competitors. The literature identifies two related but distinct mechanisms to realize a successful innovation strategy. Firms can either intensify their internal R&D activity to secure a competitive advantage by employing patents (Trajtenberg, 1987; Lerner and Zhu, 2007; Arora et al., 2008) or diversify their technological capacity by mergers and acquisitions (Cohen and Levin, 1989; Veugelers, 1997). With the former, the firm increases the knowledge intensity of its assets, signalled also by its portfolio of patents; with the latter, the acquiring firm gains access to new knowledge that combined with its own pre-existent technology generates innovation.

On the first strategy, many studies have highlighted how innovation effort is mainly persistent at firm level and determined by the technological capabilities and idiosyncratic characteristics of the firm (Del Canto and Gonzalez, 1999; Galende and de la Fuente, 2003). The existence of sunk costs (Mañez et al., 2009; Hall and Lerner, 2010), the availability of internal financial resources (Hall, 1992; Himmelberg and Petersen, 1994; Czarnitzki et al., 2011) and a sufficient stock of knowledge accumulated through time (Malerba, 1992) have been indicated as the most important factors in determining R&D level. In particular, Lee (2010) maintains that the firm's technological-knowledge base may determine a virtuous innovation growth pattern. On a dynamic perspective, higher level of technological capabilities enhances R&D investments in case of a positive change of external conditions, but represents a mitigating factor in case of negative shock (Bloom, 2007; Kang et al. 2017).

On the second strategy, there are mixed results on the innovative performance of firms engaging in M&A activity. Surprisingly, Hitt et al. (1991) and Hall (1999) find a negative effect of M&A activity on innovation, as it lowers managerial commitment and investment in R&D. Blonigen and Taylor (2000), using a panel of technology-intensive industries, confirms this inverse relationship across firms, showing however how this negative correlation can be reversed over time, within firms. Additionally, by focusing on M&A specifically motivated by the intention to acquire a new and complementary technology, Cassiman et al. (2005) highlights a positive effect of mergers on innovation activity. By the same token, Entezarkheir and Moshiri (2018) shows that mergers are positively correlated with firms' innovation. Thus, the empirical evidence is mainly supportive of the hypothesis that mergers and acquisition fosters innovation mostly though synergies and economies of scope. Consequently, M&A activity can be a successful strategy in reaction to industry-wide technological and regulatory shocks. In this direction, Mitchell and Mulherin (1996) and Andrade and Stafford (2004) find that mergers and acquisitions cluster through time, playing a pivotal role in industry restructuring.

As a result, M&A activity can help to bridge the gap after an industry-wide technological shock, as the one that occurred in 2015 in the automotive sector, with competences and technologies that would otherwise be difficult to develop internally. In addition, M&A could also allow filling the technological gap in a shorter amount of time. In fact, Cefis and Marsili, 2015 shows that M&A activity helps small firms to cross the "innovation threshold", increasing the probability of transition from the status of non-innovator to the one of active innovator. However, the literature recognize that M&A are beneficial only to firms that have the ability to assimilate new knowledge. Firms should at least master the knowledge and competences that are necessary to access, decode, and understand external knowledge, also known as "absorptive capacity" (Cohen and Levinthal, 1990; Griffith at al., 2004). Along those lines, Hagedoorn and Wang (2012) shows that internal and external innovation are complementary activities at higher levels of in-house R&D investments, but substitutive activities at lower levels. Only at higher levels of in-house R&D, the interaction with alliances and acquisitions positively reinforce firm's innovative output.

Looking specifically at green innovation of automotive firms, Aghion et al. (2016) documents a clear path dependency in the type of innovation, clean or dirty. Moreover, Rocchetta and Upadhayay (2021) posits that the amount of innovation and intangible assets play a key role in shaping firm ability to face external shocks. Thus, despite Mealy and Teytelboym (2020) assigns to Italy a high potential to succeed in reorienting the existing industrial structure, the innovation gap of the Italian productive system may delay the green transition of the domestic auto industry at the advantage of European competitors.[8] While the success of the transition can only be evaluated with hindsight, in the present work we start by empirically testing the strategic behaviour of firms in the automotive sector, highlighting the distinctive feature of the path followed by the Italian firms in reaction to the 2015 shock.

2.3. Measuring green innovation

The analysis of the strategies towards carbon-neutrality dictated by the 2015 events should be based on a reliable and widely available micro-level indicator of innovation that could also be suitable to measure "environmental" innovation. However, the lack of a unique satisfactory measure of inventive activity is often highlighted as one of the major flaws in understanding the impact of every technological change. The literature has progressively proposed several proxies that closely relates to the three main phases of the innovative process: (I) input measures of the innovation effort, such as the amount of R&D investments or the share of highly specialized and skilled workers within the

[8] See, for example, Bugamelli et al. (2012), Benvenuti et al. (2014) and Manello et al. (2016).

company; (II) measures of intermediate output related to patenting activity; (III) measures of final innovative output, usually from survey data (Acs and Audretsch, 2005).

While the input measures of the innovation effort are available only for few firms[9] and survey-based information suffers from both small samples and data quality issues, the use of patents as innovative proxy has specific strengths and weaknesses. On the one hand, many studies have highlighted the positive linkage of patenting with R&D investments (Trajtenberg, 1987; Lerner and Zhu, 2007; Arora et al., 2008). Moreover, Svensson (2015) posits that patent data are the best-suited alternative for identifying green innovation. On the other hand, sectoral changes in propensity to patent, patent value heterogeneity and the existence of trade secret protection and non-patentable innovation may diminish the importance of patents as an indicator of innovative performances (Mansfield, 1986; Archibugi and Pianta, 1996; Lanjouw et al., 1998). While concerns on the validity of a patent-based indicator are significantly limited here, as we sample firms from one jurisdiction and that belong to the same sector, the possibility of identifying "environmental" inventions by using the technological field of the patent is the main advantage that influenced our choice. Therefore, throughout this paper we measure innovation relying on a firm-level patent indicator of innovation constructed through an approximate string matching (also known as *fuzzy-matching*) between the identity of the firm and the name of the assignee of the patent.

3. Database and variables

Data are sourced from three different databases. Orbis and Zephyr databases by Bureau van Dijk (BVD) – a Moody's Analytics Company – and Patstat, a patent database managed by the European Patent Office (EPO).

3.1. Balance sheet database

Orbis is a worldwide firm-level commercial database, which includes balance sheet information (income, asset, liability and cash flow statements) and firms' characteristics, including ownership.[10] We selected a panel of firms in the automotive sector (NACE Rev. 2 29) headquartering and operating

[9] Even if the disclosure of R&D investments in the balance sheet is not compulsory, some firms voluntarily add R&D expenditure in the footnotes of their balance sheets. However, even accounting for this extra information, the number of non-missing observations hardly goes beyond a hundred in our sample.
[10] See Ribeiro et al. (2010) and Kalemli-Ozcan et al. (2015) for a thorough analysis of the characteristics of the Orbis database, the representativeness of the sample and cross-country comparability.

either in the European Union (EU27) or in the United Kingdom. To set up our dataset, we took firms whose turnover is available with no interruption between 2012 and 2019. Hence, other balance-sheet data and ancillary information might be available only for a subset of firms. We also implemented a set of additional balance sheet checks and logical tests to improve the quality of the information. Our dataset consists of 6,052 firms. By comparison with Eurostat data in 2015, our sample represents almost one third of the population of the European firms in the automotive sector (NACE Rev. 2 29). More in detail, the Italian portion of the sample represents more than half of the Italian firms in the automotive industry.

3.2. M&A database

Zephyr is a comprehensive database of deal information on domestic and cross-border M&A, IPOs and private equity transactions. The literature is increasingly using this source to study mergers, acquisitions and joint ventures (Craninckx and Huyghebaert, 2011; Clò et al., 2017; Alperovych et al., 2021). Bollaert and Delanghe (2015) compares the widely used Securities Data Company (SDC) database by Thomson Reuters with BVD Zephyr concluding that the former has greater accuracy and coverage for transactions originated in the United States. However, it posits that BVD Zephyr outperforms SDC in case of European deals with multiple bidders or targets. Hence, Zephyr can be an appropriate source of information for our work. Moreover, we easily complemented our balance sheet dataset with deal information by matching the unique identification number (BVD ID), available in both databases.

We applied standard filters, common in the M&A literature, to collect our final sample. We selected “Acquisition”, “Merger”, “Institutional buy-out”, “Joint-venture”, “Management buy-in”, “Management buy-out” involving at least one automotive acquirer headquartered in EU27 or UK. We also included those repeated “Minority stake” transactions that led to a significant control share, but we accounted them as a single transaction at the first announcement date. We then restricted the sample to the completed deals with announcement date between 2013 and 2018.[11] Finally, we dropped intra-group deals and we matched the database with the balance sheet dataset of 6,052 firms.[12] Our M&A sample consists of an average of 54 deals per year totalling 326 transactions, with

[11] Due to the time-span of the analysis, our sample does not include the merger between Fiat Chrysler Automobiles N.V. and Peugeot S.A. Group into Stellantis N.V. The tie-up, which created the fourth largest global automaker, was announced on October 31, 2019 and officially completed on January 16, 2021.

[12] We have no information about groups’ composition. Thus, we applied a string-matching algorithm to highlight string similarity between acquirers and targets, with the exclusion of joint ventures, to select transactions involving only different entities.

a peak of 72 transactions in 2017. More than 70 per cent of the deals are acquisitions and approximately 9 per cent joint-ventures.

3.3. Patent database

Patstat is a world-wide patent database, updated half-yearly by the European Patent Office (EPO), containing over 100 million patent documents. It covers legal applications from more than 90 patent authorities, including regional patent offices and international patent applications filed under the Patent Cooperation Treaty (PCT). Patent records are mainly designed for administrative purposes in order to guarantee the inventor with "the right to exclude others from making, using, offering for sale, or selling the invention".[13] However, they also represent a unique source of detailed information that allows researchers to keep track of innovative activity. Patents include information on inventors, inventions, technological areas, companies and geographical locations. Moreover, they report citations to previous granted patents and to the scientific literature.

We collected patent information for all the automotive firms in our sample. In order to integrate different micro-level sources that do not share a common company identifier, we developed an algorithm of exact and approximate (fuzzy) matching based on the string similarity of the name of the firms that balance two conflicting aims: ensuring the highest probability of matching and limiting false matches.

Starting from Hall et al. (2001) and Lotti and Marin (2013), which proposed their fuzzy matching procedures for U.S. and Italian companies respectively, we implemented an automatic routine to harmonize and match company information from 28 European countries. The procedure found 891 assignees (applicants), which belongs to the NACE Rev. 2 29 sector. This signals that only 15 per cent of the sample is involved in patenting activity. To avoid duplications and guarantee the novelty of the invention, we restrict our analysis to the priority applications, which are initially filed in one patent office before being possibly extended to other patent offices. The priority date is also the closest available date to the invention date. Overall, up to the end of 2018, these assignees have applied for 161,480 priority patents, of whom 59,454 in the 2013-2018 period. The result is a novel dataset that follows the patenting activity of automotive companies before and after 2015.

In order to extend the scope of the present analysis, we also identified environment-related technologies embodied in patent applications, using the Cooperative Patent Classification (CPC) system. In 2010, the European Patent Office (EPO) and the US Patent and Trademark Office

[13] Patent protections guaranteed by the U.S. Patent Act, Title 35 United States Code.

(USPTO) jointly initiated a common classification scheme (CPC) to enhance the International Patent Classification system (IPC).[14] Within CPC scheme, the classes Y02/Y04S identify those technologies devoted to the reduction of greenhouse gases (GHG). Here, we adopted a slightly wider look to green patents than in previous works (Angelucci et al. 2018). We included both climate change innovations related to adaptation and resilience (CCAT) and mitigation technologies (CCMT) as well as integrated technologies like *smart grids*, which may enhance interoperability, also for hybrid vehicles.[15] In fact, Hötte et al. (2021) documents the high degree of overlapping and complementarities among different types of technologies, which collectively sustain the *"green"* scientific knowledge base.

3.4. Variables

Our database contains detailed information on balance sheet data, M&A deals and patent activity for the six-year (2013-2018) balanced panel of 6,052 automotive companies (NACE Rev. 2 29). Dependent variables are alternatively the number of priority patents issued yearly, the number of priority green patents issued yearly, the number of the completed acquisitions and the number of the completed acquisition within the NACE Rev.2 high-tech sectors.[16] Time-invariant controls are evaluated for the year 2012 and derived as follows. Age is constructed as the difference (in years) between the financial year of the balance sheet and the company's date of founding. Size of the company (micro, small, medium and large) is defined according to the European Commission Recommendation 2003/361, using staff headcount and either turnover or total assets. The listing variable indicates if the company is traded in stock markets (public company) or if it is privately owned (private company). Cumulative patent is the count of company priority applications processed before 2012. Time span was divided into two periods: an initial period before the Volkswagen's

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[14] IPC is a hierarchical classification of patented technologies established in 1971. It is managed and constantly updated by the World Intellectual Property Organization (WIPO). The CPC scheme significantly extends the scope of IPC classification, including 49 million of classified patent documents (around 99 per cent of all USPTO, EPO, WIPO patents) and almost 260,000 classification symbols.
See https://www.cooperativepatentclassification.org/cpcSchemeAndDefinitions for a list of valid symbols included in the last version of the CPC scheme.

[15] Our analysis includes patents in the following 4-digit classes: technologies for adaptation to climate change (Y02A); climate change mitigation technologies related to buildings (Y02B); capture, storage and sequestration of GHG (Y02C); energy-saving in ICT (Y02D); clean energy generation (Y02E); clean production of goods (Y02P); green transportation and electrical vehicles (Y02T); clean waste management and treatment (Y02W); integrated technologies (e.g. smart grids – Y04S).

[16] Eurostat breaks down manufacturing and services industries (based on NACE Rev. 2 classification) by their technological intensity - https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries.

Dieselgate/Paris agreement (2013-2015) and the post-2015 period (2016-2018) characterized by the automotive companies activism towards electric transition.

Micro-level financial ratios for each year are constructed as follows. Turnover growth is the yearly growth rate of operating revenues. This variable measures the rate of expansion (or contraction) of the business. Profitability is proxied by the return of equity at company level. It is constructed as the percentage ratio of net income generated to shareholders' equity and evaluates the company profitability and efficiency in using its net assets (assets minus liabilities) to generate earnings. Tangibility is constructed as the ratio of company tangible assets (including fixed and current assets) to the value of total assets. This indicator measures the proportion of assets that has a physical form and can be used as collateral. Liquidity is the ratio of liquid current assets (cash, accounts receivable and short-term investments) to current liabilities. Also known as "*Acid test ratio*", it evaluates the ability to pay short-term obligations, ignoring illiquid assets such as inventory. Table 1 provides descriptive statistics of the data.

Table 1: Descriptive statistics of the sample

Variable	Obs.	Mean	St.Dev.	Min	Median	Max
Patents, dummy	36,312	0.03	0.17	0	0	1
Patents, applications	36,312	0.26	2.97	0	0	50
Cumulative patents, 2012	36,312	16.86	663.36	0	0	48,880
Green patents, dummy	36,312	0.01	0.08	0	0	1
Green patents, applications	36,312	0.14	3.27	0	0	102
M&A activity, dummy	36,312	0.01	0.08	0	0	1
M&A activity, deals	36,312	0.01	0.13	0	0	8
M&A high-tech, dummy	36,312	0.00	0.06	0	0	1
M&A high-tech, deals	36,312	0.01	0.10	0	0	6
Turnover, % log change	36,312	5.21	23.01	-44.41	4.61	55.14
Return on Equity (ROE), %	32,988	12.00	26.00	-50.35	9.73	71.13
Tangibility, % of total assets	32,988	93.82	10.42	62.22	99.03	100
Liquidity ratio	32,988	1.50	1.39	0.22	1.01	5.74
Total assets	35,588	217.63	5685.69	0.00	2.85	458,156.00
Firm's age	35,676	19.14	16.24	1	16	180
Listed firm, dummy	36,312	0.01	0.10	0	0	1

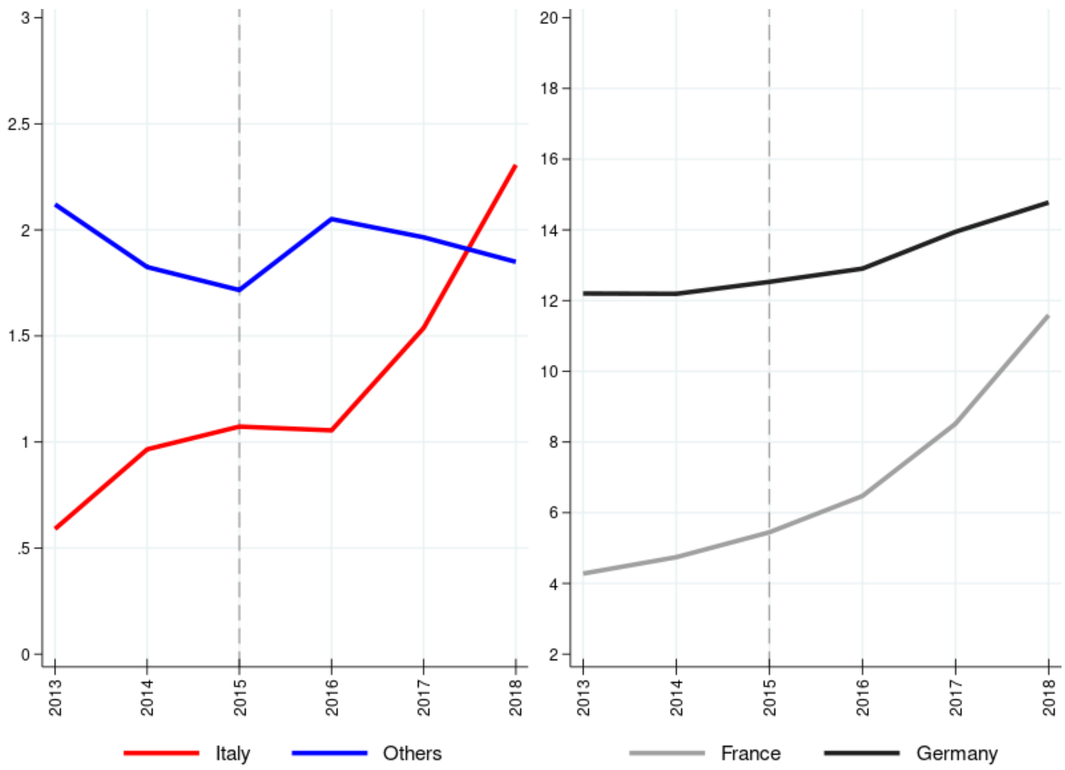
Balanced panel of 6,052 firms. Turnover (log change): winsorized at the 5th and 95th percentiles. ROE, tangible assets and liquidity ratio: winsorized at the 5th and 95th percentiles for the subsample of firms for which all balance sheet indicators are available (log change of turnover, ROE, tangible assets and liquidity ratio). Other indicators are shown upon availability of the information. Total assets in millions of euro. Firm's age as of 2012 and current listing status.

4. Main Results

4.1. Descriptive statistics

In 2015, German automotive companies (including both motor vehicles and components manufacturers) had the highest ratio in Europe between *cumulative number* of patent applications and total assets. Despite ranking after Germany and France, Italian producers were slightly above the average of the other European countries. However, with specific regard to green patents Italian automotive firms had a lower number of cumulative applications to total assets also with respect to the other European countries.

Figure 5: Patent (applications)

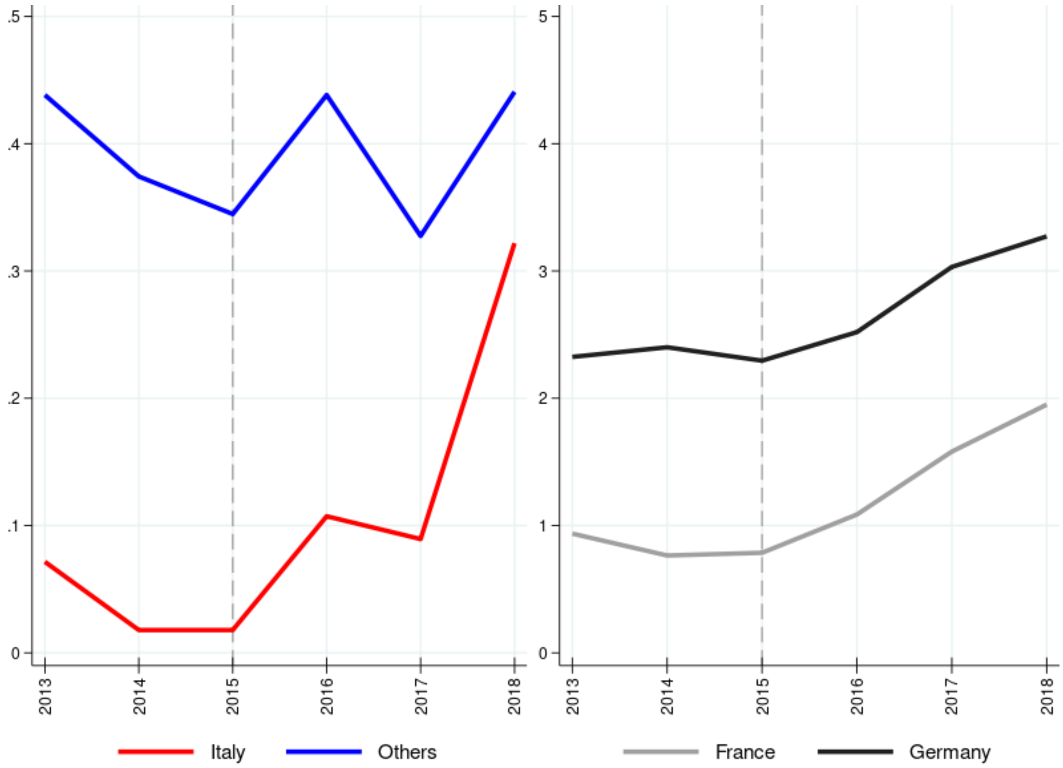


Source: Patstat. Notes: EU27 and United Kingdom. Number of applications over total assets in billions of euros in 2015. Balanced sample.

As shown in Figure 5, after 2015 the number of *patent applications* steadily increased in France and Germany. The same holds in Italy, where the increase was even stronger than in France and Germany. The number of applications in the rest of Europe remained substantially the same after 2015. However, the number of applications in Italy remained below the levels reached by French and, even more, by German companies. In 2018, automotive firms filed 15 patent applications for each billion of 2015 assets in Germany, 12 in France, while only 2 in Italy.

Figure 6 provides similar insights for green patents, which represent a fraction of total patent applications. Italian firms in the automotive sector increased their green applications more than the rest of Europe, but without matching the level of Germany and France.

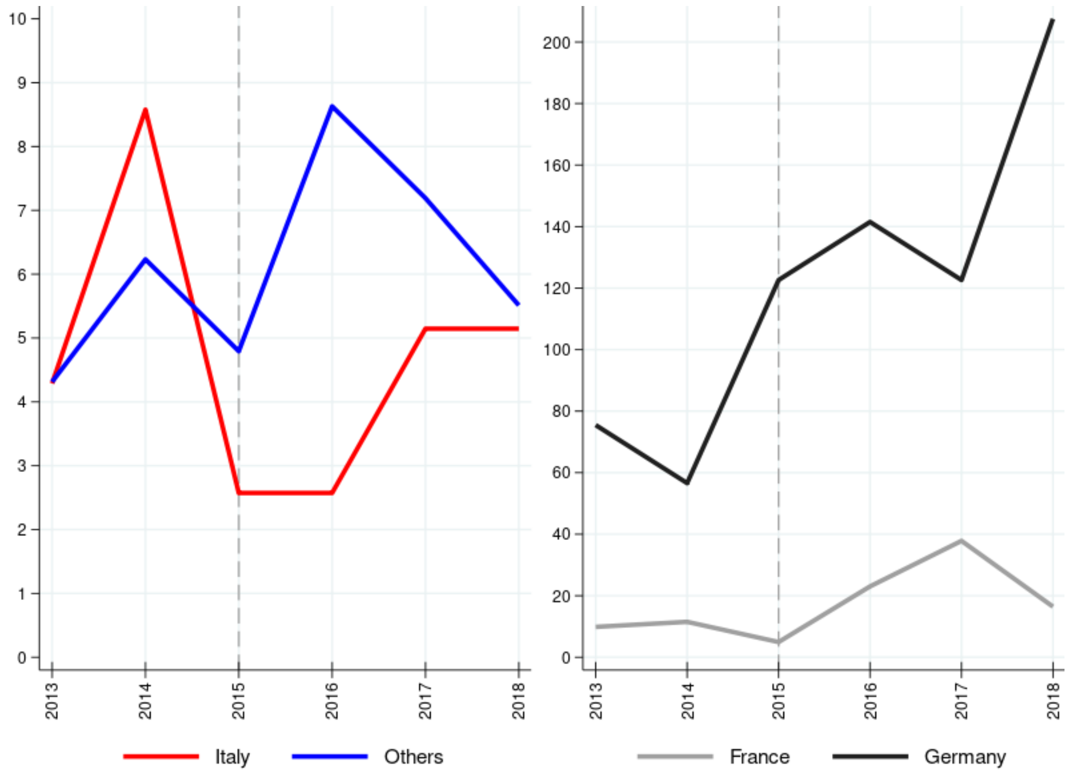
Figure 6: Green patents (applications)



Source: Patstat.
Notes: EU27 and United Kingdom. Number of applications over total assets in billions of euros in 2015. Balanced sample.

On the other side, Figure 7 shows that German firms in the automotive sector also increased their mergers and acquisitions activity, with a robust growth in the number of deals after 2015. A similar pattern can be noticed in France and in the other European countries, but not in Italy. The number of deals originated by an Italian acquirer per thousands of firms was 15 in the 2013-2015 period, and 13 in the 2016-2018 period. Thus, preliminary evidence suggests that, in response to the industry-wide shock of 2015, Italian firms did not expand their M&A activity.

Figure 7: Mergers and Acquisitions

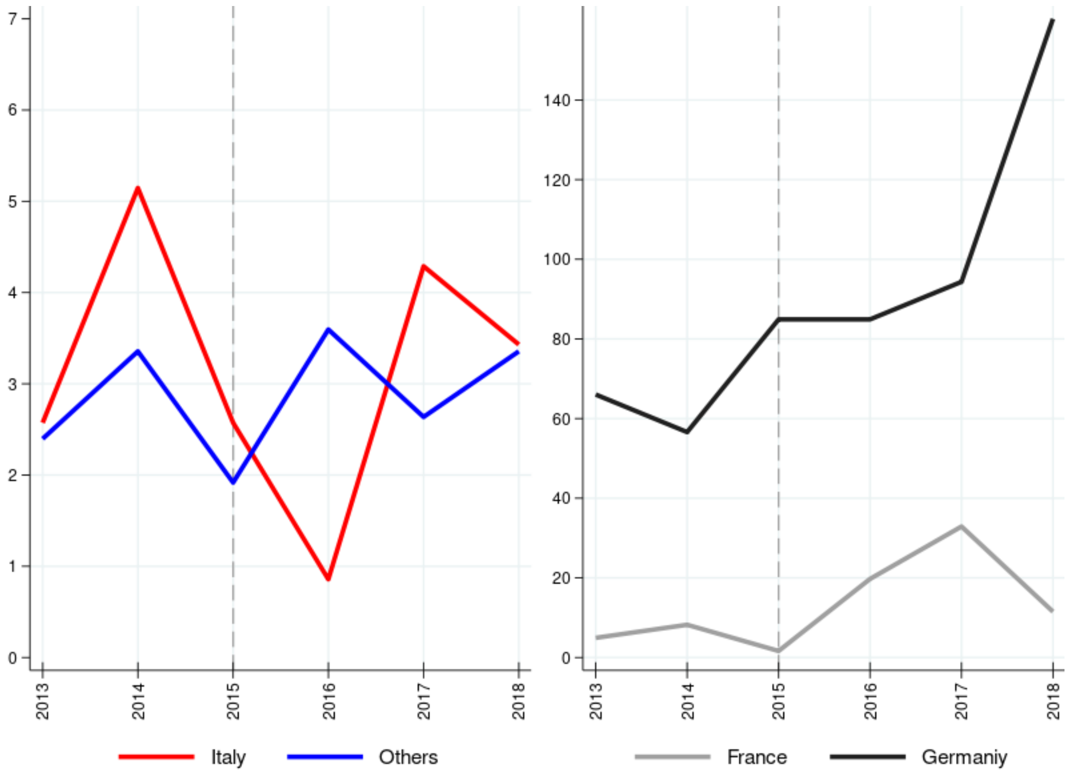


Source: Zephyr.
Notes: EU27 and United Kingdom. Number of deals by NACE Rev.2 29 firms (acquirers) over thousands of firms in the sector. Balanced sample.

Figure 8 shows a similar pattern by restricting the analysis to deals involving a target firm in a high-technology sector.[17] Additionally, the share of deals targeting firms outside the automotive sector remained below the European average. Finally, even though the portfolio of patents carried over by target firms to the acquirer increased in Italy in the 2016-2018 period with respect to the 2013-2015 period, Italian bidders increased on average their patent endowment by 3 patents per deal, against 9 in the rest of Europe, with German companies driving the higher European average.

[17] We include high-technology and medium-high technology sectors in manufacturing, and high-tech knowledge-intensive sectors in services according to the Eurostat classification.

Figure 8: Mergers and acquisitions (high-tech target)



Source: Zephyr.
Notes: EU27 and United Kingdom. Number of deals by NACE Rev.2 29 firms (acquirers) over thousands of firms in the sector. Balanced sample.

4.2. Regression analysis

4.2.1. The model

The empirical investigation is carried out through a series of different models using interactive fixed effects. We analyse both the extensive and the intensive margin of patenting and M&A activity, in order to test, in a *ceteris paribus* context, the different trends highlighted in the descriptive analysis. While the extensive margin decision focuses on whether or not to conduct innovation or M&A, the intensive margin decision determines firms' level of innovation or M&A (i.e. how much to innovate or how many companies to acquire).

On the extensive margin, we present first a pooled probit estimation and a fixed-effects model. Finally, we test the robustness of our main specification by using a pooled Heckman-corrected probit estimator to account for non-random sample selection due to a different propensity to patent. In fact, firms can use different ways to protect their innovation (e.g. trade secret). With the presence of nonpatented innovation, we would erroneously observe a similar outcome not only for firms that indeed do not pursue any innovation or do not achieve patent-worthy discoveries, but also for those that use alternative ways to protect their inventions. Therefore, we first model the propensity to patent to account for sample selection bias, then we regress the full corrected model.

By the same token, for the intensive margin, we present first a pooled Poisson estimation where the explained variable is a count variable, i.e. a variable of non-negative integer values. In fact, the usual normality assumption of linear models does not hold in a setting where the response variable is both right-skewed and has a mass probability at zero.[18] We then apply a Poisson fixed effects model. Lastly, we prove the robustness of the results by using a pooled Heckman-corrected Poisson model to account for sample selection.

Formally, the linear version of the model takes the form:

$$Y_{it} = \beta_1 Financials_{i,t-1} + \beta_2 Post2015_t + \gamma Ita * Post2015_{it} + \alpha_i + \varepsilon_{it}$$

where the outcome of interest (Y) of firm *i* and observed in year *t* is estimated as the combination of a vector of controls, including a vector of one-year lagged financial variables at the firm level ($Financials_{i,t-1}$). We also add firm fixed effects and the key interaction term γ between a dummy that is equal to one if the firm is Italian and another dummy for the years after the 2015 shock. The interaction term will allow us to test homogeneous period effects across firms (additive effects) against heterogeneous impacts.[19] Thus, the γ coefficient will test for any difference in the strategic behaviour of the Italian automotive firms with respect to the other European manufacturers in reaction to the 2015 shock. The vector of financial variables includes turnover growth rate, return on equity (ROE), asset tangibility and a liquidity measure. The remaining controls include firm size, age, a dummy equal to one if the company is publicly held and the number of priority patents before 2012. For each specification, the focus of the analysis is mainly on the interaction term γ. The probit and logit coefficients of the extensive margin cannot be directly interpreted as predicted probabilities, while the magnitudes of the Poisson coefficients in the intensive margin represent the marginal effects on the expected number of patents/acquisitions.[20]

[18] In the robustness checks at the end of this section, we also resort to simple linear models. Despite the Gauss Markov assumptions may be violated, signs and significance of the main coefficients (estimated by OLS) are similar to those of the main models.

[19] See Bai (2009) for panel data models with interactive effects.

[20] In the robustness checks, at the end of this Section, we report the post-estimated γ coefficients for the extensive margin, setting the other regressors at their mean values.

4.2.2. Results

The results of the estimations are largely in line with those of the descriptive analysis of Section 4.1. Italian firms in the automotive sector increased relatively more their internal R&D activity in the post 2015 period compared to other European manufacturers, although their R&D intensity remained lower.

Table 2 reports the results for the extensive margin of patenting. A base specification for the probability to patent is presented first, with *ad hoc* fixed effects concerning the size and the nationality of the firms and other time-invariant controls. Column 1 shows that the Italian automotive sector pursued a particular coping strategy, increasing the probability to patent in reaction to the 2015 shock. The interaction term, which is positive and significant (at the 1 per cent level), signals an increase in the likelihood to innovate and this coefficient is robust to the inclusion of size, age, past patenting behaviour (which are all highly statistically significant and positive) and listing status. Moreover, the "Post" dummy indicates that after 2015 the average European automotive company did not intensified its internal innovative effort. When we introduce in the pooled probit regression the financial controls (Column 2), we observe that patenting is positively influenced by turnover growth rate and negatively by the tangibility of firm's assets, signalling that an increasing share of tangible assets decreases the probability to be involved in patenting. The remaining controls are not significant at conventional levels. However, the inclusion of the whole set of financial variables does not alter the interaction term, which remains positive and significant. Lastly, we check if the change in the patenting behaviour of the Italian firms is specifically correlated to the decarbonisation impulse dictated by the 2015 shock. Column 3 replicates the full model including as dependent variable only priority patents devoted to the reduction of greenhouse gases (GHG). The findings reported in the previous columns are largely confirmed also for green patents: Italian companies had a significant change in the likelihood to become green innovators after 2015 and this effect is robust to the inclusions of financial variables and other controls. When all time invariant firm characteristics are directly taken into account with a fixed effect logit model (Columns 4-5), the probit results are confirmed for both sign and significance of the coefficients. The interaction coefficient turns out to be positive as in the previous estimates and statistically significant at the 5 per cent (in the most conservative estimate). None of the remaining explaining variables is significant at conventional level. The result also holds when we include the subset of GHG patents (Column 6), even if the significance level reduces to 10 per cent. Finally, the Heckman probit model (Columns 7-8) tests the robustness of the results to non-random sample selection. Column 7 estimates the full model for priority patents using a two-step approach, while Column 8 replicates the analysis for the subgroup of green patents. Sign and significance of the variables are comparable to those of the probit model with no sample correction (Column 2-3).

Table 2: Patents, extensive margin.

	Probit			FE Logit			Heck Probit	
	PT	PT	GPT	PT	PT	GPT	PT	GPT
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ita*Post	0.198***	0.151*	0.489**	0.680***	0.582**	1.437*	0.146**	0.489*
	[0.069]	[0.078]	[0.245]	[0.219]	[0.253]	[0.858]	[0.066]	[0.252]
Post	-0.011	-0.010	0.094*	-0.073	-0.047	0.559*	-0.016	0.105*
	[0.025]	[0.029]	[0.048]	[0.121]	[0.143]	[0.302]	[0.025]	[0.056]
Log change turnover$_{t-1}$		0.002**	0.002		0.003	0.002	0.002**	0.002
		[0.001]	[0.002]		[0.003]	[0.007]	[0.001]	[0.002]
ROE$_{t-1}$		-0.000	-0.002		-0.002	-0.000	0.000	-0.002
		[0.001]	[0.002]		[0.003]	[0.006]	[0.001]	[0.002]
Tangible assets$_{t-1}$		-0.017***	-0.022***		-0.004	0.025	-0.005***	-0.016***
		[0.002]	[0.003]		[0.012]	[0.026]	[0.002]	[0.004]
Liquidity ratio$_{t-1}$		0.002	-0.049		-0.179	-0.387	0.003	-0.069*
		[0.021]	[0.030]		[0.113]	[0.242]	[0.020]	[0.042]
Size	Yes	Yes	Yes	No	No	No	Yes	Yes
Age	Yes	Yes	Yes	No	No	No	Yes	Yes
Listed	Yes	Yes	Yes	No	No	No	Yes	Yes
Cumulative patent	Yes	Yes	Yes	No	No	No	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes	No	No
Sample correction	No	No	No	No	No	No	Yes	Yes
Observations	35,676	27,090	2,109	1,455	340	340	31,659	31,659
Pseudo R^2	0.184	0.208	0.00780	0.0101	0.0619	0.0600	.	.
Wald test indipendence	.		.	.	.	.	0.43	4.50**

(1)-(3) (7) (8) Standard errors clustered at firm level. (7)-(8) The selection equation regresses a dummy equal to one if the firm has ever applied for a patent on size, age and listing status. *** p<0.01, ** p<0.05, * p<0.1.

Table 3 models the intensity of patenting behaviour using a Poisson model. This analysis intends to study another dimension of the technological transition, namely, how many patents are produced. Patenting and innovation are not distributed at random, but they imply a systematic heterogeneity across firms with high persistence in innovation activity and the presence of *threshold effects* (Cefis, 2003). In fact, Pianeselli (2019) finds that large part of Italian innovation activity is clustered in a small group of good performers (usually large companies), endowed with a set of capabilities, skills and means to pursue innovation in good and bad times.

Columns 1-3 show the pooled Poisson estimation. The expected number of patents raises, *ceteris paribus*, by approximately 55 per cent more for Italian companies after 2015 with respect to the previous period. Despite the change in 2015, the Italian innovative activity was still less strong than in the other countries, as shown in the previous section. Still, the estimates are not statistically significant (Column 1-2).

Column 3 illustrates the effect of the intensive margin on the subset of GHG patents. Here, the positive effect of the interaction term is robust and statistically significant at the 1 per cent confidence level. The magnitude of the effect is larger than for the generality of priority patents: the coefficient implies that the post-2015 change in the expected number of Italian green patents was about 200 per cent higher, with respect to the pre-2015 period, all else remaining equal. Italian firms in the automotive sector tried to absorb part of the gap with the other European countries in green technologies by leveraging on their internal R&D. Columns 4–8 run the same regressions to test the stability of coefficients using a FE Poisson model and a Heckman-corrected Poisson model. Sign, significance and magnitude of the coefficients remain virtually unchanged for GHG patents while for overall patent activity the Heckman model produce a positive and highly significant coefficient for the interaction term.

We now test the alternative strategy toward to carbon-neutrality: the direct acquisition of the know-how and of new knowledge (tangible and intangible) through mergers and acquisitions (M&A). As in the previous analysis, we first test a base model. Then, we include also financial variables using probit and fixed effect logit models. Symmetrically to the patent analysis, we use as dependent variable a dummy for being an acquirer or not (extensive margin) and the number of acquisitions in each year (intensive margin). Moreover, we also restrict the sample to acquisitions of high-tech firms by using Eurostat indicators for high-tech industries and high-tech knowledge-intensive services. Despite this restriction may not be able to identify solely the “green” acquisitions within the sample, we exploit this proxy to better gauge the complexity and multifaceted aspects required by all the GHG technologies involved in the electric car.

Table 3: Patents, intensive margin.

	Poisson			FE Poisson			Heck Poisson	
	PT	PT	GPT	PT	PT	GPT	PT	GPT
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ita*Post	0.547	0.371	2.201***	0.529	0.376	2.141***	0.758***	1.471**
	[0.333]	[0.345]	[0.697]	[0.338]	[0.348]	[0.684]	[0.163]	[0.581]
Post	-0.044	0.006	0.039	0.093	0.105*	0.188*	-0.004	-0.039
	[0.066]	[0.059]	[0.120]	[0.057]	[0.057]	[0.107]	[0.027]	[0.055]
Log change turnover$_{t-1}$		-0.003	-0.009**		0.002	0.002		
		[0.004]	[0.004]		[0.002]	[0.002]		
ROE$_{t-1}$		0.000	0.005		0.001	-0.001		
		[0.004]	[0.005]		[0.001]	[0.002]		
Tangible assets$_{t-1}$		-0.018	-0.067***		0.002	0.040		
		[0.011]	[0.019]		[0.005]	[0.026]		
Liquidity ratio$_{t-1}$		-0.003	-0.037		-0.004	-0.084*		
		[0.107]	[0.210]		[0.019]	[0.044]		
Size	Yes	Yes	Yes	No	No	No	Yes	Yes
Age	Yes	Yes	Yes	No	No	No	Yes	Yes
Listed	Yes	Yes	Yes	No	No	No	Yes	Yes
Cumulative patent	Yes	Yes	Yes	No	No	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes	No	No
Sample correction	No	No	No	No	No	No	Yes	Yes
Observations	34,999	27,090	27,090	2,490	1,775	420	35,676	35,676
Pseudo R^2	0.477	0.484	0.775	.	.	.	.	.
Wald test indipendence	.		.	.	.	.	99.26***	5.34*

(1)-(3) (7) (8) Standard errors clustered at firm level. (4)-(6) Robust standard errors. (7)-(8) The selection equation regresses a dummy equal to one if the firm has ever applied for a patent on size, age and listing status. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 displays the extensive margin of M&A activity. Our focus is still on the interactive effect that describes the coping behaviour towards decarbonisation of Italian companies after 2015. After 2015, the probability to engage in an acquisition significantly decreases for the Italian automotive firms with respect to the previous period. This effect takes also in account the general trend of acquisitions in other countries, which is increasing and highly significant after 2015. However, the statistical significance of the interaction term is limited (at 10 per cent level) and appears only when the financial variable are included in the model. The FE logit model (Columns 4-5) substantially confirms the sign and significance of the coefficients. When we focus on the subset of high-tech M&A (Column 3 and 6), the coefficients are still negative, but the significance of the effects is limited by the smaller sample.

Table 4: Mergers and Acquisitions (M&A), extensive margin.

	RE Probit			FE Logit		
	M&A	M&A	HT M&A	M&A	M&A	HT M&A
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Ita*Post	-0.308	-0.384*	-0.352	-0.699	-0.833*	-0.731
	[0.191]	[0.209]	[0.265]	[0.430]	[0.483]	[0.584]
Post	0.244***	0.231**	0.135	0.543***	0.631***	0.433*
	[0.082]	[0.095]	[0.120]	[0.168]	[0.206]	[0.247]
Log change turnover$_{t-1}$		0.001	0.003		-0.007	-0.001
		[0.002]	[0.003]		[0.005]	[0.007]
ROE$_{t-1}$		0.001	0.001		0.000	0.005
		[0.002]	[0.002]		[0.006]	[0.007]
Tangible assets$_{t-1}$		-0.038***	-0.039***		0.034	0.042
		[0.004]	[0.004]		[0.025]	[0.031]
Liquidity ratio$_{t-1}$		0.133***	0.160***		0.237*	0.203
		[0.032]	[0.037]		[0.136]	[0.173]
Size	Yes	Yes	Yes	No	No	No
Age	Yes	Yes	Yes	No	No	No
Listed	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Observations	35,676	27,090	27,090	894	630	415

(1)-(3) Standard errors clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

Lastly, we test the M&A behaviour of firms at the intensive margin. Table 5 fits a pooled Poisson model and then a FE Poisson model to account for the time-invariant unobservable characteristics of the firms. Pooled regressions (Columns 1-3) and FE regressions (Columns 4-6) confirm the distinctive trajectory chosen by the Italian automotive firms, also on the intensive margin. While the post-2015 coefficient is positive and significant, showing that the expected number of acquisitions generally increased for the average firm, the magnitude and significance of the interaction term shows how the chance of repeated deals almost dried up after 2015 for Italian companies. The marginal effect of post-2015 change is sizeable, from about 73 to about 95 per cent reduction with respect to the other European firms. The results are also robust to the inclusion of the financial variables in the model.

Table 5: Mergers and Acquisitions (M&A), intensive margin

	Poisson			FE Poisson		
	M&A	M&A	HT M&A	M&A	M&A	HT M&A
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Ita*Post	-0.735**	-0.810**	-0.942**	-0.735**	-0.778**	-0.788*
	[0.320]	[0.353]	[0.427]	[0.320]	[0.358]	[0.446]
Post	0.553***	0.457***	0.516***	0.553***	0.564***	0.610***
	[0.139]	[0.147]	[0.193]	[0.139]	[0.148]	[0.196]
Log change turnover$_{t-1}$		0.005	0.009**		-0.007	-0.002
		[0.004]	[0.004]		[0.004]	[0.006]
ROE$_{t-1}$		0.003	0.004		0.002	0.008
		[0.003]	[0.003]		[0.005]	[0.005]
Tangible assets$_{t-1}$		-0.069***	-0.075***		0.032*	0.042**
		[0.007]	[0.008]		[0.018]	[0.020]
Liquidity ratio$_{t-1}$		0.188***	0.238***		0.148	0.115
		[0.066]	[0.077]		[0.096]	[0.135]
Size	Yes	Yes	Yes	No	No	No
Age	Yes	Yes	Yes	No	No	No
Listed	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Observations	35,676	27,090	27,090	900	650	420

(1)-(3) Standard errors clustered at the firm level. *** p<0.01 ** p<0.05 * p<0.1.

4.2.3. Robustness checks

In this section, we test the robustness of our results to different model specifications. We post-estimate the probabilities of the fixed effect logit models (setting the predictors at mean values) comparing the estimates with a simple linear model. While modelling the extensive margin by a linear probability model (henceforth LPM) may produce inconsistencies and biases, in particular when fitted values fall outside the unit interval, the estimator provide a simple linear approximation of the non-linear response for values of the independent variables close to the centre of the sample (Wooldridge, 2010). Moreover, we test the robustness of the effect of our full model (hereafter benchmark) to the inclusion of additional financial ratios, not included in the previous regressions, covering profitability, liquidity and capital structure.

In Table 6, we report only the coefficient of interest (the interaction term). For Model 1, the extensive margin of patenting, sign and statistical significance of the LPM (Column 1) are comparable to the one we estimated in Table 2 using non-linear models. However, the predicted increase in the probability of patenting by Italian firms increases only by 1 per cent in the post 2015 period. In addition, the weighted least square regression (Column 2), which assigns different weights to the observations, does not change the magnitude of the estimate. Yet, when we measure the marginal effect of the more robust fixed effect logit model (Column 3), we obtain a 15 per cent increase in the probability to engage in patented innovation after 2015 for the Italian firms. The effect is significant both in statistical and economic terms. Column 4 shows the post-estimated coefficient of the interaction term of our benchmark regression (as in Table 2 – Column 5). The analysis confirms that the change, with respect to the previous period, is still sizeable (14 per cent increase) and statistically significant. Columns 5-14 include each one additional financial indicator to the benchmark model, showing sign and statistical significance of the coefficients. The post-estimated interaction term remains significant and similar to the one in Column 3 or 4, while the controls do not have any statistically significant effect at conventional levels.

Similarly, in Model 2, we measure the intensity of the marginal change in the post-2015 number of patents. Despite the normality assumption is violated due to the corner solution (at zero) of the outcome variable, the interaction coefficients of the linear specifications (Columns 1-2) are positive, but not statistical significant at conventional levels, as in the base fixed effect Poisson specification (Column 3) and in our benchmark regression (Columns 4). Furthermore, the inclusion of other financial ratios (Columns 5-14) does not modify sign and significance of the results.

Model 3 shows the extensive margin of M&A activity. While the sign and significance are similar throughout all models, the estimated marginal effects are weak for the models that do not include firm fixed effects. Conversely, our fixed effect model without financial variables (Column 3) predicts a significant post-2015 decrease of 17 per cent in the probability for an Italian firm to engage in M&As. When we include the set of financial controls of the benchmark model, the negative effect reduces to 5 per cent (significant at 10 per cent level). The other financial variables do not affect the estimate and are not statistically significant.

Model 4 studies the intensive margin of M&A activity. Columns 1-2 show a negative and significant effect of the interaction term, as in Table 5. The magnitude of the effects is however limited. When we take into account non-normality of the dependent variable and non-observable time-invariant firm characteristics the effects are sizeable (Columns 3-4) and robust to the inclusion of the other financial variables (Columns 5-14).

Finally, we test the robustness of the estimates to different sample compositions to check if the significant effects revealed by our analysis may be driven by a particular subsample of firms. In Table 7, we first exclude from our sample all large car makers according to the categorical classification of the European Commission (Panel A). Then, within those large firms, we exclude only the ones that belong to the third and fourth quartile of the distribution of the turnover (Panel B). In the table, we report the interaction term of our benchmark models, as previously described, both for the extensive and intensive margin. Signs and significances remain virtually unchanged for patent activity, while in most of the cases the effects are slightly stronger for M&A deals. Table 8 shows the results of our benchmark models, broken down by firm size. The behavior of small and medium sized Italian firms is similar to the overall sample of firms, but it is not anymore statistically significant at conventional levels (Panel A). However, when we test the subsample of large companies, sign and significance of the results are substantially confirmed, showing how the effect is mostly concentrated among those companies with the potential to plan and carry out patenting and acquisitions more easily.

Overall, the analysis confirms the hypothesis of a distinct trajectory of the Italian firms in the automotive sector to cope with the 2015 market shock. The additive and interactive effects indicate that the Italian sector is undertaking a path that is both distinct to its immediate past of the “pre-2015 era” and alternative to the one chosen by the other of European automotive companies. Results are robust to different model specifications, sample compositions and to the presence of relevant outliers. The concluding section will discuss the implications of these results for the Italian productive system and possible lines for future research.

Table 6: Robustness checks. Model specification analysis

Patent extensive margin

		(1) LPM	(2) WOLS	(3) FE LOGIT	(4) BENCHMARK Turnover growth	ROE	Tangibility	Liquidity ratio	(5) ROA	(6) EBITDA	(7) Leverage	(8) Solvency ratio	(9) Debt ratio	(10) Interest coverage ratio	(11) Current ratio	(12) Cash total assets	(13) Cash ratio	(14) Cash flow
Model (1)	Ita*Post	.011***	.030***	.153***	.141**				.141**	.139**	.132**	.140**	.130**	.123**	.137**	.128**	.130**	.140**
	$balsheet_{t-1}$				(+)	(-)	(-)	(-)	(+)	(+)	(+)	(-)	(-)	(-)	(+)	(+)	(+)	(+)
	N	35,676	34,530	2,109	1,455				1,455	1,431	1,383	1,455	1,383	1,400	1,455	1,412	1,412	1,431

Patent intensive margin

		(1) OLS	(2) WOLS	(3) FE POISSON	(4) BENCHMARK Turnover growth	ROE	Tangibility	Liquidity ratio	(5) ROA	(6) EBITDA	(7) Leverage	(8) Solvency ratio	(9) Debt ratio	(10) Interest coverage ratio	(11) Current ratio	(12) Cash total assets	(13) Cash ratio	(14) Cash flow
Model (2)	Ita*Post	0.015	0.120	0.529	0.376				0.373	0.36	0.323	0.364	0.327	0.344	0.372	0.386	0.402	0.351
	$balsheet_{t-1}$				(+)	(+)	(+)	(-)	(-)	(-)	(-)	(+)	(-)	(+)	(+)	(+)	(+)	(-)
	N	34,999	33,860	2,490	1,775				1,775	1,739	1,696	1,775	1,696	1,705	1,775	1,726	1,726	1,739

M&A extensive margin

		(1) LPM	(2) WOLS	(3) FE LOGIT	(4) BENCHMARK Turnover growth	ROE	Tangibility	Liquidity ratio	(5) ROA	(6) EBITDA	(7) Leverage	(8) Solvency ratio	(9) Debt ratio	(10) Interest coverage ratio	(11) Current ratio	(12) Cash total assets	(13) Cash ratio	(14) Cash flow
Model (3)	Ita*Post	-.003**	-0.009*	-.170***	-0.047*				-0.043*	-0.050*	-0.087*	-0.031*	-0.155*	-0.075*	-0.048*	-0.062*	-0.055*	-0.037*
	$balsheet_{t-1}$				(-)	(+)	(+)	(+)*	(+)	(+)	(-)	(+)	(-)	(-)	(+)	(+)	(+)	(+)
	N	35,676	34,530	894	630				630	605	596	630	596	584	630	627	627	600

M&A intensive margin

		(1) OLS	(2) WOLS	(3) FE POISSON	(4) BENCHMARK Turnover growth	ROE	Tangibility	Liquidity ratio	(5) ROA	(6) EBITDA	(7) Leverage	(8) Solvency ratio	(9) Debt ratio	(10) Interest coverage ratio	(11) Current ratio	(12) Cash total assets	(13) Cash ratio	(14) Cash flow
Model (4)	Ita*Post	-.006***	-.029***	-.735**	-.778**				-.751**	-.794**	-.795**	-.764**	-.808**	-.861**	-.782**	-.775**	-.781**	-.817**
	$balsheet_{t-1}$				(-)	(+)	(+)*	(+)	(+)	(+)	(-)	(+)***	(-)	(-)	(+)	(+)*	(+)	(+)
	N	35,676	54264	900	650				650	625	619	650	619	604	650	647	647	620

(2) Observations are weighted by the logarithm of total assets as of 2012. Frequency weights. * p<0.10, **p<0.05, ***p<0.01.

Table 7: Robustness checks. Large and top car makers subsample

	(A) Without large car makers (1)				(B) Without top car makers (2)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pat. ext.	Pat. int.	M&A ext.	M&A int.	Pat. ext.	Pat. int.	M&A ext.	M&A int.
Ita*Post	.530**	0.069	-1.10**	-.807**	.585**	0.088	-1.02**	-.771**
N	1,365	1,605	540	555	1,425	1,685	560	575

Benchmark models. (1) - This subsample excludes all car makers (Nace Rev. 2 class 29.10) of large size (according to the European Commission Recommendation 2003/361). (2) - This subsample exclude only the top (turnover above the median as of 2015) car makers (Nace Rev. 2 class 29.10) within the large size class (according to the European Commission Recommendation 2003/361). * p<0.10, **p<0.05, ***p<0.01.

Table 8: Robustness checks. SME and Large firms subsample

	(A) SME (1)				(B) Large firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pat. ext.	Pat. int.	M&A ext.	M&A int.	Pat. ext.	Pat. int.	M&A ext.	M&A int.
Ita*Post	0.292	0.184	-0.911	-0.470	1.26***	0.523	-0.712	-.823**
N	1,020	1,115	270	270	435	660	360	380

Benchmark models. To define the size of a firm we use the criteria of the European Commission (Recommendation 2003/361) (1) - We include micro, small and medium firms. * p<0.10, **p<0.05, ***p<0.01.

5. Discussion and conclusion

In this exploratory analysis, we documented the strategic behaviour of the European firms in the automotive industry in reaction to the 2015 shocks. The main events described in the paper generated the largest industry-wide shock in the history of this sector, dictating a rapid redirection from “dirty” internal combustion engines towards “clean” electric technologies. Following the literature, we looked into two strategies to realize the “green” transition. Firms can either intensify their internal R&D activity to preserve their competitive advantage or gain access to a new knowledge through mergers and acquisitions. By constructing a novel dataset that combines patent and M&A data, we have been able to measure firm-level innovation efforts and to test the existence of different paths between Italian and other European firms.

Descriptive evidence showed that before 2015 Italian automotive firms exhibit a significant gap on the development of green technologies with respect to firms in other European countries. After 2015, Italian companies intensified their internal R&D, devoted both to general and green innovations, more than the rest of Europe, while still not bridging the gap with the main European producers. At the same time, Italian firms resorted to mergers and acquisitions less than their European counterparts. The regression analysis confirmed this evidence. The Italian automotive sector followed a path that is both distinct to its immediate past of the "pre-2015 era" and alternative to the one chosen by the other European automotive companies. With respect to their European competitors, Italian automotive companies significantly increased the innovative efforts as a reaction to the green shock, but were not able to speed up the technological transition via acquisition of existing competences and technologies in the market.

On the one hand, our analysis highlighted that the post-2015 likelihood to conduct innovation increased for the cohort of Italian companies by around 14 per cent with respect to the other European firms. This result is robust to the inclusion of a large set of firms' characteristics, financial variables and time-invariant fixed effects. In particular, financial ratios covering firms' growth, profitability, liquidity and capital structure are not able alone to explain the diverse outcome for the Italian automotive sector. The results still hold when we focus on the subset of green patent applications. The extensive margin of Italian green innovators partially increased after the 2015 shock. Looking instead at the intensive margin, proxying the level and depth of patent innovation, we obtain different insights. After 2015, the smaller cohort of persistent Italian innovators, those with the skills to manage the complexity of carbon-neutral innovations, prioritized their efforts mainly on developing green technologies. While there is not a significant diversity in patent applications between Italian automotive companies and its European competitors at the aggregate level, we observe a major post-2015 increase in the expected number of Italian green inventions with respect to the pre-2015 period, all else remaining equal.

On the other hand, after 2015, the probability to engage in an M&A for the Italian automotive firms decreased with respect to the other European companies by 17 per cent in the fixed effects specification without financial controls and by 5 per cent when these effects are included. The fact that the financial variables and other controls only partially affect the estimates indicates how this strategic choice does not depend exclusively on the financial soundness of the Italian firms. Moreover, the effects are stronger when we look at the intensive margin. The chance of repeated deals from Italian bidders almost dried up after 2015. In comparison to their European competitors, the marginal effect is sizeable (a reduction of about 70 per cent, in the most conservative estimate) and the negative effect is even stronger for high-tech acquisitions. The Italian automotive sector was virtually cut out from the highly competitive acquisition wave fuelled by the intense demand for green technology.

These findings raise doubts on the effectiveness of the Italian automotive sector in managing the rapid transition to low emission cars required by European regulations. While the main European competitors appear now to be actively involved in the race for taking a hold on the key green technologies throughout acquisitions, Italian producers are lagging behind, still involved in the preliminary step of improving their internal innovative capacity.

Our results could also be useful to inform the design of public policy intervention. On the one hand, programs designed to subsidize consumers to buy low-emissions cars will probably benefit companies that lead the race in the green transition, and not those lagging behind. Therefore, a swift technological change by the Italian firms in the automotive industry is required if they want to reap the benefits of present and future demand-side policies in Italy and in the rest of Europe.[21] On the other hand, also tax schemes directly supporting companies in green R&D may be a sub-optimal response in the present context. In fact, when the green production capabilities are weak, the internal development of complex green technologies may be difficult or take a considerable amount of time.[22] Thus, policy measure aiming to support collaborations and mergers and

[21] Starting from 2019, Italian government launched and renewed a wide incentives program (the so called "Ecobonus") to sustain the replacement of polluting models with electric vehicles. Purchase grants directed to consumer and commercial vehicles were also coupled with fiscal benefits directed to wave or reduce ownership taxes of electric vehicles and deduct the costs of their charging structures.

[22] General R&D tax credit varied significantly in Italy in the recent years as a result of several amendments, shifting from the incremental R&D tax credit, towards the volume-based tax relief, introduced in 2020. Additionally, the special fiscal regime connected to the direct and indirect use of intangible assets (the so called "Patent box"), introduced in Italy in 2014 with a 50 per cent tax exemption to the related profits, has been recently modified towards a cost-based incentive scheme with 190% extra-deduction of qualifying expenditures. Overall, R&D tax support in Italy markedly increased after 2015, but, in 2019, it placed just below the OECD average in terms of total government support to business R&D (OECD, 2021).

acquisitions between firms might be more effective than other policies in timely converting the Italian automotive sector to the new green paradigm. [23]

Finally, several factors may explain the different patterns among European automotive firms. For instance, the limited number of domestic high-tech firms operating in key green sectors, the prevalence of family-run businesses (usually reluctant to extraordinary finance operations) and, lastly, the limited access to international bond markets may play a role in hindering a secure and fast sustainable transition. The use of the novel dataset presented here may also contribute to test some of these hypotheses. Yet, all these issues are beyond the scope of the present analysis and we leave them to future research.

[23] As of 2022, Italy has introduced two main incentive schemes for business combinations and acquisition of innovative assets. The so-called "Bonus Aggregazioni", re-introduced with the Law Decree 34/2019 and subsequent amendments, grants tax credit, up to a maximum of € 5 million to companies resulting from mergers, demergers and business contributions. Even equity investment in innovative startups and small and medium enterprises (SMEs) are entitled to a deduction of Italian corporate tax (IRES). Starting from the year 2017, Italian companies benefited from tax deduction of 30 per cent up to € 1.8m for each fiscal year. The Law Decree 145/2018 increased the tax relief to 50 per cent in case of companies acquiring the entire share capital of innovative startups and SMEs, but the provision never entered into force due to the lack of authorization by the European Commission.

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