Oldenburg Discussion Papers in Business Administration and Business Education

Breaking The ICE? The Impact of Demand-Pull and Technology-Push Policies on Technology Decline in Incumbent Firms

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Discussion Paper B-002-24

June 6th, 2024

Abstract

As sustainability challenges like climate change intensify, pressure grows to transition away from unsustainable technologies like internal combustion engine (ICE) vehicles. However, the impact of policies to foster innovation in emerging technologies, such as technology-push and demand-pull measures for electric vehicles (EVs), on the decline of incumbent technologies like ICE vehicles has so far received little attention. This paper addresses this knowledge gap by investigating whether innovation policies promoting an emerging technology reduce firms' innovation activities in the incumbent technology. Three hypotheses are derived and empirically tested in the automotive industry using data on 29 automakers between 2009 and 2020. We find robust evidence that demand-pull policies and their interaction with technology-push policies contribute to technology decline by inducing firms to reduce innovation activities in the incumbent technology. In contrast, we find some evidence that technology-push policies may not discourage firms from continuing innovation activities in the incumbent technology. These findings contribute to the literature on technology decline, innovation policy, and sustainability transitions and have important implications for addressing global sustainability challenges.

Keywords: Demand-pull; Technology-push; Policy mix; Technology decline; Incumbent adaptation; Electric vehicles

1 Introduction

The urgency of the climate crisis is forcing countries worldwide to reassess the technologies they use and find ways to reduce greenhouse gas emissions. One major challenge is substituting technologies based on fossil fuels (e.g., internal combustion engine (ICE) vehicles) with others that are more environmentally friendly, such as electric vehicles (EVs). Against this background, it is unsurprising that in recent years, the topic of technology decline has received increased attention from practitioners and academics alike. Studies in this field seek to understand how different drivers (e.g., public policies) shape decline to derive recommendations for how to most effectively transition industries or entire economies toward environmentally benign, low-carbon technologies (Bento et al., 2021; Rosenbloom and Rinscheid, 2020; Trencher et al., 2022).

Interestingly, while evidence of the drivers of technology decline is accumulating, thus far, studies seeking to understand the impact of public policies on decline have primarily focused on the impact of instruments for deliberate technology decline, such as phase-out policies in the form of prospective sales bans (Rinscheid et al., 2022; Rosenbloom and Rinscheid, 2020). At the same time, we currently lack insights into how policy instruments that are primarily targeted at fostering innovation in emerging technologies, such as technology-push and demand-pull policies, shape technology decline. Demand-pull policies stimulate demand for new technologies, for instance, via purchase grants for consumers (e.g., Peters et al., 2012), while technology-push policies foster the supply of new technologies, such as by reducing the cost of research and development (R&D) (e.g., Nemet, 2009). The impact of demand-pull and technology-push policies on innovation in new technologies has been extensively analyzed (Ghisetti, 2017; Hoppmann et al., 2013; Luetkehaus, 2024; Plank and Doblinger, 2018). However, although it has been suggested that the same policy mix could simultaneously stimulate the "creation" of a technological innovation system (TIS) around an emerging technology and the "destruction" of the incumbent technology's TIS (Kivimaa and Kern, 2016), we currently lack empirical studies on the impact of innovation policies on incumbent technologies.

The lack of insights into the impact of innovation policies on technology decline is surprising, given that innovation policies have been used extensively by policymakers around the world to foster innovation in different technologies. Given their widespread use, understanding how different innovation policies influence the decline of environmentally inferior technologies is important to design policy mixes in a way that accelerates the ongoing transition toward sustainability. Specifically, if, in addition to fostering the diffusion and innovation of novel technologies, a specific policy instrument fosters the decline of incumbent technologies, such an instrument can be considered superior to one that does not since this will free up market space for the emergent technology, speed up technology substitution, and reduce incumbents' resistance to change.

In this paper, we argue that demand-pull and technology-push policies influence not only the emergent but also the incumbent technology. For instance, demand-pull policies create markets for not-yet-competitive technologies, leading to new business opportunities for firms, thereby potentially encouraging them to pursue a new technology path and abandon the incumbent technology, hence supporting the latter's decline (e.g., Di Stefano et al., 2012). In general, firms may alter their resource allocation between established and emergent technologies in response to policy-induced changes in market and knowledge conditions. Therefore, by studying the impact of policies at the firm level, in this paper, we investigate *whether innovation policies promoting alternative technologies influence firms' innovation activities in incumbent technology*.

We investigate our research question through quantitative Poisson regression analysis and set our study in the automotive industry using a sample of 29 publicly listed automotive original equipment manufacturers (OEMs) between 2009 and 2020. Our findings show that demand-pull policies induce firms to reduce innovation activities in incumbent technology, thus contributing to its decline. Moreover, our findings indicate that there is a significant interaction between technology-push and demand-pull policies that yields synergies for incumbent technology decline. However, we also provide some evidence suggesting that technology-push policies may inhibit this decline. While our findings regarding demand-pull policies and their interaction with technology-push policies are robust, our findings regarding technology-push policies are significant only in some models.

Our study makes three contributions to the literature on technology decline, innovation policy, and sustainability transitions. First, we show that demand-pull policies and technology-push policies are not only instruments to support emergent technology in niches (Kivimaa and Kern, 2016) but potentially also instruments that lead to technology decline by inducing firms to reduce innovation activities in the incumbent technology. This suggests that to understand the full impact of innovation policies on technological change, one must study their impact on both emerging and incumbent technologies. Second, we add to the literature on innovation policy and transitions by showing that the effect of technology-push policies on firms' innovation activities may be ambiguous and dependent on the complementary use of demand-pull policies. Third, we provide evidence that the joint use of technology-push and demand-pull policies is better suited to persuading firms to withdraw from incumbent technology than either of them individually. In combining both policy types, technology-push policies create technological variety and increase the availability of knowledge about emerging technologies to firms, while demand-pull policies help to put market dynamics into play.

2 Literature Review and Hypotheses

2.1 Innovation Policy and Firms' Incumbent Technology Strategies

Innovation policies, such as demand-pull and technology-push policies, spur the development of new technologies (Costantini et al., 2017; Peters et al., 2012). When new technologies disrupt incumbent technologies, innovation policies may also lead to the decline of incumbent technologies. In the following, we elaborate on disruptive technologies and how incumbents might embrace them by altering their innovation strategies. Subsequently, we discuss and derive hypotheses on how demand-pull and technology-push policies favor different strategic responses by firms due to their respective mechanisms for promoting innovation.

Disruptive technologies simultaneously threaten firms and present them with long-term market opportunities should they pursue emergent technologies (Cooper and Smith, 1992; Hill and Rothaermel, 2003; Jiang et al., 2011; Tripsas, 1997). However, a core problem in responding to technology disruption is that it is usually uncertain whether technological substitution will occur and at what pace (Cooper and Smith, 1992; Furr and Snow, 2015). In the case of potentially disruptive innovations, the new technology initially offers new features that might appeal to niche markets but demonstrate inferior performance in key attributes valued by mainstream customers, have a higher price, or both (Adner, 2002; Govindarajan and Kopalle, 2006). For example, initially, EVs outperformed ICE vehicles on tailpipe emissions but had higher purchase prices and inferior performance in driving range and complementary infrastructure (Bohnsack and Pinkse, 2017). For the threat of technological substitution to become a reality, subsequent technological developments must improve the performance of initially inferior attributes to a level that satisfies the needs of mainstream customers at a competitive price (Adner, 2002; Govindarajan and Kopalle, 2006).

Previous research has shown that firms active in the incumbent technology respond to the threat of technological substitution by altering their innovation strategy in the incumbent technology in one of two ways: through (1) elevation or (2) withdrawal. Through *elevation*, firms aim to elevate the incumbent technology's performance by increasing their innovation activity. In this way, they try to stay ahead of firms pursuing the emerging technology in a performance race that could delay or entirely prevent technological substitution (Adner and Kapoor, 2016; Adner and Snow, 2010; Sarkar et al., 2018). For example, in the automotive case, an elevating strategy would increase innovation efforts to reduce the tailpipe emissions of ICE vehicles to counter the value proposition of EVs and to manufacture larger vehicles competitively to make it harder for EV manufacturers to achieve long driving ranges at competitive prices as large EV vehicles are heavier and require costlier batteries. In a *withdrawal* strategy, firms reduce innovation activity in the incumbent technology and reallocate resources from related innovation activities. This may be part of a deliberate market exit anticipating future challenges (e.g., to compete in the market) spurred by the upcoming technology (Howells, 2002). However, the most common form of this approach is arguably an exit from the older technology as part of a reorientation toward the new technology.

These two strategies can be perceived as the endpoints of a continuum along which firms active in the incumbent technology can combine elements of both to pursue hybrid strategies. For example, firms attempting to improve the performance of the incumbent technology (elevation) may reduce innovation in aspects of the older technology (withdrawal strategy) to introduce "intergenerational hybrids." Such hybrids are products based on the incumbent technology that integrate features from the emerging technology that substantially improve performance in key attributes, for example, hybrid vehicles that can run on fossil fuels and electricity (Ansari and Garud, 2009; Bergek et al., 2013; Furr and Snow, 2015). Hybrid strategies allow firms to maintain existing capabilities while learning about the emerging technology, facilitating a switch further down the line (Furr and Snow, 2015). Their implications for firms' overall innovation activity in the incumbent technology are mixed. Some hybrid strategies might require firms to increase overall innovation in the incumbent technology to integrate the new features (Bergek et al., 2013), while others may allow firms to focus efforts on a few subfields and reduce overall innovation activity in the incumbent technology (Aghion et al., 2016).

Firms need to continuously adapt their strategy choices to align with changing environmental conditions, such as the pace and likelihood of technological substitution (Bidmon and Bohnsack, 2019; Furr and Snow, 2015; Sick et al., 2016; Song and Aaldering, 2019). As a result, it seems plausible that technology-push and demand-pull policies could influence firms' positioning on the strategy continuum. Both policies accelerate the development of alternative technologies (e.g., Costantini et al., 2017; Hille et al., 2020; Johnstone et al., 2010; Peters et al., 2012), thereby spurring incumbent firms to respond to the threat of substitution. However, technology-push and demand-pull policies rely on two distinct mechanisms of technology change (Di Stefano et al., 2012; Dosi, 1982; Mowery and Rosenberg, 1979); therefore, they might incentivize different responses by firms active in incumbent technologies.

In the following section, we elaborate on the mechanisms of each innovation policy type and derive hypotheses regarding how they influence firms' innovation activity in incumbent technology. In outlining our hypotheses, we structure our line of reasoning along three dimensions: (1) resources, (2) market, and (3) technology. Here, 'resources' refers to how innovation policies shape firm-internal resources. The second dimension, "market," describes how innovation policies influence market dynamics for firms. Finally, the "technology" dimension explains how innovation policies shape technological developments in firms.

2.2 The Role of Technology-Push Policies in Firms' Incumbent Technology Strategy

Technology-push policies aim to foster the emergence of new technologies by increasing the knowledge supply in at least two ways, including broadening and deepening knowledge within firms. Technology-push policies have been shown to broaden firms' search for technological opportunities, contributing to technological variety and even creating new technological trajectories (Di Stefano et al., 2012; Dosi, 1982; Freeman, 1996). For example, funds deployed to universities and public institutions through technology-push policies build up public knowledge about a technology, which, in turn, can be absorbed by private firms (Audretsch and Link, 2019; Becker, 2015; Koch and Simmler, 2020; Szücs, 2018). In addition, technology-push policies reduce the private cost of R&D and induce firms to accelerate innovation (Nemet, 2009), particularly encouraging more basic research and riskier innovations (Beck et al., 2016; Plank and Doblinger, 2018), which deepens their knowledge of current technologies. These two mechanisms play out across the three different dimensions – resources, market, and technology – and influence firms' responses to the threat of technology substitution.

Resources. Faced with a substitution threat, firms have an interest in participating in the new technology as a precaution (Cooper and Smith, 1992). However, simultaneously exploring new technologies while continuing to exploit existing ones increases resource-allocation tensions within firms because both efforts draw from the same pool of resources (Lavie et al., 2010; March, 1991). This changes if technology-push policies provide firms with additional resources. In that case, firms can use the additional resources to broaden their knowledge and gain competencies in the new technology without reducing their allocation of internal resources to the incumbent technology. Therefore, technology-push policies that provide additional resources might reduce resource-allocation tensions within firms and encourage them to continue allocating resources to the incumbent technology at existing or increased levels.

Market. Technology-push policies tend to have little direct impact on market conditions or adoption challenges (Adner and Kapoor, 2016; Nemet, 2009). Although the new technologies that policymakers support through technology-push policies may eventually disrupt entire industries, it often takes decades for a new technology to move from its first application to commercialization and early adoption (Bento and Wilson, 2016). Therefore, we argue that technology-push policies do not directly incentivize firms facing a substitution threat to switch to new technologies (Dosi, 1982). Instead, firms active in the incumbent technology may continue to invest in it to increase the barriers to entering the market for the new technology (Adner and Kapoor, 2016; Adner and Snow, 2010).

Technology. As mentioned, technology-push policies can encourage firms to broaden their knowledge, learn about new technologies, and develop related capabilities. When faced with the threat of substitution, these capabilities facilitate the integration of features of the new technology into the incumbent one to achieve performance improvements, for example, through intergenerational hybrids (Furr and Snow, 2015). However, to successfully integrate these new features, firms may need to deepen their knowledge of aspects of the incumbent technology and increase their innovation activity (Bergek et al., 2013; Furr and Snow, 2015). In this way, firms compete to maintain the incumbent technology's dominance by improving it (Adner and Kapoor, 2016). In turn, this raises the bar for the mass adoption of the new technology (Adner and Snow, 2010) and makes it more difficult for the new technology to become competitive through economies of scale and learning by doing (Hoppmann et al., 2013; Sagar and van der Zwaan, 2006).

Based on these considerations across resources, market, and technology dimensions, we propose the following hypothesis:

> *H1: The stronger the technology-push policy for alternative technologies is, the higher firms' innovation activities are in the incumbent technology.*

2.3 The Role of Demand-Pull Policies in Firms' Incumbent Technology Strategies

Demand-pull policies aim to foster the emergence of new technologies by stimulating demand for them. With instruments such as tax credits, purchase grants, public procurement, or disincentives for incumbent technologies, demand-pull policies try to increase demand for the new technologies despite their lower performance or lack of competitiveness (Dechezleprêtre and Glachant, 2014; Nemet, 2009; Peters et al., 2012). These interventions influence the resources, market, and technology conditions that firms face, leading them to adjust their technology strategies in response (Aghion et al., 2016; Barbieri, 2016; Popp and Newell, 2012).

Resources. Demand-pull policies might increase tensions within firms around allocating resources between incumbent and new technologies. Although sales induced by demand-pull policies could increase the revenues of firms that commercialize the new technology, augmenting their available resources for innovation activities (Hoppmann et al., 2013), this is not necessarily true for firms active in the incumbent technology. First, the new product's profit margin is often initially smaller than the margin for products based on the incumbent technology. For example, most EV models were reported to have negative profit margins in 2018 (Hertzke et al., 2019). Second, new product sales often do not add to but rather cannibalize the sales of products based on the incumbent technology. For instance, drivers may buy an EV *instead of* an ICE car, but they may not buy an EV *and* an ICE vehicle. Therefore, when a new product with lower profit margins is substituted for products based on the incumbent technology, demand-pull policies might increase tensions around resource allocation within firms and lead to less innovation activity in the incumbent technology.

Market. Demand-pull policies create market dynamics that may lead firms to face a concrete substitution threat and choose a withdrawal strategy. Initially, policy support enhances market opportunities for the new technology, increasing entrepreneurial activity (Hoppmann and Vermeer, 2020) and the viability of early movers' entry into the new technology (Wesseling et al., 2015b). As increased demand leads to market diffusion of the new technology, firms begin to benefit from economies of scale and learning by doing, which often triggers considerable cost reductions (Hoppmann et al., 2013). This feedback loop accelerates the progress of the new technology toward price competitiveness and renders the threat of substitution even more acute, increasing the pressure on firms to switch to the new technology. In line with this, Popp and Newell (2012) found that alternative energy patents crowd out other patents of multi-technology firms in the energy industry and suggested that this is a response to changing market opportunities.

Technology. Demand-pull policies for alternative technologies set several incentives for firms to withdraw from the incumbent technology. Policy support for an emergent technology is a powerful signal to firms that shapes expectations regarding future market developments (Nemet, 2009). Additionally, this signal might direct managers' attention toward a new technology. This managerial attention is then decisive in firms' technology strategies (Kaplan, 2008). Moreover, demand-pull policies can reduce uncertainty regarding firms' future innovation trajectories. Recent publications have shown that demand-pull policies tend to favor more mature technologies and narrow firms' search scope, which might lead to technology lock-ins (Hoppmann et al., 2013; Hoppmann et al., 2021). While this is negatively connotated from an innovation perspective (e.g., Barbieri, 2016), it can be beneficial from a technology decline perspective. Reduced uncertainty about the fundamental future technology trajectory reduces the risk of committing to a losing technology and can facilitate firms' decision to initiate a transformation (Penna and Geels, 2015) and, thus, to withdraw from the incumbent technology.

Overall, we see strong reasons to propose that demand-pull policies incentivize firms to withdraw from innovation in incumbent technologies. Hence, we advance the following hypothesis:

> *H2: The stronger the demand-pull policy for alternative technologies is, the lower firms' innovation activities are in the incumbent technology.*

2.4 The Interaction of Demand-Pull and Technology-Push Policies in Firms' Incumbent Technology Strategies

Demand-pull and technology-push policies are distinct but complementary ways of promoting innovation and technological change (Di Stefano et al., 2012; Mowery and Rosenberg, 1979). Previous research has shed light on the benefits of combining both policy types for the emergence of new technologies, from boosting firms' expenditures on innovation (Guerzoni and Raiteri, 2015) and innovation activity (Costantini et al., 2017) to the creation of innovation networks (Cantner et al., 2016) and even job creation (Nuñez-Jimenez et al., 2022). Although previous research has not investigated this question, it seems likely that the interactions between technology-push and demand-pull policies also affect the decline of incumbent technologies by influencing firms' innovation strategies across the resources, market, and technology dimensions.

Resources. In the previous sections, we suggested that demand-pull policies increase tensions in resource allocation within firms and lead to a reduction in innovation activity in the incumbent technology. However, how a firm allocates its resources between novel and established technologies depends on the expected impact of investments. If policymakers implement technology-push policies in parallel with demand-pull policies, the former directly reduce the private cost of R&D and help firms build capabilities in novel technologies, which facilitates future knowledge absorption (Cohen and Levinthal, 1990; Levinthal and March, 1993; Levitt and March, 1988). As a result, the additional use of technology-push policies increases the incentive for firms to use the scarce resources generated through demand-pull policies for novel instead of established technologies.

Market. The previous sections argued that technology-push policies encourage firms to increase their innovation activity in the incumbent technology to enhance its performance and to attempt to keep new technologies off the market. However, when demand-pull policies are also in place, these explicitly create opportunities for the targeted new technologies to enter the market (Fabrizio et al., 2017; Wesseling et al., 2015b); thus, they make fending off the new technology through innovation in the incumbent technology much more difficult. Furthermore, as demand-pull policies increase the deployment of the new technology, this triggers learning effects and economies of scale (Hoppmann et al., 2013), making a defensive stance increasingly unlikely to succeed.

Technology. The combined use of technology-push and demand-pull policies to target a new technology signals a more robust commitment of policymakers to supporting technological change and a higher credibility of their policy mix (Nemet et al., 2017; Rogge and Dütschke, 2018). Firms might be persuaded to invest more heavily in the new technology (Rogge and Schleich, 2018) and, therefore, be more inclined to reduce innovation activity in the incumbent technology.

Combining technology-push and demand-pull policies provides a stronger incentive for firms to withdraw from the incumbent technology. Therefore, we formulate an additional hypothesis proposing a negative policy interaction.

> *H3: The interaction of demand-pull and technology-push policies reduces firms' innovation activities in incumbent technology.*

Figure 1 provides an overview of our hypotheses.

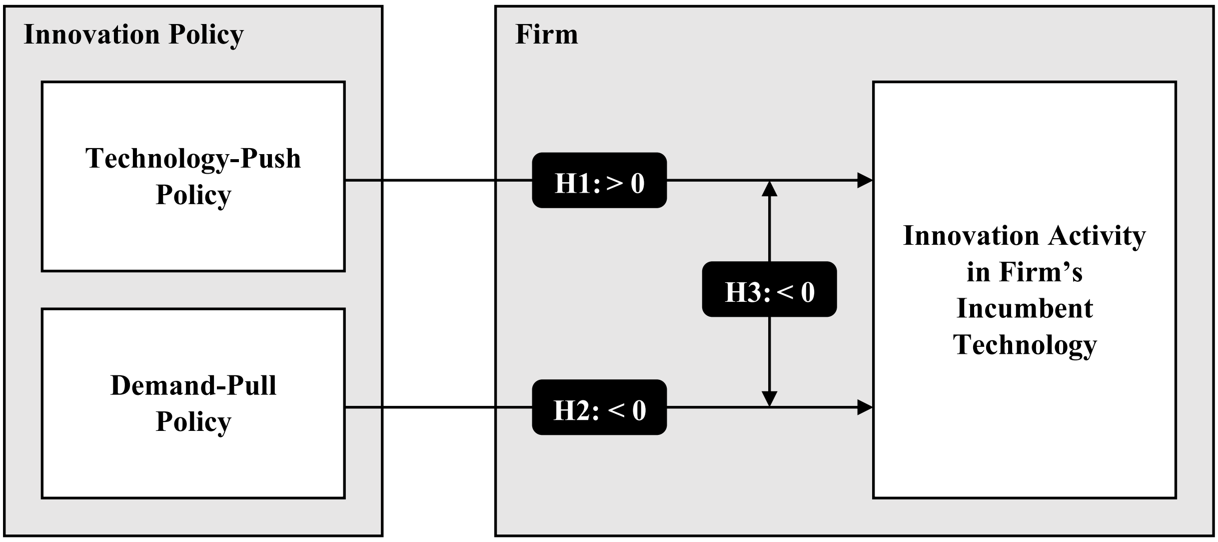


Figure 1: Hypotheses

3 Method

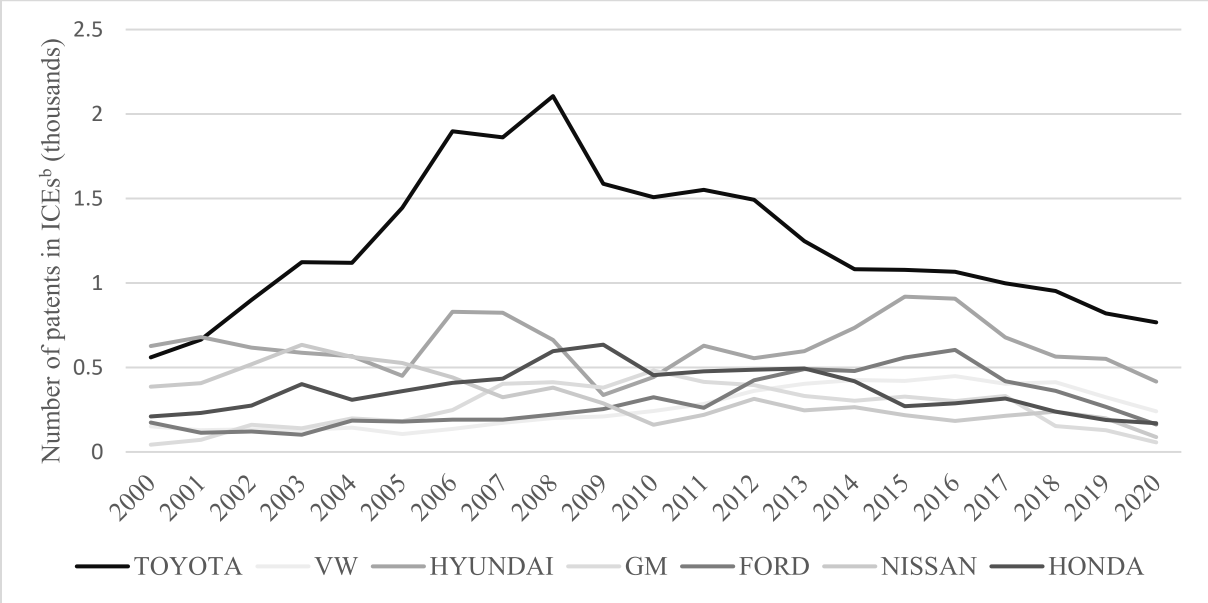
3.1 Research Setting

To test our hypotheses on the link between innovation policies promoting alternative technologies and innovation in incumbent technologies, we chose the automotive industry as our research setting. This setting is suitable for three main reasons.

First, the sector is currently seeing a transition from incumbent ICE vehicles to electric vehicles. ICE technology is well established, with large automotive manufacturers that have been producing ICEs for more than 100 years and have historically been committed to that technology, as shown, for example, by continuous incremental innovation in the technology. In this sense, the automotive sector represents an ideal setting for studying incumbent responses to technological change. In addition, automotive OEMs are multi-technology firms (i.e., they produce both gasoline and diesel engines) and are accustomed to facing tensions in resource allocation between different technologies. Thus, they are suitable candidates for investigating how firms manage various technologies simultaneously and deal with (technological) transitions.

Second, given the important role that the transportation sector plays in climate change, we have seen an increase in policy instruments (demand-pull and technology-push) being implemented to promote the development and market diffusion of EVs and the phasing out of ICE technology. The first policy initiatives go back to the 1990s (e.g., the California zero-emission vehicle mandate of 1990 or Japan's Clean Energy Vehicles Project of 1996). However, most of these policy instruments failed to make EVs economically and technologically competitive. Therefore, all major automotive manufacturers stopped any serious efforts in EV development (Bedsworth and Taylor, 2007; Sierzchula et al., 2012). Only in the late 2000s did governmental efforts to foster the development and market diffusion of EVs pick up again in countries such as Germany, France, China, and the United States. For instance, a large project by the US government to foster EV drivetrain and battery development with a funding sum of $2.4 billion was announced in 2009, and Germany initiated tax exemptions for EVs in 2008. China introduced a public procurement program in 2009 and installed subsidies for new energy vehicles in 2010. Hence, policy initiatives to support the rise of EVs intensified. In recent years, the phase-out of ICE cars has appeared on the political agenda (Meckling and Nahm, 2019), although it has mostly remained a statement of ambition. As a notable exception, in the EU, Regulation (EU) 2023/851 has legally enforced a regulation prescribing zero CO_2 emissions for newly registered vehicles starting in 2035 (European Parliament, 2023).

Third, many automotive OEMs have recently announced a shift of resources from ICE innovation and production toward EV technology, a development whose outcome is shown in Figure 2. Figure 2 illustrates how patenting in ICE technology by the seven largest OEMs has declined since 2016 despite no binding phase-out policy being passed in major automotive markets. For instance, General Motors announced that it would prioritize investments in its future EV architectures and redirect resources to achieve this goal (General Motors Company, 2018). Other firms, such as Nissan, have also declared their intention to end ICE development for most major markets, with the exception of the United States, and to shift resources toward EV and hybrid development.



[a] Firms with the largest production of passenger cars in 2017, according to the International Organization of Motor Vehicle Manufacturers (OICA, (n.d.b), accounting for more than 50% of total production

[b] Patents identified by international patent classification codes and automotive keywords (balanced)

Figure 2: Innovation activity in ICE vehicles for the seven largest OEMs[a] from 2000–2020

Hence, in this setting, there are (1) large incumbent firms rooted in ICE technology, (2) strong innovation policies with the goal of technological substitution, and (3) ambitions of incumbents to gradually withdraw from ICE technology without phase-out policies.

Our analysis focuses on the 2009–2020 period. This period is characterized by an increased use of technology-push and demand-pull policies for EVs. At the same time, policies to phase out ICEs were not yet prominent. This period has also seen upcoming market pressure from new entrants offering EVs, most prominently Tesla. Founded in 2003, Tesla launched the Roadster in 2008, the Model S in 2012, and the Model X in 2015, producing more than 100,000 vehicles in 2017 (OICA, n.d.b). We cut off our data in 2020 since patents have an 18-month confidentiality period, and we allow one additional month for their registration in the relevant databases for our analysis.

3.2 Data collection

To analyze the relationship between innovation policy and firms' incumbent technology strategy, we used a panel data set of 29 publicly listed incumbent OEMs in the automotive industry, which combines multiple data sources. Using International Organization of Motor Vehicle Manufacturers (OICA) world production data over the time horizon 2000–2017, we identified large OEMs.[1] The sample was limited to firms that (1) are publicly listed to ensure reliable access to financial data sourced from DataStream and (2) enable a reliable assignment of patent data from the Derwent Innovation Index database (see Table A.1).

To approximate firms' incumbent technology strategies in the automotive industry, we build on patents in the ICE technology field. Patent data offer the following advantages: (1) the data availability is good, and (2) patent data allows for differentiating investments in distinct R&D areas, which is not possible with aggregated investment data (Kaplan, 2008). Firm-specific patent families were extracted from the Derwent Innovation Index database using unique firm identifiers.[2] In line with our research interest, we sought to identify patents that are related to the ICE powertrain or its manufacturing processes. Ideally, a patent search strategy optimizes the error rate of both falsely included and excluded patents (Bruns and Kalthaus, 2020). However, since ICE technology has represented the dominant standard in the industry, many relevant patents do not contain any reference to the technology. Prior research has also observed this (Song and Aaldering, 2019). Therefore, the trade-off between errors is strong (i.e., not using technology keywords sharply increases the likelihood of falsely identified patents, while using technology-specific terms leads to the exclusion of many relevant patents). Hence, we applied three alternative search strings – comprehensive, balanced, and precise – that build on a previously defined search string (Luetkehaus, 2024). The comprehensive search string is based on international patent classification codes, the balanced search string includes automotive keywords, and the precise string adds propulsion technology-specific terms (Table A.2). Moreover, we extracted all patents of the firms in the data set by means of firm identifiers to calculate supplementary measures (i.e., patent scaling factors).

Data on public policies were obtained from various sources. For demand-pull policies, we followed two approaches. First, we acquired detailed new registration data for EVs from IHS Markit covering the years 2000–2020 and 85 countries, which represent more than 95% of the

[1] After 2017, production figures per manufacturer are not reported by the OICA. Tesla Motors is part of the data set but not included in the sample as it was founded only during our sampling period and exclusively focuses on BEVs.
[2] Firm identifiers are assigned to firms that have more than 500 patent applications. For Tata Motors, the identifier is on a higher company level than the financial data; therefore, we supplemented the Derwent standard code with firm names. We consolidated standard codes in cases of mergers and acquisitions where the database continues the codes of formerly independent firms. To avoid the double-counting of patents from different jurisdictions, we used patent families. We applied a 19-month cut-off period to account for the 18 months until publication and allowed time for database indexing. Patents were extracted for index dates between 01/01/1990 and 07/31/2022. Hence, the last year of available patent data in our sample is 2020.

global vehicle market (OICA, 2022).[3] Second, qualitative data on single demand-pull instruments applied in OECD, EU, and BRICS countries were obtained from various sources, including the PWC Global Automotive and ACEA Tax Guides, the IEA Policy Database, the Climate Policy Database, government reports and websites, and newspaper articles. Data on technology-push policies were obtained in the form of scientific publications on EVs. The scientific publication data were extracted from the Science Citation Index Expanded (SCIE) using a keyword search string (Mirzadeh Phirouzabadi et al., 2020; Schmoch, 2007). We used previously defined key term search strings to identify publications on hybrid electric vehicles, battery electric vehicles, and fuel cell electric vehicles (see Luetkehaus, 2024). To ensure a quality threshold, we limited the publications to articles. For additional policy controls, we obtained data on average fuel consumption in major LDV markets from 2005–2019 and phase-out policy announcements,[4] both sourced from the IEA (GFEI and IEA, 2021; IEA, 2020, 2021). To construct firm-specific weight matrices for demand-pull as well as policy controls, we collected data on production locations and volumes in 2009 from the OICA (OICA, n.d.a).

3.3 Variables and Measures

Our hypotheses suggest links between *demand-pull* and *technology-push policies for EV*s (independent variables) and OEMs' *technology-specific innovation activities in ICE vehicles* (dependent variable). In the following sections, we discuss how we operationalized these focal variables. Furthermore, we explain our controls for firm-level factors implied by former work and consider additional policies to rule out alternative explanations.

3.3.1 Dependent Variable

We followed previous literature to measure *technology-specific innovation activity in ICE vehicles* by means of respective patents. A problem with using patents lies in inter-firm differences in propensity to patent, which are, for example, caused by different requirements in the process of patent registration imposed by national patent offices (Bruns and Kalthaus, 2020). To account for this phenomenon, we followed the "scaling factor approach" proposed by Luetkehaus (2024). This approach is based on the idea that the ratio of R&D investment to

[3] EVs include PHEVs, BEVs, and FCEVs. Data gaps for Japan (2015–2020) and Mexico were supplemented using IEA (2023) and Statista (2023) data.
[4] Major markets comprise China, the EU-27, Japan, the USA, and developing and emerging countries (Argentina, Brazil, Chile, Egypt, Malaysia, Mexico, Peru, the Philippines, the Russian Federation, and Ukraine). Missing data points are imputed using linear interpolation.

patents is indicative of differences in the propensity to patent (Rassenfosse and van Pottelsberghe de Potterie, 2009; Scherer, 1983) and, as such, can be used to harmonize patent counts for the comparison of firms embedded in different jurisdictions. Specifically, firms' patent counts were multiplied by firm-level scaling factors and rounded to the nearest integer to level measurements while keeping the original count data format. The scaling factors represent the focal firms' R&D investment to patent ratio relative to the average of all firms in the data set, calculated as follows:

$$Scaling\ factor_i = \left(\frac{\sum_{t-1} R\&D\ investment_{i,t-1}}{\sum_t Patents_{i,t}}\right) / \sum_{i}^{n} \frac{1}{n}\left(\frac{\sum_{t-1} R\&D\ investment_{i,t-1}}{\sum_t Patents_{i,t}}\right), \quad (1)$$

where i = firm, t = year ranging from 2000–2020, and *R&D investment* reflects purchase power parity adjusted for USD_{2015}. In the case of missing R&D investment data at t-1, the corresponding patent count in t is excluded.

Luetkehaus (2024) shows that these scaling factors are correlated with triadic patent shares of firms and resemble country-specific propensities to patent (e.g., due to the different requirements of domestic patent offices). However, in comparison with alternative methods, such as multinational patents or citation weights (Bruns and Kalthaus, 2020), the scaling factor approach holds two important advantages: (1) no additional cut-off periods are imposed, which allows for the analysis of more recent developments, and (2) the assumption of the necessity of patents in several jurisdictions to protect an invention internationally is relaxed, which arguably does not hold in the automotive industry (Hägler, 2020).

3.3.2 Independent Variables

For the first independent variable, *demand-pull policies for EVs*, we see that many different policy instruments have been implemented in the automotive industry. Such instruments include, among others, tax credits, purchase subsidies for consumers, and public procurement. Since every country has its own policy mix, the strength of the instruments depends on their exact design and the overall setting in which they are embedded. Hence, this poses the challenge of measuring demand-pull policies internationally and comparing them with one another (Hoppmann and Vermeer, 2020).

While much of the previous research has relied on output measures, such as market volume, to capture the effect of demand-pull policies (Peters et al., 2012), some studies have used input measures, such as binary variables, to account for the different types of demand-pull instruments that are used (Hille et al., 2020). Since both approaches have their drawbacks in operationalizing demand-pull instruments, we proxy demand-pull policies via an integrated approach that uses both battery electric vehicle market volume and the quality of the demand-pull policy mix for battery electric vehicles (Luetkehaus, 2024). Specifically, we draw on new BEV registrations and multiply them by a qualitative evaluation of the demand-pull policy mix. In doing so, we use both output and input measures to construct the variable:

$$Demand - pull\ policies_{c,t} = New\ registrations\ of\ BEVs_{c,t} * DP\ policy\ mix\ quality_{c,t}, \qquad (2)$$

where c = country and t = year.

Following Luetkehaus (2024), we determine the quality of the demand-pull policy mix for BEVs by measuring their average score on a five-item scale. This scale is based on the policy mix concept described by Rogge and Reichardt (2016), which, although developed for the holistic evaluation of policy mixes, is well suited to capturing the instrument mix of demand-pull policies. To assess the quality of the instruments, we rate the demand-pull instruments according to the four key characteristics of policy mixes, which are classified into subcategories in the paper by Luetkehaus (2024).

Since demand-pull policies are measured at the country level and firms vary in market coverage, it is necessary to both link and apply firm-specific weights to account for direct market access. We use this approach because prior research has shown that trade barriers inhibit demand-pull policy effects (Dechezleprêtre and Glachant, 2014). Accordingly, we argue that it is more challenging for firms to take advantage of demand-pull policies in countries where they have no production locations. Therefore, we consider firms' access to demand-pull policies by means of dummy variables for production locations. We assign them a value of 1 if firms have a production site in the market and 0 otherwise. Firms' decisions regarding production location may also arise from strategic choices. To avoid endogeneity, we keep the weights for production sites constant over time, as prior research has done (Costantini et al., 2017).[5] Since some markets are linked through free trade zones, we aggregate them accordingly.[6]

The second independent variable is *technology-push policies for EVs,* which we approximate with publicly funded science activity in electric vehicles. Science is an integral part of the

[5] Weights are based on production locations in 2009.
[6] We treat the European Economic Area (EEA) and the North American Free Trade Area (NAFTA) as single markets.

technology-push mechanism (Di Stefano et al., 2012). In accordance with former work, we measure science activity by publications recorded in the SCIE (Meyer, 2000; Schmoch, 2007). Compared to alternative measures, this operationalization based on publication data has the advantage of good data availability and coverage. Previous studies on renewable energies draw on public funding data from the IEA (e.g., Costantini et al., 2017). However, this data set does not cover all relevant countries for our study (e.g., China) and contains major data gaps with respect to automotive technology funding. Hence, to enable comprehensive coverage of OEMs in our analysis, we use an approximation of technology-push policies by scientific publications, as previously used in Luetkehaus (2024).

As an approximation of technology-push policies, among all scientific publications on EVs, we only consider those that have been publicly funded for two reasons: (1) not all scientific work is (directly) publicly funded and therefore may not align with policies, and (2) country-level differences in the number of higher education institutions could bias the raw publication count. We analyzed the funding information in the SCIE, which is available with full coverage from 2009 onward (Paul-Hus et al., 2016), to identify publicly funded articles.[7] Since previous work shows that the effect of technology-push policies is limited to domestic policies (e.g., Peters et al., 2012), we measured the variable by scientific articles on EV technology attributed to firms' domestic countries. Lastly, we deferred the publication date by one year to consider the time it takes to publish an article (Schmoch, 2007).

3.3.3 Control Variables

In our econometric analysis, we controlled for firm and time fixed effects to account for the time-constant heterogeneity of firms and macro-level time-related effects. Moreover, we included time-variant firm-level variables that prior studies have shown have an impact on firms' innovation activity. Lastly, we also considered distinct policies that might be alternative explanations for firms' changes in incumbent technology research activity.

First, *firm size* can influence the innovation activity of firms in general (e.g., due to the availability of resources), but it can also impact the trajectory of innovation as larger firms tend to be the focus of environmental stakeholders and governments (Kesidou and Demirel, 2012). We captured firm size by total assets in million USD_{2015}.

[7] To this end, we took three steps. (1) We filtered the SCIE database for a country. (2) We identified all national and supranational (e.g., EU) governmental or governmentally financed institutions and programs that account for more than 1% of funded publications assigned to the respective country (Table A.3). (3) We extracted the publication data of articles funded by these institutions and counted the number of publications for each year.

We also include *R&D intensity* since it is not only related to increased innovative activity (Audretsch, 1995), but prior studies have also identified it as a driver of eco-innovation (Hojnik and Ruzzier, 2016). We measured R&D intensity by the share of R&D expenditures on sales.

Financial performance can have an immediate impact on innovation activity due to the availability of funds (Audretsch, 1995). Moreover, when a decline in financial performance persists, firms might respond to it with innovation but also rigidity (McKinley et al., 2014). Therefore, we controlled for financial performance by including firms' return on assets.

Previous literature has shown that *slack resources* are a determinant of innovation in general (Marlin and Geiger, 2015; Nohria and Gulati, 1996) and are also positively linked to radical innovation (Troilo et al., 2014). We operationalized slack resources as the ratio between firms' cash and long-term debt (Hoppmann et al., 2021).

Moreover, we controlled for alternative explanations of the proposed mechanisms by including *knowledge stocks and R&D cooperation* in internal combustion engine technologies. Prior learning and the resulting competencies can form a strong source of path dependency (Levinthal and March, 1993). Therefore, we considered firms' *ICE knowledge stock*, measured as the depreciated sum of previous patents in ICE technologies.[8] Another way to increase innovation performance is through research collaboration (Ahuja, 2000; Sampson, 2007). Similar to Luetkehaus (2024), we used the number of distinct firms and institutions with which a firm jointly signed patents in the focal technology to proxy for *R&D cooperation*.[9]

Previous literature implies that uncertainties in the firm environment influence firms' innovation investment timing and trajectories (Hoffmann et al., 2009; Jansen et al., 2006). In the case of the transition from ICE vehicles to EVs, uncertainties (e.g., in the EV market development or regarding the chip shortage) might diminish or postpone the shift of resources to the new technologies. Thus, we proxied *environmental uncertainty* by the coefficient of variation of the firm's sales calculated over five periods (Ghosh and Olsen, 2009).

Besides pure demand-pull or technology-push policy, a major policy type is regulatory policies, such as fleet- or corporation-wide fuel economy standards (e.g., CAFE in the USA), whose impact the prior literature has termed "regulatory push/pull" (Rennings, 2000). Such standards may increase innovation in incumbent technologies (Nemet, 2014), but it is also possible that

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[8] The first year considered for knowledge stock calculation is 1990. The knowledge depreciation rate is set at the usual value of 0.15. We also tested alternative depreciation rates of 0.1 and 0.25 for our main model estimations. The results were largely unchanged. Regression tables are available upon request.
[9] Only entities with a Derwent standard code are included to avoid double counting. Balanced patent search strings were used.

they might spur a shift toward EV technologies (Sen et al., 2017), especially in cases where incumbent technologies approach technological boundaries. Although how these policies impact innovation in incumbent technologies remains unresolved, they represent an alternative explanation for either a decrease or an increase in ICE vehicle innovation activity. We computed the stringency of *fuel economy regulation* by taking the inverse of the average fuel consumption of new light-duty vehicles multiplied by 100; thus, higher values signal higher stringency. We preferred realized fuel economy over targets because the former is comparable across countries and mirrors the actual impact of diversely designed regulations. Obviously, not every firm is equally impacted by regulations in various markets. Therefore, we weighted regulation stringency with firm-specific production shares in respective markets.[10]

Finally, we controlled for the announcement of long-term *phase-out targets* for ICEs. Phase-out policies can be considered a form of demand-pull policy due to their impact on market expectations (Rogge and Johnstone, 2017). However, during our observation period, demand-pull policies focused on the deployment of EVs, while phase-out announcements remained mostly aspirational. Hence, we do not expect phase-out announcements to be a relevant mechanism. However, to disentangle potential effects, we explicitly used a control variable. We captured *phase-out targets* with dummies, signifying whether phase-out targets have been announced, and weighted them with firms' production shares in respective markets.[11] Tables A4 and A5 provide an overview of descriptive statistics and pairwise correlations for the 2009–2020 time horizon.

3.4 Empirical Strategy

To test our hypotheses regarding the impact of demand-pull and technology-push policies on *firms' ICE innovation activities*, we used a fixed effects Poisson model (FEP) with clustered robust standard errors (Cameron and Trivedi, 2013). Since unobserved firm characteristics likely impact patenting in incumbent technologies, we prefer FEP over a fixed effects negative binomial model, which fully captures firm-level fixed effects only under certain conditions (Allison and Waterman, 2002; Guimarães, 2008). In the main models, we conducted our

[10] Production shares are calculated relative to production in covered markets (China, the EU-27, Japan, the USA, Argentina, Brazil, Chile, Egypt, Malaysia, Mexico, Peru, the Philippines, the Russian Federation, and Ukraine). Including production volumes in other markets would entail the assumption that other markets are unregulated, which might bias our results. This also prevents us from accounting for FTAs. To avoid endogeneity of weights, weights are based on 2009 data and kept constant.

[11] Countries with an announced phase put target are assigned a value of 1, and 0 otherwise. We account for FTAs (i.e., EEA and NAFTA) by aggregating phase-out policies and production shares. To aggregate phase put policies on the FTA level, we weight country-level dummies with GDP shares on the FTA. To avoid endogeneity, we draw on 2009 data and keep weights constant.

estimations using scaled patent counts retrieved by the balanced identification strategy with the time horizon of 2009–2020. To test the robustness of our results, we repeated our analysis using alternative patent identification strategies and unscaled patent counts as the dependent variable. Moreover, we extended our sample to 2001–2020 at the cost of a slightly weaker measurement of technology-push policies (see Section 4.1 for details) and dropping fuel economy regulation as a control due to data constraints. In addition, we tested the influence of potential multicollinearity. To avoid omitted variable bias, we included time-fixed effects and controls employed by previous literature in all models.

To ensure the reliability of our results, we addressed endogeneity concerns. Demand-pull and technology-push policies have the potential to be somewhat endogenous (e.g., if policymakers consider developments in ICE technology when implementing policies). We addressed this issue in two ways. First, we lagged all explanatory variables by one year to avoid simultaneity, as is common practice in policy research. Second, following Li et al. (2021), we operationalized demand-pull and technology-push policies based on a higher level (national) than the dependent variables (firm) and subsequently tested for dynamic endogeneity by estimating the effect of lagged incumbent innovation on policy variables (Table A.6, Model S1, and Model S2). Significant coefficients would signal a substantial risk of endogeneity, which was not found in our case.

The measurement of EV demand-pull policies is potentially particularly vulnerable to endogeneity because the innovation activity of OEMs might impact the competitiveness of EVs and, in turn, the effectiveness of demand-pull policies. Therefore, we additionally used the two-step IV control function approach for Poisson regression models suggested in Wooldridge (2002) to test for endogeneity of demand-pull policies (for a recent application, see Dechezleprêtre and Glachant, 2014). In the first step, we regressed *EV demand-pull policies* on instrument variables, *EV technology-push policies,* and controls. As instrument variables, we used installed on-grid wind power and solar photovoltaic capacity. These are suitable instruments because (1) market creation for renewable energy technology is unlikely to impact innovation in automotive technology, and (2) to tackle the grand challenge of climate change, the diffusion of renewable energies is heavily supported alongside the diffusion of electric vehicles. From a statistical viewpoint, the variables are correlated with Pearson correlation coefficients of *EV demand-pull policies*, with wind and solar photovoltaic instrument variables of 0.434 and 0.541, respectively. In the second step, the residuals of the first-stage regression were included in the main model. A significant coefficient for *Residuals stage 1* would lead to the rejection of the null hypothesis: *EV demand-pull policies* are exogenous. The coefficient is not significantly different from zero, and the null hypothesis is therefore not rejected (i.e., endogeneity must not be assumed; see Table A.7, Model S3).

4 Results

Table 1 shows the results of the main FEP regression models, which we use as the basis for discussing the outcome of our hypothesis tests. We first calculated a baseline model that included only controls (Model 1). Subsequently, we added the independent variables step by step. To analyze the interplay of demand-pull and technology-push policies, we included an interaction term (Model 5). The Akaike information criterion indicates that including the independent variables improves the fit of the regression models and that the full model with the interaction term (Model 5) best describes our data.

Hypothesis H1 proposed that *technology-push policies for EVs* are positively related to *technology-specific innovation activities in ICE vehicles.* In contrast to our hypothesis, Models 2 and 4 show negative coefficients (β = -0.000259; β = -0.000415), but neither is statistically significantly different from zero (p > 0.1). Hence, the models without the interaction term provide no support for H1. However, in Model 5, with an interaction term between technology-push and demand-pull policies, we find a positive and highly significant coefficient for EV technology-push policies (β = 0.0023, p < 0.001). This suggests that technology-push policies positively affect innovation in ICE vehicles, in line with H1, but that the effect depends on the level of complementary demand-pull policies. Thus, the statistical insignificance of the coefficients in Models 3 and 4 may be due to divergent effects depending on the magnitude of demand-pull policies. In our test of hypothesis H3 below, we explain the interaction term in more detail.

Hypothesis H2 suggested that *demand-pull policies for EVs* are negatively linked to *technology-specific innovation activities in ICE vehicles*. We find unambiguous support for this hypothesis in all models (Models 3–5). Model 4 without the interaction term (β = -6.62e-07, p < 0.001) shows a very highly significant and negative coefficient. The coefficient for *EV demand-pull policies* in Model 4 can be directly interpreted as semi-elasticity. Accordingly, the results indicate that an increase of 100,000 units in demand-pull policies leads to a decrease in ICE vehicle patenting by 6.22%. It is worthy of note that the statistically highly significant (p < 0.001) coefficient in Model 5 with the interaction term (β = -5.25e-07) is lower than in

Model 4 (β = -6.62e-07). This suggests that the strength of the demand-pull policy effect partly depends on complementary technology-push policies.

Hypothesis H3 posited that *technology-push* and *demand-pull policies for EVs* interact and that their joint effect is negatively related to *technology-specific innovation activities in ICE vehicles.* In support of this hypothesis, Model 5 shows a negative and highly significant coefficient for the interaction term (β = -2.86e-09, $p < 0.001$). In addition, the coefficient of *EV technology-push policies* is positive (β = 0.0023), while that of the EV demand-pull policies is negative (β = -5.25e-07), and both coefficients are statistically significant at a very high level ($p < 0.001$). Beyond the negative interaction effect, these results highlight two aspects.

First, both the magnitude and direction of the impact of *EV technology-push policies* on *innovation in the incumbent technology* depend on complementary *EV demand-pull policies*. Due to the positive coefficient of *technology-push policies for EVs* and the negative coefficient of the interaction with *EV demand-pull policies*, the impact of technology-push policies highly depends on the level of demand-pull policies. When EV technology-push policies are not complemented by demand-pull policies (*EV demand-pull policies* = 0), an increase of one unit leads to an increase of 0.23% in incumbent innovation activity. However, the positive effect is reduced when *demand-pull policies for EVs* are implemented (> 0). Eventually, when demand-pull policies surpass 804,195.8 units, the overall effect direction switches to a negative impact (i.e., each unit increase in *EV technology-push policies* leads to lower innovation activity in the incumbent technology). To illustrate, demand-pull policies$_{(t-1)}$ exceeded this threshold for VW in 2018, Mazda in 2019, and Renault in 2020.

Second, the negative impact of *EV demand-pull policies* on *innovation in the incumbent technology* also depends on complementary EV technology-push policies, but only in magnitude, as both the coefficients of the demand-pull policies and the interaction are negative. In particular, the impact of *EV demand-pull policies* is intensified by increasing complementary technology-push policies. Model 5 indicates that an increase of 100,000 units in demand-pull policies leads to a decrease in ICE vehicle patenting by 5.25% when no technology-push policies are implemented. This effect is strengthened by 0.54% when technology-push policies increase by one unit.

Table 1: Results of the main model (FEP with scaled ICE patents from balanced identification strategy as dependent variable)

VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Firm size$_{(t-1)}$	0.00132	0.00130	0.00183†	0.00180†	0.00161†
	(0.00113)	(0.00112)	(0.000972)	(0.000947)	(0.000845)
R&D intensity$_{(t-1)}$	1.065	1.054	0.123	0.0940	1.645
	(3.198)	(3.122)	(2.823)	(2.711)	(2.929)
Financial performance$_{(t-1)}$	0.603***	0.604***	0.535***	0.536***	0.498***
	(0.117)	(0.114)	(0.121)	(0.118)	(0.0966)
Slack resources$_{(t-1)}$	-0.00208	-0.00238†	-0.00109	-0.00161	-0.00207†
	(0.00145)	(0.00134)	(0.00146)	(0.00108)	(0.00114)
ICE knowledge stock$_{(t-1)}$	9.33e-05*	9.83e-05*	0.000112**	0.000121**	0.000142**
	(4.05e-05)	(4.57e-05)	(4.01e-05)	(4.56e-05)	(4.73e-05)
R&D cooperation$_{(t-1)}$	0.0315***	0.0321***	0.0255***	0.0263***	0.0259***
	(0.00703)	(0.00651)	(0.00756)	(0.00684)	(0.00643)
Environmental uncertainty$_{(t-1)}$	-0.798†	-0.880*	-0.520	-0.653†	-0.499
	(0.414)	(0.409)	(0.371)	(0.379)	(0.363)
Fuel economy regulation$_{(t-1)}$	0.119	0.129	0.136	0.155	0.194
	(0.137)	(0.151)	(0.117)	(0.135)	(0.138)
Phase-out announcements$_{(t-1)}$	0.568**	0.540*	0.0944	0.0389	-0.330
	(0.216)	(0.222)	(0.342)	(0.375)	(0.368)
EV technology-push policies$_{(t-1)}$		-0.000259		-0.000415	0.00230***
		(0.000782)		(0.000701)	(0.000666)
EV demand-pull policies$_{(t-1)}$			-6.51e-07***	-6.62e-07***	-5.25e-07***
			(1.78e-07)	(1.87e-07)	(1.45e-07)
EV technology-push policies$_{(t-1)}$*					-2.86e-09***
EV demand-pull policies$_{(t-1)}$					(7.59e-10)
Observations	293	293	293	293	293
Number of firms	28	28	28	28	28
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
AIC	5,111	5,109	4,826	4,816	4,528

Robust standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$

4.1 Robustness Tests

To test the robustness of our results, we conducted several additional analyses. First, we replicated our main model analyses (Models 4 and 5) using scaled patent counts based on alternative identification strategies as the dependent variable because the patent identification approach might significantly influence econometric results (Bruns and Kalthaus, 2020). In the main models, we used a search string that balances the false inclusion of unrelated patents and the false exclusion of relevant patents. We tested the robustness of our results using two alternative identification strategies: (1) a precise strategy that emphasizes correct identification but falsely excludes more patents (Table 2, Models 6 and 7), and (2) a comprehensive strategy with a broader coverage that allows more falsely identified patents (Table 2, Models 8 and 9). The results for *EV demand-pull policies* and the interaction term are fully robust. While in

Model 9, the coefficient of EV technology-push policies is also robust, in Model 7, the coefficient remains positive but is no longer statistically significant ($p > 0.1$). Drawing on Model 9, we test at which values of *EV demand-pull policies* the coefficient of *technology-push policies* changes its sign due to the interaction with *EV demand-pull policies.* Based on these results, the effect direction becomes positive when complementary *EV demand-pull policies* reach 734,265.73 units, which is reasonably close to the 804,195.8 units based on the main results of Model 5.

Second, we tested the robustness of our results to unscaled patent counts as dependent variables (Table 2). The scaling factor approach controls for firms' propensity to patent but might unintendedly cancel out inter-firm differences stemming from research productivity. Hence, a robustness test is advisable (Luetkehaus, 2024). The test yields results that are in line with the conclusions of our hypothesis tests (Models 10 and 11), except that the coefficient for *EV technology-push policies* is positive but no longer statistically significant in Model 11. Accordingly, this robustness test does not support a positive effect of EV technology-push policies at lower levels of supplementary demand-pull policies.

Third, in the main models, we used an integrated approach to measure *EV demand-pull policies.* To test whether our results hold when using alternative operationalizations of *EV demand-pull policies*, we reran our models using only the output measure of demand-pull policies (i.e., new registrations of EVs; Table 3, Models 12 and 13) and only using the input measure (i.e., demand-pull policy mix quality; Table 3, Models 14 and 15). While the output-based measure emphasizes the effectiveness of policies in market creation, the input-based measure highlights the qualitative characteristics of the policies. All results are robust, but some significance levels are lower in Models 14 and 15 compared to the main analysis.

Table 2: Robustness tests for alternative measurements of the dependent variable (FEP with scaled ICE patent counts from the precise [Models 6 and 7] and comprehensive [Models 9 and 10] identification strategies, as well as unscaled patent counts [Models 11 and 12] as the dependent variable

VARIABLES	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**
Firm size$_{(t-1)}$	0.00285**	0.00264**	0.00177	0.00157	0.00179†	0.00185*
	(0.000935)	(0.000839)	(0.00121)	(0.00107)	(0.000943)	(0.000886)
R&D intensity$_{(t-1)}$	-1.689	0.547	0.811	2.296	2.136	2.477
	(2.528)	(2.776)	(3.100)	(3.389)	(2.941)	(3.012)
Financial performance$_{(t-1)}$	0.550***	0.523***	0.362**	0.313**	0.691***	0.651***
	(0.134)	(0.0976)	(0.122)	(0.0992)	(0.154)	(0.148)
Slack resources$_{(t-1)}$	-0.00391**	-0.00436***	-0.00178†	-0.00230*	-0.00157	-0.00181
	(0.00124)	(0.00119)	(0.00100)	(0.00107)	(0.00163)	(0.00154)
ICE knowledge stock$_{(t-1)}$	0.000191*	0.000205***	0.000107*	0.000128*	3.74e-05	5.34e-05
	(7.66e-05)	(5.62e-05)	(4.78e-05)	(5.18e-05)	(4.47e-05)	(5.52e-05)
R&D cooperation$_{(t-1)}$	0.0325***	0.0318***	0.0214**	0.0205**	0.0377***	0.0376***
	(0.00671)	(0.00612)	(0.00802)	(0.00766)	(0.00638)	(0.00654)
Environmental uncertainty$_{(t-1)}$	-1.438**	-1.328**	-0.441	-0.233	-1.029*	-0.974*
	(0.483)	(0.406)	(0.385)	(0.357)	(0.464)	(0.482)
Fuel economy regulation$_{(t-1)}$	0.135	0.190	0.206	0.247†	0.106	0.143
	(0.128)	(0.138)	(0.149)	(0.150)	(0.102)	(0.114)
Phase-out announcements$_{(t-1)}$	-0.00108	-0.405	-0.243	-0.625†	-0.0654	-0.272
	(0.376)	(0.385)	(0.329)	(0.333)	(0.300)	(0.314)
EV technology-push policies$_{(t-1)}$	-0.00272	0.00107	-0.000542	0.00210***	-3.93e-05	0.00119
	(0.00252)	(0.00160)	(0.000683)	(0.000629)	(0.000577)	(0.000740)
EV demand-pull policies$_{(t-1)}$	-6.42e-07***	-4.76e-07***	-7.38e-07***	-6.18e-07***	-5.32e-07***	-5.20e-07***
	(1.84e-07)	(1.43e-07)	(1.90e-07)	(1.37e-07)	(1.48e-07)	(1.43e-07)
EV technology-push policies$_{(t-1)}$*		-3.45e-09***		-2.86e-09***		-1.35e-09*
EV demand-pull policies $_{(t-1)}$		(7.49e-10)		(7.80e-10)		(6.43e-10)
Observations	286	286	293	293	293	293
Number of firms	27	27	28	28	28	28
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
AIC	3,255	3,082	6,138	5,742	5,696	5,602

Robust standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$

Table 3: Robustness tests for demand-pull policies measured as new registrations of EVs or demand-pull policy quality (FEP with ICE patents from balanced identification strategy as dependent variable)

VARIABLES	**Model 12**	**Model 13**	**Model 14**	**Model 15**
Firm size$_{(t-1)}$	0.00181†	0.00159†	0.00179†	0.000508
	(0.000942)	(0.000843)	(0.00102)	(0.00114)
R&D intensity$_{(t-1)}$	0.102	1.676	-0.0418	-0.579
	(2.706)	(2.917)	(2.514)	(1.913)
Financial performance$_{(t-1)}$	0.533***	0.493***	0.546***	0.417***
	(0.118)	(0.0952)	(0.116)	(0.107)
Slack resources$_{(t-1)}$	-0.00158	-0.00206†	-0.00167†	-0.00187
	(0.00108)	(0.00114)	(0.000958)	(0.00116)
ICE knowledge stock$_{(t-1)}$	0.000122**	0.000145**	0.000133**	0.000263***
	(4.57e-05)	(4.77e-05)	(4.64e-05)	(4.17e-05)
R&D cooperation$_{(t-1)}$	0.0261***	0.0258***	0.0204**	0.0253***
	(0.00685)	(0.00640)	(0.00757)	(0.00486)
Environmental uncertainty$_{(t-1)}$	-0.647†	-0.493	-0.729†	-0.501
	(0.381)	(0.369)	(0.402)	(0.457)
Fuel economy regulation$_{(t-1)}$	0.155	0.193	0.128	0.0357
	(0.135)	(0.137)	(0.114)	(0.102)
Phase-out announcements$_{(t-1)}$	0.0345	-0.334	0.306	0.194
	(0.378)	(0.367)	(0.233)	(0.239)
EV technology-push policies$_{(t-1)}$	-0.000429	0.00228***	-0.000345	0.00179**
	(0.000700)	(0.000652)	(0.000630)	(0.000567)
EV demand-pull policies – registrations$_{(t-1)}$	-5.85e-07***	-4.57e-07***		
	(1.67e-07)	(1.28e-07)		
EV technology-push policies$_{(t-1)}$*		-2.55e-09***		
EV demand-pull policies – registrations $_{(t-1)}$		(6.56e-10)		
EV demand-pull policies – quality$_{(t-1)}$			-7.08e-08**	-3.47e-08†
			(2.60e-08)	(1.83e-08)
EV technology-push policies$_{(t-1)}$*				-2.22e-10***
EV demand-pull policies – quality $_{(t-1)}$				(6.39e-11)
Observations	293	293	293	293
Number of firms	28	28	28	28
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
AIC	4,810	4,514	4,713	4,295

Robust standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$

Fourth, we extended the time frame of our analysis to cover the 2001–2020 period, which allows us to study the years before the uptake of EV diffusion starting in 2010 (Table 4). With this, we significantly increased the number of observations but imposed two limitations: (1) Funding information for scientific publications is only available from 2009 onwards; therefore, we construct the variable *EV technology-push policies extended*, drawing on all scientific publications on EVs instead of those containing funding information.[12] Nevertheless, the

[12] We used an approach similar to Luetkehaus (2024) that uses fractional counts of institutional addresses to assign an article to one or several countries.

resulting measure *EV technology-push policies extended* is highly correlated with *EV technology-push policies*, with a pairwise correlation of 0.991 (see Table A.5). (2) The underlying data for *fuel economy regulation* were only available from 2005 onwards, as such, the control had to be excluded in a fully extended sample. We report estimation results for both using *EV technology-push policies extended* (Models 16 and 17) and, additionally, dropping *fuel economy regulation* (Models 18 and 19). The conclusions from the main models regarding demand-pull policies and the policy interaction term are robust, as the respective coefficients are all statistically significant, at least at a moderate level ($p < 0.05$). The coefficients for *EV technology-push policies extended* are positive in all models with policy interaction but not statistically significant ($p > 0.1$).

Table 4: Robustness tests for extended sample (FEP with scaled ICE patents from balanced identification strategy as dependent variable)

VARIABLES	**Model 16**	**Model 17**	**Model 18**	**Model 19**
Firm size$_{(t-1)}$	0.000199	0.000329	0.000148	0.000366
	(0.000971)	(0.000863)	(0.000747)	(0.000664)
R&D intensity$_{(t-1)}$	3.265	4.089	2.055	2.515
	(3.602)	(3.416)	(3.618)	(3.316)
Financial performance$_{(t-1)}$	0.430***	0.365***	0.423*	0.359*
	(0.121)	(0.104)	(0.164)	(0.143)
Slack resources$_{(t-1)}$	-0.00278**	-0.00262*	-0.00252++	-0.00225++
	(0.00105)	(0.00110)	(0.00131)	(0.00119)
ICE knowledge stock$_{(t-1)}$	0.000171**	0.000179***	0.000190**	0.000184**
	(5.82e-05)	(5.28e-05)	(6.92e-05)	(6.39e-05)
R&D cooperation$_{(t-1)}$	0.0184*	0.0193**	0.0168*	0.0174*
	(0.00736)	(0.00628)	(0.00776)	(0.00759)
Environmental uncertainty$_{(t-1)}$	-0.260	-0.271	0.105	0.186
	(0.584)	(0.597)	(0.479)	(0.470)
Fuel economy regulation$_{(t-1)}$	0.105	0.142		
	(0.156)	(0.167)		
Phase-out announcements$_{(t-1)}$	0.000651	-0.386	0.122	-0.226
	(0.441)	(0.437)	(0.334)	(0.250)
EV technology-push policies – extended$_{(t-1)}$	-0.000376	0.00138	-9.79e-05	0.00180
	(0.000948)	(0.000993)	(0.000947)	(0.00115)
EV demand-pull policies$_{(t-1)}$	-7.17e-07***	-4.57e-07*	-7.90e-07***	-5.19e-07*
	(1.83e-07)	(1.92e-07)	(2.06e-07)	(2.46e-07)
EV technology-push policies – extended$_{(t-1)}$* EV demand-pull policies $_{(t-1)}$		-1.75e-09***		-1.87e-09***
		(4.39e-10)		(5.03e-10)
Observations	360	360	455	455
Number of firms	29	29	29	29
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
AIC	8,056	7,665	11,480	11,007

Robust standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$

Finally, we tested for a potential bias due to multicollinearity by estimating additional models that either exclude all controls (Table 5, Models 20 and 21) or controls with a pairwise correlation of +/- 0.3 (Table 5, Models 22 and 23), as suggested by Kalnins (2018). In our study, *EV demand-pull policies* show moderate correlations with controls for *firm size*, *fuel economy regulation,* and *phase-out announcements.* While this is plausible and to be expected, it raises multicollinearity concerns. Multicollinearity can inflate effect sizes and, even more severely, lead to changes in estimated effect directions (Kalnins, 2018). However, neither was observed for the coefficients of *EV demand-pull policy registrations* or *EV demand-pull policy instruments* (see Table 5).

Table 5: Robustness test for multicollinearity (FEP with scaled ICE patents from balanced identification strategy as dependent variable)

VARIABLES	Model 7	Model 8	Model 20	Model 21	Model 22	Model 23
Firm size$_{(t-1)}$	0.00180†	0.00161†				
	(0.000947)	(0.000845)				
R&D intensity$_{(t-1)}$	0.0940	1.645			1.697	2.937
	(2.711)	(2.929)			(2.632)	(2.777)
Financial performance$_{(t-1)}$	0.536***	0.498***			0.602***	0.574***
	(0.118)	(0.0966)			(0.102)	(0.0851)
Slack resources$_{(t-1)}$	-0.00161	-0.00207†			-0.00206*	-0.00266**
	(0.00108)	(0.00114)			(0.00103)	(0.00103)
ICE knowledge stock$_{(t-1)}$	0.000121**	0.000142**			0.000107**	0.000123**
	(4.56e-05)	(4.73e-05)			(3.79e-05)	(3.75e-05)
R&D cooperation$_{(t-1)}$	0.0263***	0.0259***			0.0194*	0.0199**
	(0.00684)	(0.00643)			(0.00766)	(0.00725)
Environmental uncertainty$_{(t-1)}$	-0.653†	-0.499			-0.231	-0.0783
	(0.379)	(0.363)			(0.366)	(0.327)
Fuel economy regulation$_{(t-1)}$	0.155	0.194				
	(0.135)	(0.138)				
Phase-out announcements$_{(t-1)}$	0.0389	-0.330				
	(0.375)	(0.368)				
EV technology-push policies$_{(t-1)}$	-0.000415	0.00230***	0.000351	0.00232***	-0.000311	0.00235***
	(0.000701)	(0.000666)	(0.000461)	(0.000472)	(0.000679)	(0.000576)
EV demand-pull policies$_{(t-1)}$	-6.62e-07***	-5.25e-07***	-6.56e-07***	-4.70e-07***	-6.39e-07***	-4.29e-07***
	(1.87e-07)	(1.45e-07)	(1.61e-07)	(1.31e-07)	(1.76e-07)	(1.25e-07)
EV technology-push policies$_{(t-1)}$* EV demand-pull policies $_{(t-1)}$		-2.86e-09***		-2.19e-09**		-2.69e-09***
		(7.59e-10)		(7.06e-10)		(6.31e-10)
Observations	293	293	320	320	293	293
Number of firms	28	28	28	28	28	28
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
AIC	4,816	4,528	6,040	5,813	4,975	4,692

Robust standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$

5 Discussion

This paper investigated whether innovation policies in alternative technologies contribute to technology decline by influencing firms' innovation activities in incumbent technologies. Specifically, we quantitatively analyzed the influence of technology-push and demand-pull policies on the innovation activity of 29 publicly listed automotive firms in the context of the transition from ICE to EV cars between 2009 and 2020, gleaning three major findings. First, demand-pull policies negatively correlate with firms' innovation activity in incumbent technologies. Second, we uncovered robust evidence that the interaction between demand-pull and technology-push policies negatively correlates with firms' innovation activity in incumbent technologies. Third, technology-push policies might increase firms' innovation activity in incumbent technologies; however, their effect diminishes and switches direction when combined with strong demand-pull policies.

5.1 Contributions to the Scientific Literature

Our findings make three contributions to the literature. First, we show quantitatively that policy mixes with instruments for supporting new technologies (e.g., technology-push and demand-pull policies) also contribute to technology decline by inducing firms to reduce innovation activity in incumbent technologies. This confirms the suggestion by Kivimaa and Kern (2016) that one policy mix could contribute to both the "creation" of a technological innovation system (TIS) around an emerging technology and the "destruction" of the incumbent technology's TIS.

More specifically, our findings suggest that policy mixes that support key functions in the development of a new TIS, such as resource mobilization and market creation (Bergek and Jacobsson, 2003), might also influence key processes in the decline of the incumbent TIS, such as resource demobilization and guidance toward exit (Bento et al., 2021). For example, the significant correlation between stronger demand-pull policies and less innovation activity in the incumbent technology supports our argument that such policies induce firms to withdraw resources from the incumbent technology, contributing to resource demobilization. Our findings on the interaction effect between strong technology-push and demand-pull instruments also support the argument that policy mixes with these characteristics negatively influence managers' expectations about the incumbent technology's future, contributing to guiding them toward exiting the incumbent technology. Therefore, to fully understand the behavior of incumbent firms, future research on policy mixes for deliberate technology decline should consider the role played by instruments supporting new technologies besides instruments addressing incumbent technologies, such as phase-outs and bans.

Second, we also contribute to the literature on innovation policy by demonstrating that the effect of technology-push policies on firms' innovation activities in the incumbent technology can be ambiguous. Prior research has shown that technology-push policies are linked to increases in firms' innovation activities in new technologies (e.g., Costantini et al., 2017). Here, our findings suggest that such policies could also be linked to increased innovation activities by firms in incumbent technologies when combined with weak demand-pull policies. Although this finding may be unsurprising, given the well-documented history of incumbents improving old technologies in order not to fall behind across many technological races (De Liso et al., 2023), it has major implications. For instance, it advises caution when applying the notion that innovation policies should be sequenced, starting with a strong emphasis on technology-push and, in later stages, adding demand-pull (Albrecht et al., 2015; Pakizer et al., 2023). Our findings suggest that concentrating efforts on technology-push policies, as was the case in Germany and Japan (Narassimhan et al., 2024), may have unintended policy outcomes that reduce the effectiveness of technology-push policies as transition policies and potentially delay technological substitution. Such an effect might partly explain why the transition to EVs has been so slow.

More broadly, our study highlights that to understand the full impact of innovation policies on technological change, one must study their impact on both emerging and incumbent technologies. If technology-push policies for emerging technologies indeed stimulate innovation in incumbent technologies, research that exclusively measures the impact of such policies only on emerging technologies might overestimate their effect on technological change. On the contrary, studies that exclusively investigate the impact of demand-pull policies only on emerging technologies might underestimate the potential of such policies by neglecting the positive impact of such policies on the decline of incumbent technologies.

Third, we further contribute to the literature on sustainability transitions by demonstrating that the joint use of technology-push and strong demand-pull policies is best suited to persuade incumbents to withdraw from legacy technology. This underscores the importance of considering the joint effects of simultaneous policy instruments (Rogge and Reichardt, 2016) and suggests that technology-push policies should not be phased out too early since they unfold synergies with demand-pull technologies and support the technology-decline effect. The latter finding complements previous research that suggests that using technology-push policies in combination with demand-pull policies yields superior outcomes in several dimensions, such as innovation (Costantini et al., 2017) and job creation (Nuñez-Jimenez et al., 2022). Moreover, the finding that innovation policies are an effective means of incentivizing firms to withdraw from incumbent technologies has important implications for policymaking for sustainability transitions. Previous work has shown that powerful incumbents tend to resist policies that mandate the decline or phase-out of their legacy technologies (Liu and Chao, 2022; Trencher et al., 2019). If innovation policies, as a side effect, contribute to technology decline, this has a positive impact on transitions since (a) incumbents might not fight innovation policies given that their impact on decline is not directly obvious, and (b) over time, the decline in incumbent technologies might weaken the power of and reduce resistance by incumbent firms. Indeed, our findings suggest that the waning importance of incumbent technologies might force incumbent firms to move toward a more proactive policy strategy as policy stimulates demand for emerging technologies, which may help overcome battles with incumbents over technology phase-outs (Wesseling et al., 2015a).

5.2 Practical Implications

In addition to its contributions to the literature, our study has important implications for policymakers. First, policymakers should clearly define the goals of their policy mix and consider the side effects of the policy instruments they use. For instance, our study shows that demand-pull policies are instruments well suited to inducing technology decline in innovation activity in the incumbent technologies. This can be problematic when technology substitution is not the goal and, instead, policymakers wish to promote the use of multiple technologies (e.g., to increase the resilience of complex systems like the electricity grid). If applied to the energy sector, innovation policies for one technology type (e.g., solar energy) may unintentionally lead to a decline in innovation in other energy technologies. While this is beneficial if policymakers seek to achieve decarbonization (e.g., by reducing fossil energy technologies, such as gas and coal), it may be problematic if reduced innovation in alternative renewable energy technologies is the outcome.

Second, our findings suggest that policymakers should combine demand-pull and technology-push policies to accelerate technological substitution. By stimulating a “sail ship effect,” technology-push policies might increase firms’ innovation efforts in incumbent technology, except when combined with demand-pull policies. While this reduces the effectiveness of technology-push instruments as transition policies, policymakers can also purposefully exploit the potential of technology-push policies to induce firms to boost their innovation activity in the dominant technology. For example, if sustainable technology alternatives are competing, it might be beneficial to increase the threat of substitution to the dominant technology design through R&D support for less mature technologies in order to stimulate innovation in the technology field.

5.3 Limitations and Future Research

Our study has several limitations that offer avenues for future research. First, one limitation of our study is that we studied automotive OEMs, which are large companies that have traditionally pursued multiple technologies (e.g., using diesel and gasoline technologies simultaneously). The effects of demand-pull and technology-push policies on incumbent technology may be different for specialized firms, such as component suppliers, which may defend themselves against emergent technologies since they may not possess the necessary resources to adapt to the technological shift. Consequently, our findings may only apply to comparable companies. Future research could extend our findings by analyzing companies that may be more inclined to increase innovation in incumbent technologies as a defense mechanism.

Second, future research could investigate the effectiveness of individual innovation policy instruments (e.g., tax credits) on technology decline to learn how specific instruments shape firms' strategic responses to technology innovation. Our paper addresses technology-push and demand-pull measures without isolating the effect of specific instruments. In this regard, the study of whether general R&D funding, as provided in the UK, yields similar effects for technology decline as technology-specific technology-push instruments may yield important insights.

Third and finally, we bring forth different explanations for why firms may respond to innovation policies either by embracing incumbent technology decline or defending against it, with many alternatives possible between these two ends of the continuum. Our reasoning draws on prior research to formulate different arguments for our hypotheses, but this study cannot attribute the effects to individual mechanisms. This opens an avenue for future work, possibly qualitative, to shed light on the mechanisms by which innovation policies lead to technology decline. In this context, given that our analysis did not yield unambiguous results, we particularly call for future work on technology-push policies to better understand their impact on incumbent technologies.

Appendix

Table A.1: Firm sample with Derwent standard codes

Firm	DII Code	DII codes of consolidated subsidiaries (see Luetkehaus, 2024)
AVTOVAZ	ATVZ-C (until 2017)	none
BMW	BAYM-C	BMCC-C (1994–1999)
BYD	BYDB-C	none
DAIMLER	DAIM-C	CHRY-C (1998–2006); DTDI-C (since 2000); MOTU-C (1985–2002); MESR-C (1993–1999)
FCA	FIAT-C	COUA-C; ITMA-C (until 2017); AUTV-C (2001–2017); CHRY-C (since 2011)
FORD	FORD-C	BMCC-C (2000–2007)
GAC	GAIG-C	none
GM	GENK-C	OPEL-C (until 2016); HUGA-C (1985–2002); DELP-C (until 1998)
GREAT WALL	GRWA-C	none
HONDA	HOND-C	YACH-C (since 2006)
HYUNDAI	HYMR-C	KIAK-C (1999–2010)
ISUZU	ISUZ-C	none
JAC	JIAN-C	none
KIA	KIAK-C (consolidated by Hyundai 1998–2010)	none
LIFAN	LIFG-C	none
MAHINDRA & MAHINDRA	MAHI-C	SSAN-C (since 2011)
MAZDA	MAZD-C	none
MITSUBISHI	MITM-C	none
NISSAN	NSMO-C	JATC-C
PORSCHE	PORS-C (until 2011)	none
PSA	CITR-C	FAUR-C (1998–2014)
RENAULT	RENA-C	ATVZ-C (since 2017)
SAIC	SAMO-C	
SSANGYONG	SSAN-C (until 2010)	none
SUBARU	FUJH-C	none
SUZUKI	SUZM-C	none
TATA	TTTA-C AND AN=("Tata Motors Ltd" OR "Jaguar Land Rover" OR "Jaguar Cars")	none
TOYOTA	TOYT-C	DAHM-C (since 1998); HINM-C (since 2001); MSWA-C (since 2017)
VW	VOLS-C	NSUM-C; SKOD-C (since 1994); SCNI-C (since 2008); MAUG-C (since 2011); RENK-C (2011–2019); PORS-C (since 2012)

Table A.2: Comprehensive, balanced, and precise search strings for ICE patent identification

		Comprehensive	Balanced	Precise
Index dates	01/01/1990 to 07/31/2022	x	x	x
Firm identifier	(AC=(ATVZ-C OR BAYM-C OR BMCC-C OR BYDB-C OR DAIM-C OR CHRY-C OR DTDI-C OR MOTU-C OR MESR-C OR FIAT-C OR COUA-C OR ITMA-C OR AUTV-C OR CHRY-C OR FORD-C OR GAIG-C OR GENK-C OR OPEL-C OR HUGA-C OR DELP-C OR GRWA-C OR HOND-C OR YACH-C OR HYMR-C OR KIAK-C OR ISUZ-C OR JIAN-C OR LIFG-C OR MAHI-C OR SSAN-C OR MAZD-C OR MITM-C OR NSMO-C OR JATC-C OR PORS-C OR CITR-C OR FAUR-C OR RENA-C OR SAMO-C OR FUJH-C OR SUZM-C OR TESM-C OR MAXW-C OR TOYT-C OR DAHM-C OR HINM-C OR MSWA-C OR VOLS-C OR NSUM-C OR SKOD-C OR MAUG-C OR SCNI-C OR RENK-C) OR (AC=TTTA-C AND AN=("JAGUAR LAND ROVER" OR "TATA MOTORS LTD" OR "JAGUAR CARS")))	x	x	x
IPC codes	AND IP=(B01D-046* or B01D-053* or B01J-023* or B01J-035* or B60k-005* or B60K-013* or B60K-015* or B60W-010/06 or F01L-001* or F01L-013* or F01M-013/02 or F01M-013/04 or F01N* or F01P* or F02B* or F02D* or F02F* or F02M* or F02N* or F02P* or F16H*) NOT IP=(B60K-001* or B60K-006* or B60L-003* or B60L-007/1* or B60L-007/20 or B60L-011* or B60L-015* or B60L-050/1* or B60L-050/30 or B60L-050/40 or B60L-050/6* or B60L-050/7* or B60L-053/2* or B60L-058/1* or B60L-058/2* or B60L-058/3* or B60L-058/40 or B60W-010/08 or B60W-010/24 or B60W-010/26 or B60W-010/28 or B60W-020* or F17C* or H01G-011* or H01M-002* or H01M-004* or H01M-008* or H01M-010* or H01M-012* or H01M-050* or B61* or B62B* or B62C* or B62H* or B62J* or B62K* or B62L* or B62M* or B63* or B64*)	x	x	x
Automotive keywords	AND TS=(vehicle* or car or cars or automobil* or automotive)		x	x
Technology specific keywords	AND TS=("internal combustion engine*" or "ic engine*" or "gasoline engine*" or "gasoline direct inject*" or "gdi engine*" or "petrol engine*" or "spark ignition engine*" or "si engine*" or "spark ignition direct inject*" or "sidi engine*" or "diesel engine*" or "compression ignition engine*" or "ci engine*" or "exhaust system*" or "exhaust control*" or "exhaust gas recirculat*" or "egr" or "catalytic converter*" or "turbocharg*" or "fuel tank*" or "fuel supply system*" or "fuel inject*")			x
Patents in the sample with priority years 2000 to 2020		**163,716**	**104,609**	**46,679**

Table A.3: Public institutions funding publications related to EV technology

Country	Funding agencies and programs
China	National Natural Science Foundation Of China Nsfc; Fundamental Research Funds For The Central Universities; National Key Research And Development Program Of China; China Postdoctoral Science Foundation; National Key R D Program Of China; China Scholarship Council; National High Technology Research And Development Program Of China; National Basic Research Program Of China; Natural Science Foundation Of Jiangsu Province; Ministry Of Science And Technology China; National Natural Science Foundation Of Guangdong Province; Beijing Natural Science Foundation; Hong Kong Research Grants Council; Natural Science Foundation Of Zhejiang Province
United States	United States Department Of Energy Doe; National Science Foundation Nsf; Office Of Naval Research; Nsf Directorate For Engineering Eng; United States Department Of Defense
South Korea	National Research Foundation Of Korea; Ministry Of Trade Industry Energy Motie Republic Of Korea; Ministry Of Education Science Technology Mest Republic Of Korea; Korean Government; Ministry Of Science Ict Future Planning Republic Of Korea; Korea Institute Of Energy Technology Evaluation And Planning Ketep; Ministry Of Education Moe Republic Of Korea; Ministry Of Trade Industry Energy Motie Of The Republic Of Korea; Basic Science Research Program Through The National Research Foundation Of Korea Nrf Ministry Of Education; National Research Foundation Of Korea Nrf Korea Government Msit; Korea Institute Of Energy Technology Evaluation Planning Ketep; Ministry Of Science Ict Msit Republic Of Korea; National Research Foundation Of Korea Nrf Korea Government Msip; Ministry Of Education Human Resources Development Moehrd Republic Of Korea; Ministry Of Trade Industry And Energy Motie Of The Republic Of Korea
Germany	Federal Ministry Of Education Research Bmbf; European Commission; German Research Foundation Dfg; Alexander Von Humboldt Foundation; Helmholtz Association; German Federal Ministry For Economic Affairs And Energy; European Commission Joint Research Centre; Ministry Of Economic Affairs Labour And Housing In Baden Wurttemberg; German Federal Ministry Of Transport And Digital Infrastructure; European Union S Horizon 2020 Research And Innovation Programme; Federal Ministry For Economic Affairs And Energy Bmwi
Japan	Ministry Of Education Culture Sports Science And Technology Japan Mext; Japan Society For The Promotion Of Science; Grants In Aid For Scientific Research Kakenhi; New Energy And Industrial Technology Development Organization Nedo; Japan Science Technology Agency Jst; Core Research For Evolutional Science And Technology Crest; Ministry Of The Environment Japan
Italy	European Commission; Ministry Of Education Universities And Research Miur; European Commission Joint Research Centre; European Research Council Erc; Enea Italy; Istituto Italiano Di Tecnologia Iit
France	European Commission; French National Research Agency Anr; Region Hauts De France; Centre National De La Recherche Scientifique Cnrs; European Union S Horizon 2020 Research And Innovation Programme; Region Auvergne Rhone Alpes; Region Bourgogne Franche Comte; Ademe France; Region Nouvelle Aquitaine; European Union S Horizon 2020 Research And Innovation Program; Region Ile De France
India	Department Of Science Technology India; Council Of Scientific Industrial Research Csir India; Science Engineering Research Board Serb India; University Grants Commission India; Fist Project; Science And Engineering Research Board; Ministry Of Electronics And Information Technology Government Of India; Ministry Of Skill Development And Entrepreneurship Government Of India
Russia	Russian Foundation For Basic Research Rfbr; Russian Science Foundation Rsf; Ministry Of Education And Science Russian Federation; Government Of The Russian Federation; Ministry Of Science And Higher Education Of Russian Federation; Act 211 Government Of The Russian Federation; Act 211 Of The Government Of The Russian Federation; Complex Program Of The Ural Branch Of The Russian Academy Of Sciences; Government Assignment For Scientific Research From The Ministry Of Science And Higher Education Of Russia; Government Of Russian Federation; Ministry Of Science And Higher Education Of The Russian Federation As Part Of World Class Research Center Program Advanced Digital Technologies; Ministry Of Science And Higher Education Of The Russian Federation In The Framework Of The Increase Competitiveness Program Of Nust Misis; Russian Academy Of Sciences; Russian Government; Russian Government

Note. Funding agencies and programs are displayed as formatted and used in Web of Science.

Table A.4: Descriptive statistics with time horizon 2009–2020

Variable	Obs	Mean	Std. Dev.	Min	Max
(1) scaled patents – balanced$_{(t)}$	320	184.597	251.673	0	1,483
(2) scaled patents – comprehensive$_{(t)}$	320	245.912	326.412	0	1,723
(3) scaled patents – precise$_{(t)}$	320	93.313	143.519	0	793
(4) patents – balanced$_{(t)}$	320	209.769	254.436	0	1,587
(5) EV demand-pull policies$_{(t-1)}$	320	331,912.27	482,901.39	0	1,729,431.8
(6) EV demand-pull policies – registrations$_{(t-1)}$	320	384,129.85	553,558.48	0	1,975,029
(7) EV demand-pull policies – quality $_{(t-1)}$	320	19,363,867	13,090,202	0	41,206,468
(8) EV technology-push policies$_{(t-1)}$	320	110.063	244.51	0	1142
(9) EV technology-push policies extended$_{(t-1)}$	320	170.018	287.272	0	1,425.727
(10) Firm size$_{(t-1)}$	319	97.529	112.798	.945	501.458
(11) R&D intensity$_{(t-1)}$	302	.031	.015	.002	.088
(12) Financial performance$_{(t-1)}$	319	.03	.081	-.552	.772
(13) Slack resources$_{(t-1)}$	305	3.354	14.83	.002	184.311
(14) ICE knowledge stock$_{(t-1)}$	320	1,076.693	1,355.848	.183	6,325.853
(15) R&D cooperation$_{(t-1)}$	320	3.6	6.649	0	47
(16) Environmental uncertainty$_{(t-1)}$	312	.186	.158	.015	1.028
(17) Fuel economy regulation$_{(t-1)}$	320	13.107	4.287	0	18.315
(18) Phase-out announcements$_{(t-1)}$	320	.035	.139	0	1

Table A.5: Pairwise correlations with time horizon 2009–2020

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) scaled patents – balanced$_{(t)}$	1.000							
(2) scaled patents – comprehensive$_{(t)}$	0.989	1.000						
(3) scaled patents – precise$_{(t)}$	0.986	0.970	1.000					
(4) patents - balanced$_{(t)}$	0.535	0.585	0.504	1.000				
(5) EV demand-pull policies$_{(t-1)}$	0.034	0.019	0.029	0.060	1.000			
(6) EV demand-pull policies – registrations$_{(t-1)}$	0.040	0.025	0.034	0.066	1.000	1.000		
(7) EV demand-pull policies – quality $_{(t-1)}$	0.470	0.459	0.432	0.474	0.508	0.519	1.000	
(8) EV technology-push policies$_{(t-1)}$	-0.168	-0.174	-0.157	-0.161	0.213	0.199	-0.302	1.000
(9) EV technology-push policies extended$_{(t-1)}$	-0.099	-0.111	-0.089	-0.133	0.278	0.265	-0.235	0.991
(10) Firm size$_{(t-1)}$	0.655	0.688	0.633	0.651	0.298	0.305	0.606	-0.194
(11) R&D intensity$_{(t-1)}$	0.499	0.512	0.469	0.321	0.201	0.206	0.500	-0.113
(12) Financial performance$_{(t-1)}$	0.096	0.090	0.078	0.076	0.009	0.010	0.092	-0.003
(13) Slack resources$_{(t-1)}$	-0.115	-0.115	-0.110	-0.099	0.125	0.127	0.042	0.054
(14) ICE knowledge stock$_{(t-1)}$	0.875	0.864	0.861	0.534	0.260	0.267	0.608	-0.173
(15)) R&D cooperation$_{(t-1)}$	0.265	0.335	0.229	0.875	0.061	0.066	0.400	-0.192
(16) Environmental uncertainty$_{(t-1)}$	-0.301	-0.293	-0.289	-0.311	-0.354	-0.359	-0.545	0.079
(17) Fuel economy regulation$_{(t-1)}$	0.192	0.199	0.188	0.217	0.327	0.330	0.484	0.026
(18) Phase-out announcements$_{(t-1)}$	-0.058	-0.060	-0.052	-0.012	0.384	0.386	0.140	-0.083

Table A.5: Pairwise correlations with time horizon 2009–2020 (ctd.)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)										
(2)										
(3)										
(4)										
(5)										
(6)										
(7)										
(8)										
(9)	1.000									
(10)	-0.145	1.000								
(11)	-0.063	0.417	1.000							
(12)	0.002	0.024	0.021	1.000						
(13)	0.046	-0.139	-0.007	0.036	1.000					
(14)	-0.085	0.740	0.550	0.038	-0.121	1.000				
(15)	-0.193	0.590	0.242	0.026	-0.094	0.336	1.000			
(16)	0.028	-0.349	-0.389	0.124	0.059	-0.392	-0.233	1.000		
(17)	0.042	0.301	0.411	0.060	0.083	0.254	0.134	-0.336	1.000	
(18)	-0.073	0.023	0.159	0.050	0.165	0.017	0.014	-0.136	0.212	1.000

Table A.6: Test for dynamic endogeneity of demand-pull and technology-push policies (FEP)

	Model S1	**Model S2**
VARIABLES	EV demand-pull policies$_{(t)}$	EV technology-push policies$_{(t)}$
scaled patents – balanced$_{(t-1)}$	-5.03e-05	0.000274
	(4.53e-05)	(0.000885)
Observations	318	294
Number of firms	27	28
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
AIC	2.900e+06	3,330

Robust standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$

Table A.7: Endogeneity test with IV control function approach (FEP with scaled ICE patents from balanced identification strategy as dependent variable)

VARIABLES	**Model S3**
Firm size$_{(t-1)}$	0.00219
	(0.00184)
R&D intensity$_{(t-1)}$	-0.0755
	(2.813)
Financial performance$_{(t-1)}$	0.491**
	(0.186)
Slack resources$_{(t-1)}$	-0.00131
	(0.00160)
ICE knowledge stock$_{(t-1)}$	0.000127**
	(4.48e-05)
R&D cooperation$_{(t-1)}$	0.0237*
	(0.0116)
Environmental uncertainty$_{(t-1)}$	-0.581
	(0.467)
Fuel economy regulation$_{(t-1)}$	0.175
	(0.120)
Phase-out announcements$_{(t-1)}$	-0.0846
	(0.530)
EV technology-push policies$_{(t-1)}$	-0.000505
	(0.000691)
EV demand-pull policies$_{(t-1)}$	-8.58e-07
	(6.95e-07)
Residuals stage 1	2.34e-07
	(9.15e-07)
Observations	291
Number of firms	28
Year fixed effects	Yes
Firm fixed effects	Yes
AIC	4,810

Robust standard errors in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0$.

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