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Looking Under the Hood – How Incumbent Characteristics Shape the Innovation Impact of Demand-Pull Policies for Battery Electric Vehicles

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Abstract

Policymakers increasingly implement demand-pull policies to support the rise of environmentally benign technologies. Previous studies provide important insights into how these policies drive innovation. However, we still lack a detailed understanding of the role that incumbents' heterogeneity plays in the impact of policy on innovation. In this context, it is valuable to understand the determinants of incumbents' responses to policies, as these firms might hinder but also enable sustainability transitions. Toward this end, we investigate how firm characteristics shape the impact of demand-pull policies on incumbent carmaker innovation activity. Building on the literature on incumbent adaptation, we find robust empirical evidence that technological capabilities, firm performance, and the commitment to incumbent technology inhibit demand-pull policy impact on incumbents' innovation activity. These insights shed new light on the linkage between policy and innovation by highlighting that demand-pull policy impact depends on incumbents' heterogeneity and, as such, on a higher level, also on the incumbent firm population of a country. This provides starting points for complementary policies in the policy mix to render demand-pull policies more effective. Moreover, we demonstrate that firm characteristics that inhibit incumbents' adaptation to technological change also constrain their responsiveness to deployment policies. Thus, we suggest that incumbents who are successful in old technologies are at risk of being caught in a double trap, impeding their adaptation.

Keywords: environmental innovation; innovation policy; demand-pull policy; incumbent adaptation; policy mix; electric vehicle

JEL Classification: L62, O31; O38; Q55; Q58

1 Introduction

In the face of sustainability challenges, policymakers increasingly use demand-pull policies to support environmentally benign technologies, e.g., biofuels (Costantini et al., 2015), wind power (Peters et al., 2012), and electric mobility. These policies act as drivers of innovation activity (Costantini et al., 2017; Dechezleprêtre and Glachant, 2014) and, thus, can accelerate sustainability transitions.

One group that plays a particularly important role when trying to understand transitions is incumbent firms since they might act as hindrances and enablers of sustainability transitions (e.g., Turnheim and Sovacool, 2020). Yet while previous studies have investigated the role of incumbents in transitions (Magnusson and Werner, 2022; Mori, 2021; Skeete, 2019; Steen and Weaver, 2017) and have also investigated responses to policy support at the firm level (Doblinger, 2015; Guerzoni and Raiteri, 2015; Hoppmann et al., 2013; Plank and Doblinger, 2018), there are only few studies that have addressed how characteristics of incumbent firms shape their responses to market support policies. The literature demonstrates that demand-pull policies can have unintended adverse effects on sustainability transitions, such as premature technology lock-ins arising from firm behavior (Hoppmann et al., 2013). Therefore, understanding which internal factors shape incumbents' reactions to demand-pull policies can yield valuable insights for theory and practice. A better understanding of how demand-pull policies affect incumbents can help policymakers in their efforts to transform incumbents from inhibitors to accelerators of transitions by highlighting opportunities to increase the overall effectiveness and efficiency of the policy mix, e.g., through complementary policies such as technology-push or phase-out policies.

To shed light on the impact of demand-pull policy on innovation for heterogeneous incumbents, we examine the moderating roles of firm characteristics. Building on previous literature, we propose that the effect of deployment policies is not uniform but depends on firm-level factors. By linking insights from innovation studies focusing on policy (e.g., Costantini et al., 2017; Dechezleprêtre and Glachant, 2014; Peters et al., 2012) with business studies on incumbent adaptation to technological change (e.g., Chandy and Tellis, 2000; Cohen and Levinthal, 1990; Eggers and Park, 2018; Kaplan, 2008), we identify three potential moderators: technological capabilities, firm performance, and commitment to incumbent technology.

First, we propose that the technological capabilities of an incumbent inhibit demand-pull policies' innovation effect because of the path dependency of absorptive capacity and the so-called competency trap (Cohen and Levinthal, 1990; Levinthal and March, 1993; Levitt and March, 1988). Second, incumbents with leading economic performance have little incentive to cannibalize their own products; rather, it is in their interest to leave costly exploration to early movers (Conner, 1988; Lieberman and Montgomery, 2013; Wesseling et al., 2015; Zachary et al., 2015). Accordingly, we hypothesize that firm performance negatively moderates the impact of demand-pull incentives. Lastly, we suggest that the level of commitment to incumbent technology determines incumbents' unwillingness or inability to change strategies towards innovation involving emerging technologies in response to policy-induced markets (Eggers and Park, 2018; Kaplan, 2008; Rosenbloom, 2000; Rosenbloom and Christensen, 1994; Sull et al., 1997).

This study applies a quantitative empirical design to test the hypotheses in the automotive industry context, which is well suited due to strong incumbency and the use of demand-pull policies in all major markets. We use a novel panel data set of 30 listed light-duty vehicle manufacturers and their innovation activities, which allows us to cover a time horizon from 2001 to 2020. Our analysis provides robust results that the effectiveness of demand-pull policies is inhibited by incumbents' technological capabilities, performance position, and commitments to the incumbent technology. These findings hold practical implications for policymakers and managers alike, and we make the following important contributions to the extant literature.

First, we show that firm-level characteristics shape incumbents' responses to demand-pull policies, suggesting that country-level effects also depend on the characteristics of a country's incumbents. Furthermore, identifying specific firm characteristics allows for a discussion of ways to increase the effectiveness of demand-pull policies by implementing complementary policies that overcome or address inhibiting firm-level factors.

Second, our study adds new insights to the literature on incumbent adaptation to technological change, showing that firm characteristics known to inhibit technological adaptation also cause incumbents to miss out on the benefits of early market support. This implies that those incumbents who are inert and, therefore, may be most in need of policy support are also those who are least responsive to it and thus may be caught in a double trap.

2 Literature Review and Hypotheses

2.1 Demand-Pull Policies as Drivers of Innovation

Demand-pull policies are policy instruments that alter demand conditions or shape expectations about future demand (growth) for a technology and may include different types of policy instruments, such as economic, regulatory, or informational instruments (Nemet, 2009; Reichardt and Rogge, 2016). By creating markets or signaling market growth, demand-pull policies, such as subsidies, public procurement, or market-inducing regulations, reduce the uncertainty of innovators and increase the rewards for successful innovation (Nemet, 2009; Peters et al., 2012).

The notion of (anticipated) demand as a driver of innovation activity and determinant of innovation pathways dates back as far as the 1960s (Godin and Lane, 2013). The literature to date provides ample evidence of demand-pull policies as drivers of innovation at the aggregate country level (Costantini et al., 2015; Dechezleprêtre and Glachant, 2014; Hille et al., 2020; Johnstone et al., 2010; Peters et al., 2012) and the firm-level (Guerzoni and Raiteri, 2015; Hoppmann et al., 2013; Rogge et al., 2011; Schmidt et al., 2012a). Moreover, the related literature on environmental regulation, i.e., demand-pull when inducing markets, shows that stricter regulations spur environmental innovation (Ambec et al., 2013; Dechezleprêtre and Sato, 2017). Fabrizi et al. (2018) find that market-based regulations are particularly promising in this regard. In addition, by altering market expectations, regulation in the form of a gradual or scheduled technology ban on an incumbent technology recently discussed as a phase-out policy (Trencher et al., 2022), can encourage innovation in sustainable technologies (Rogge and Dütschke, 2018; Rogge and Johnstone, 2017). Importantly, demand-pull policy effects are not limited to domestic industries but also induce innovation abroad (Dechezleprêtre and Glachant, 2014; Peters et al., 2012). Here, the magnitude of policy spillovers depends on the similarity of the policy (mix) between two countries, which can be leveraged for mutual benefit through policy coordination (Costantini et al., 2017). Recent research has focused on more complex policy mixes rather than single policies, discussing the role of demand-pull policies as part of a broader mix (Reichardt and Rogge, 2016; Rogge and Johnstone, 2017; Rogge and Schleich, 2018).

2.2 The Role of Incumbent Characteristics for Demand-Pull Policy Impact on Innovation

The literature provides convincing evidence that demand-pull policies stimulate innovation activity, but as firms are heterogeneous, they do not respond equally to policies (Garcia Hernández et al., 2021; Hoppmann et al., 2013; Reichardt and Rogge, 2016; Shao et al., 2020). Regarding demand-pull policies, Rogge et al. (2011) find that in response to the EU ETS in the power sector, large incumbents, in particular, have significantly increased their R&D activities, but mostly in established technological trajectories close to their existing competencies. In a similar setting, Schmidt et al. (2012a) clustered firms with respect to their behavior. They found that clusters differed significantly in terms of firms' value chain position, size, technology portfolio, and technology capabilities. Further pursuing these ideas on firm-level factors shaping responses to demand-pull policies, we explore how and why incumbents differ in their innovation activity in response to demand-pull policies. A more detailed understanding of the behavior of incumbents is valuable because they have the ability to drive innovation in a technology field and shape technological trajectories (Bergek et al., 2013; Feng and Magee, 2020), and as such can act as both inhibitors and enablers of transitions (Steen and Weaver, 2017; Turnheim and Sovacool, 2020). To this end, we combine innovation studies focusing on policy with business research on incumbent adaptation to technological change to derive three hypotheses on firm characteristics that shape incumbent responses to demand-pull policies.

2.2.1 The Moderating Role of Firms' Technological Capabilities

We propose that an incumbent's innovation activity in response to demand-pull policies depends on the firm's technological capabilities. Technological capability is built up by firms by accumulating knowledge and experience in a technology domain (Zhou and Wu, 2010). The literature on absorptive capacity suggests that such accumulated experience in a technology domain is decisive for a firm's ability to acquire and assimilate technological knowledge from its environment and facilitates subsequent innovation and commercialization (Cohen and Levinthal, 1990; Lane et al., 2006). Specifically, the more a firm knows, the more easily it can perceive, relate to, and reconfigure related knowledge in its environment. In this way, technological capabilities can facilitate incumbents' adaptation process to a new technology, which entails acquiring and assimilating new knowledge (Eggers and Park, 2018). Therefore, firms wishing to change their technological trajectory need to invest in research and development to acquire, build, and reconfigure knowledge as the basis for developing new capabilities (Cohen and Levinthal, 1990; March, 1991). Indeed, the success of firms might depend on a deliberate shift from the exploitation of extant competencies to the accumulation of new ones at the right time (Mudambi and Swift, 2014).

While technological capabilities and underlying research and development are important for firms' transformation, technological capabilities and related absorptive capacity also have downsides that may hinder incumbent adaptation to technological change (Zhou and Wu, 2010). Specifically, we argue that technological capabilities reduce the responsiveness of incumbents to demand-pull policies for four reasons:

First, technological capabilities and related absorptive capacity are domain-specific and developed over time. Since this path-dependent nature of knowledge shapes firms' expectations, it may lead incumbents to (deliberately) overlook or underestimate the potential of emerging technology alternatives (Cohen and Levinthal, 1990). Second, past experiences in a domain make future exploitation more efficient, fostering increased exploitation of current capabilities and raising opportunity costs of alternatives. This so-called competency trap reduces the extent to which firms (despite great competencies) invest in novel and more exploratory technologies (Levinthal and March, 1993; Levitt and March, 1988). Third, revenues from exploration are more distant and uncertain than those from exploitation (March, 1991), so firms with a strong technology base may prefer to exploit existing technologies rather than explore new ones (Zhou and Wu, 2010). Fourth and finally, there is a recurring tendency for incumbents to incorporate new technology knowledge into their current technology competencies to develop hybrids that preserve the value of their competencies (Bergek et al., 2013; Furr and Snow, 2015). While this can be an intermediate step in changing technology trajectories, it can also be a source of inertia if firms overinvest in hybrid technologies (Furr and Snow, 2015).

Taken together, we expect that the inertial mechanisms of current technological capabilities reduce the responsiveness of incumbents to demand-pull policies as higher technological capabilities might (1) lead them to underestimate the potential of the emerging new technology, (2) favor more efficient incumbent innovation activities, (3) increase the desire to maintain them and (4) incentivize to focus on hybrid technologies.

> *H1: The effect of demand-pull policies on incumbents' innovation activity is negatively moderated by firms' technological capabilities.*

2.2.2 The Moderating Role of Firms' Performance

The previous hypothesis suggests that the impact of demand-pull policies depends on firms' technological capabilities. However, we propose that the former is not sufficient to explain incumbents' heterogeneous responses to demand-pull policies. In addition, we hypothesize that firms' performance shapes incumbents' strategic decisions on R&D investments in reaction to demand-pull policies. The literature argues that incumbents per se have a lower incentive than entrants to introduce radical innovation that renders their existing capabilities obsolete because they generate revenues from the current technology (Chandy and Tellis, 2000; Henderson, 1993). However, in the face of technological change, incumbents eventually must adapt and invest in new technology to protect their core market (Kaplan, 2008).

The best timing for a firm to adapt to technological change depends on the respective firm's market position and related economic incentives, as well as the need for repositioning (Bohnsack et al., 2020; Conner, 1988). Less-profitable firms have the incentive to seize the opportunity of demand-pull policy-induced markets and heavily invest in innovation to gain market share or reputation. In contrast, more profitable firms might wait to not cannibalize their products prematurely and learn from early movers' failures and costly explorative activities (Conner, 1988; Lieberman and Montgomery, 2013; Zachary et al., 2015). For instance, Wesseling et al. (2015) show that the early movers in electric vehicle technology were incumbents with below-average net income, arguing that lower firm performance incentivizes this strategy. Still, initially lagging firms can overtake early movers if they have sufficient resources and incentives to leap (Lieberman and Montgomery, 2013; Urban et al., 1986). A shift in market position (e.g., due to an accelerating displacement of the incumbent market or shocks that impair the revenues from conventional technology, such as 2016's "Dieselgate") might be such a motivation. Therefore, we expect that firms' relative performance not only shapes the initial early mover decision but also the innovation timing and magnitude more generally. We propose that a better performance position incentivizes an incumbent to respond less to demand-pull policies and to keep lagging to avoid cannibalizing its own products and to benefit from early mover exploration until its performance is impaired.

> *H2: The effect of demand-pull policies on incumbents' innovation activity is negatively moderated by firms' performance.*

2.2.3 The Moderating Role of Firms' Commitment to Incumbent Technology

Lastly, we suggest firms' commitment to incumbent technology as a moderator of the demand-pull effect on incumbents' innovation activity. Commitments play a significant role in incumbents' adaptation to technological change (Eggers and Park, 2018) and "should be considered, along with competencies and economic incentives, in examining how incumbents respond to technological discontinuities" (Sull et al., 1997, p. 497). Although firm performance, along with economic incentives, might be related to a firm's commitment,[1] the determinants of commitment are more diverse and extensive. The roots of incumbents' commitment to existing technology include but are not limited to institutional pressure from financial markets (Benner, 2007), organizational inertia (Chandy and Tellis, 1998), or managers' inclination towards commitment-maintaining investment decisions (Sull et al., 1997). Eggers and Park (2018) abstract these causes to path dependency and fear of cannibalization, pointing out the inertial effect on technology adaptation. In this regard, an incumbent's inertia might not depend on the inability to adapt or explore a new technology but rather the inability or unwillingness to change strategies (Rosenbloom, 2000; Rosenbloom and Christensen, 1994). Eventually, managers might make economically suboptimal decisions if they crave to maintain their commitments (Sull et al., 1997). In brief, firm commitments to existing technology impair incumbents' incentive and ability to acquire or assimilate new knowledge or assets (Eggers and Park, 2018). We propose that this manifests itself in the response of incumbents to demand-pull policies. An incumbent firm might refrain from (higher) innovation investments in reaction to a policy-induced market when it is firmly committed to currently dominant technology, even if it might have economic incentives to do so. Accordingly, we expect that the stronger a firm's commitment to incumbent technology, the less it will respond to demand-pull incentives by increasing innovation activity.

> *H3: The effect of demand-pull policies on incumbents' innovation activity is negatively moderated by firms' commitment to the incumbent technology.*

[1] Statistically, the variables are only weakly correlated; see Table A.4.

3 Research Setting

We test our hypotheses in the context of the global automotive industry and innovation in battery electric vehicles (BEVs). In recent years, the diffusion of electric vehicles has been fostered by governments around the globe using demand-pull policies such as consumer subsidies, tax exemptions, public procurement, or disincentives for conventional vehicles (IEA, 2020). Under the given policy conditions, with both new entrants and incumbents entering the market, BEVs experienced rapid global market growth from less than 7,000 BEV registrations in 2010 to more than 2.1 million in 2020.

In the 1990s, California's zero-emission vehicle mandate spurred a first wave of BEVs, but it fell short of economic and technological competitiveness, which led to a downturn (Bedsworth and Taylor, 2007; Sierzchula et al., 2012). While the mandate brought about the introduction of the first contemporary BEVs, such as GM's EV1, after several amendments, it failed to create a sustained electric vehicle market (Pilkington and Dyerson, 2006). Although the 1990s BEV wave is mostly attributed to California's zero-emission vehicle mandate, it is worth noting that several markets had already implemented policies to encourage the adoption of electric vehicles, such as a tax credit under the US Energy Policy Act of 1992, subsidies under Japan's Clean Energy Vehicles Project from 1996, or an electric vehicle subsidy program in France launched in 2002. Yet, in the early 2000s, all major incumbents withdrew from producing BEVs, and the 1990s wave became an example of failed radical innovation (Sierzchula et al., 2012). Nevertheless, technological change toward BEVs picked up again in the aftermath but was now driven by entrants and small incumbents serving niche markets (Sierzchula et al., 2012). In 2003, the prominent electric vehicle start-up Tesla Motors was incorporated, which has since become a mass-market car manufacturer.

Starting in the late 2000s, governments in countries with mature automotive industries, such as France, Germany, Japan, the United States, and China, began to implement more comprehensive demand-pull policies accompanied by deployment targets. While the automotive industries in the first four countries were export-oriented, the automotive industry in China was predominantly domestically oriented. In France, EV subsidies were replaced by a bonus-malus system based on CO_2 emissions (2008), and the national plan for electric and hybrid vehicles proclaimed the goal of having 2 million low-carbon vehicles on the road by 2020 (2009). Germany introduced its first deployment incentive, granting an annual exemption from vehicle tax for five years (2008), and announced a target of 1 million EVs by 2020 (2009).

Lastly, it also introduced a public procurement quota (2014) and purchase subsidies (2016). In Japan, additional tax exemptions were added to long-standing subsidy and procurement programs (2009), and the Next-Generation Vehicle Strategy 2010 was published. In the United States, a new tax credit scheme was introduced after the previous one expired in 2007 (2010), and in 2011, then-President Barack Obama set a new ambition of one million EVs by 2015 in his State of the Union Address. Simultaneously, China launched a public procurement program (2009), the first subsidy program for new energy vehicles (2010), and the State-Owned Assets Supervision and Administration Commission (SASAC) announced a plan to produce 500,000 energy-efficient vehicles annually from 2011 to 2013 (2009). In 2019, global government spending on EV deployment incentives amounted to USD 11 billion (IEA, 2020). Beyond these deployment-oriented demand-pull policies, in recent years, the debate on the politically induced phase-out of international internal combustion engine cars has intensified (Meckling and Nahm, 2019), culminating for the time being in Regulation (EU) 2023/851 - a de facto technology ban for new conventional internal combustion engine vehicles in the EU from 2035 (European Parliament, 2023).

During this period, with increased demand-side policy support and advances in lithium-ion battery technology, several automakers increasingly saw BEVs as a promising business model (Magnusson and Berggren, 2011). Not long after, the first incumbents introduced mass-market BEV models such as the Nissan Leaf (2010), Mitsubishi i-MiEV (2010), Daimler Smart EV (2011), Ford Focus EV (2012) or BMW i3 (2013) (Bohnsack et al., 2020). Other incumbents, such as Honda (2020) or hybrid pioneer Toyota (2022), took much longer to introduce a fully battery electric vehicle offering. In fact, both the leaders and the laggards in BEV launches were Japanese carmakers, showing that companies differ significantly in their adaptation to battery electric vehicles despite similar domestic environments, such as environmental constraints or technology-push policies.

The time horizon of our analysis is 2001 to 2020 to cover incumbents' inactivity and the policy-supported uptake of BEV markets. We do not include the first wave of BEVs in the 1990s because the innovation was mainly driven by regulatory pressure (Magnusson and Berggren, 2011; Pilkington and Dyerson, 2006).

4 Data and Methods

4.1 Data Collection

For this study, we combined several data sources in a novel firm-level panel data set of 30 publicly listed original equipment manufacturers (OEMs) in the light-duty vehicle industry from 2000 to 2020.[2] The scope is limited to light-duty vehicle manufacturers because demand-pull policies might have different impacts depending on the industry chain position (Rogge et al., 2011; Schmidt et al., 2012a; Wang et al., 2020). Moreover, policies for heavy-duty vehicles are non-identical. Firms were identified by being listed in the OICA (International Organization of Motor Vehicle Manufacturers) world production data in at least one period from 2000 to 2017.[3] The list was whittled down to publicly listed firms with standard codes assigned by the Derwent Innovation Index to ensure access to reliable firm-level data obtained from DataStream and the adequate assignment of patents.[4] Since this study focuses on incumbents, Tesla Inc., founded during the observation period, is excluded from the regression analysis. The remaining 29 incumbent OEMs accounted for around 87% of world motor vehicle production in 2016 and 2017 (OICA, n.d.b). While the focus of the sample allows an in-depth analysis of firm-level factors for downstream incumbents, it does not allow the generalization of findings to upstream suppliers and new entrants.

Innovation activities in the battery electric vehicle technology field are approximated by patent data, which have good data availability and are highly accepted in research (Bruns and Kalthaus, 2020; Griliches, 1990). Moreover, patents allow distinguishing among various technologies, whereas data on R&D investments are usually not available on such a disaggregated level (Popp, 2005). Patent data are obtained from the curated Derwent Innovation Index database, which excels by accounting for patent families and assigning unique standard codes to firms with more than 500 patent applications and their subsidiaries.[5] We use these standard codes to rule out any measurement bias due to the patenting of unidentified subcompanies. However, in some cases of mergers and acquisitions, standard

[2] Due to a one-year lag for the independent variables in this study, the time horizon for the analysis is 2001 to 2020.
[3] After 2017, production data per manufacturer are not reported by OICA.
[4] Firms with Derwent standard codes and public listing on different company levels were excluded if it was not possible to reliably assign patent data (e.g., BAIC Motor Corp Ltd.).
[5] Patent families are a cluster of filings for the same invention in different jurisdictions, avoiding double counting. A patent family is assigned to the earliest priority year. For brevity, we use the term *patent(s)* in the remainder of this work.

codes are not consolidated (Derwent, n.d.). Hence, we made manual adjustments based on the Refinitiv Eikon – M&A database and verified information by company reports if applicable (see the supplementary material, Appendix B). We use a 19-month cut-off to account for the buffer period before publication in major patent offices (Tegernsee Experts Group, 2012) and to allow one extra month for database indexing.[6]

When developing a patent-identification strategy, three critical points are to be addressed: (1) the consistent definition of system boundaries and research question, (2) the exclusion of relevant patents (type II error), and (3) the inclusion of patents that are not related to the technology of interest (type I error) (Bruns and Kalthaus, 2020). To this end, we defined a novel search string that builds on key terms and International Patent Classifications (IPCs) (detailed documentation in the supplementary material, Appendix B).

First, in accordance with the research objective, patents that describe the BEV powertrain or parts thereof (e.g., traction battery or electric motor), as well as patents that relate to the manufacturing of the former, are in scope.

Second, to minimize type II errors, we defined a comprehensive key term search string in an iterative process. We identified a broad range of key terms used for BEV-related patents, which we split into separate keywords and recombined to form 240 distinct key terms. In addition, we included component search terms that retrieve patents that belong to a technology group but are not labeled as such (Wesseling et al., 2014) and combined them with automotive keywords to ensure automotive usability (Borgstedt et al., 2017). Since BEVs share components with hybrid and fuel cell vehicles (HEVs and FCEVs, respectively), we exclude patents in the component search that key term search strings for HEVs and FCEVs have already identified.[7] For an indication of comprehensiveness, we calculate the share of retrieved patents in patents covered by relevant Derwent Manual Codes (MAN) (Stephan et al., 2017). The defined key term search string demonstrates good coverage of over 91% of identified patents.[8]

[6] Extraction of patent data with index dates from 01/01/1990 to 07/31/2022.

[7] Key term search strings for HEVs and FCEVs are defined according to the process for BEVs; all search strategies are documented in the supplementary material.

[8] Patent search for patents with index dates from 01/01/1990 to 07/31/2022. Patents found with MANs = 59,438 and with the key term search string = 54,167 (91.13%). MANs are valuable to indicate the comprehensiveness of key term search strings but do not match our patent scope.

Third, to address type I errors, we refined our search string by incorporating IPCs. Applying a top-down approach, we selected IPCs based on technology components and a review of former studies. In a bottom-up approach, we manually assessed the IPCs of patents found with our key term search string for IPCs with at least 0.5% share of total patents. In addition, we exclude an IPC if it comprises other propulsion technologies not relevant to BEVs.[9] The final BEV patent data set for the firms in our sample comprises 37,661 patents, with priority years from 1990 to 2020. We tested for error type I by manually checking a random subsample of 5% (1,884 patents). Within our defined scope are 87.79% (1,654 patents), which is on par with former work and generally considered to represent good reliability (Borgstedt et al., 2017).

Moreover, our study design requires several supplementary patent measures. Firms' total patents are extracted using firm identifiers. Firms' total car-related patents are extracted using firm identifiers and these automotive keywords: *vehicle*, car, cars, automobile*,* or *automotive*. Incumbent technology-related patents (i.e., for internal combustion engine vehicles) are extracted via automotive keywords in combination with IPCs. In line with previous work, we do not use propulsion-technology-specific terms because incumbent technologies are often not explicitly labeled (Song and Aaldering, 2019).

To measure demand-pull policies, we (1) obtained annual new car registration data from IHS Markit for the years 2000 to 2020 and (2) collected information on policy instruments for OECD, EU, and BRICS countries from the ACEA Tax Guides, the PWC Global Automotive Tax Guides, the IEA Policy Database, and the Climate Policy Database, supplemented by reports, newspaper articles, and government websites. This data set covers 47 countries, representing over 90% of global light-duty vehicle sales (OICA, 2022).[10] Data for production locations used to construct firm-specific weights of demand-pull policies are obtained from OICA (n.d.a). Scientific publication data used to measure technology-push policies is extracted from the Science Citation Index Expanded (SCIE) using a keyword search (Schmoch, 2007).[11] For a robustness check that includes the stringency of fuel economy regulations, we draw on

[9] To identify IPCs for exclusion, all steps are also conducted for the technology fields – HEV, FCEV, and internal combustion engine vehicles.
[10] BEV registration data: Data gaps for Japan from 2015 to 2020 and Mexico are supplemented by data from the IEA; data for Costa Rica is not available and, therefore, not included in the data set.
[11] We draw on the key term search string defined for the identification of BEV patents without component search terms. The component search terms predominantly identify non-BEV-related publications.

IEA data on average fuel consumption in major LDV markets from 2005 onwards (GFEI and IEA, 2021; IEA, 2021).[12]

4.2 Variables and Measures

To test our hypotheses about the links between incumbents' innovation activity and demand-pull policies, we need measurements of *technology-specific innovation activities* as the dependent variable and four independent variables: *demand-pull policies, technological capability, firm performance,* and *commitment to incumbent technology*. Moreover, we include control variables implied by former literature.

4.2.1 Dependent Variable

To capture innovation activity in the battery electric vehicle field, we use technology-specific patent-based measures in line with previous work. Due to different requirements and costs for patenting, the propensity to patent and average patent quality significantly differ across distinct patent offices (e.g., Rassenfosse and van Pottelsberghe de Potterie, 2009; van Pottelsberghe de Potterie, 2011). Moreover, firms are embedded in different jurisdictions and differ in their patent strategies, organization, and the sophistication of their patent processes (Agostini et al., 2022). Accordingly, when analyzing innovation activity based on patents, they should be counted on an equal quality basis (Bruns and Kalthaus, 2020). To this end, we propose a firm-level scaling factor approach that accounts for firms' different propensities to patent.

The scaling factor approach is based on the long-standing idea that firms' propensities to patent can be measured by their R&D investments to patent ratios (Scherer, 1965, 1983). More recently, Rassenfosse and van Pottelsberghe de Potterie (2009) provide empirical evidence that these ratios mainly reflect differences in the propensity to patent (on the country level) when no quality hurdle (e.g., triadic patents[13]) is applied. Building on this, we suggest using firms' R&D investment to patent ratios to harmonize patent counts for an international interfirm analysis.

[12] Major markets include China, EU27, Japan, USA, Developing and Emerging (Argentina, Brazil, Chile, Egypt, Malaysia, Mexico, Peru, the Philippines, Russia, and Ukraine). Missing data points are imputed using linear interpolation.
[13] Restricting patent counts to patents with filings at three major patent offices (Bruns and Kalthaus, 2020).

To this end, firm-level patent counts are scaled to equalized ground by multiplication with a firm-specific scaling factor:[14]

$$Scaled\ patent\ count_{i,t} = Patent\ count_{i,t} * scaling\ factor_i, \tag{1}$$

where i = firm and t = year.

The scaling factor represents a firm's R&D investment to patent ratio relative to the average of all firms in the sample:

$$Scaling\ factor_i = \frac{R\&D\ investment\ to\ patent\ ratio_i}{R\&D\ investment\ to\ patent\ ratio_{average}}, \tag{2}$$

where i = firm.

The underlying firm-specific R&D investment to patent ratios are calculated by dividing the number of patents of a firm by its purchasing power parity (PPP) and inflation-adjusted R&D investments over the period 2000 to 2020. R&D investments are lagged by one year to account for the non-contemporaneousness of research and patenting.

$$R\&D\ investment\ to\ patent\ ratio_i = \left(\frac{\sum_{t-1} R\&D\ investment_{i,t-1}}{\sum_t Patents_{i,t}}\right), \tag{3}$$

where i = firm, t = year ranging from 2000 to 2020 and R&D investment is expressed in PPP-adjusted USD_{2015}. In the case of missing R&D investment data in t–1, the corresponding patent count in t is excluded.

Scaling factors for our firm sample are reported in Table A.1. The scaling factors show geographical clusters that are in line with previous literature, i.e., below-average factors for Chinese and Japanese firms (Bruns and Kalthaus, 2020; Fisch et al., 2017; Peters et al., 2012), reflecting country-level determinants such as costs at national patent offices. Moreover, Pearson correlation tests provide evidence that our novel approach is related to the established triadic patent approach for patent quality, with a highly significant correlation coefficient of 0.66 ($p < 0.01$) for firms' scaling factors and triadic patent shares. Therefore, we are confident that the scaling factor approach adequately accounts for differences in firms' propensity to

[14] Scaled patent counts are rounded to the nearest integer to retain the original count data format.

patent. However, the scaling factors might also cancel out differences in research productivity. Therefore, we advise running robustness tests using, e.g., unscaled patent counts.

In comparison with former methods to account for patent quality, such as triadic patents or patent citations, our approach has two significant advantages. First, the approach requires no additional cut-off periods to allow time for citations or patent applications in different jurisdictions, enabling the analysis of recent developments. Second, it does not impose the assumption of multinational patent measures (e.g., triadic patents), which presumes that individual patents are required to protect an invention in several markets (Bruns and Kalthaus, 2020). The second advantage is particularly important when analyzing patent activity in the automotive industry, as Peter Moeldner, vice president of Robert Bosch GMBH (automotive supplier), stated that patent protection in one region entails a global effect in practice (Haegler, 2020).

4.2.2 Independent Variables

Demand-Pull Policies for Battery Electric Vehicles

The most important independent variable is *demand-pull policies* for battery electric vehicles. For consistency with the scope of innovation activity (patent in the BEV technology field), we capture demand-pull policies for battery electric vehicles and not include demand-pull for plug-in hybrids or fuel cell electric vehicles. Still, a wide range of heterogeneous demand-pull policies are implemented in the automotive industry. These policies include, for example, purchase subsidies, tax credits or exemptions, non-monetary consumer benefits, or public procurement. The strength of the instruments used in each country might depend on the design of the individual instruments, how they interact with each other, and the specific setting in which they are implemented. This makes it difficult to compare policies internationally at the instrument level. For this reason, an aggregate measure that abstracts from individual instruments is useful for assessing demand-pull strength in different countries (Hoppmann and Vermeer, 2020).

To this end, much of the quantitative empirical literature to date has used output measures based on market volume to approximate the strength of demand-pull policies (Dechezleprêtre and Glachant, 2014; Hille et al., 2020; Peters et al., 2012). Such measures can abstract from individual policy instruments and serve as proxies for joint effects, but they have a significant drawback. These measures presume that all demand is policy-induced (Peters et al., 2012). Still, demand can be induced not only by demand-pull policies but also, for example, by technology-push factors (Hötte, 2023) or lifestyle purchases. As an alternative, previous studies have used input measures, such as dummy variables for the types of policy instruments combined with the duration of implementation, to capture their intensity (Hille et al., 2020). To abstract from individual policy instruments, Schmidt and Sewerin (2019) introduced an approach to assess qualitative aspects of a policy mix, such as balance, intensity, and specificity. While input-based measures can overcome the shortcomings of output-based measures, they are less suitable to capture the effectiveness of individual policies due to their complex (unobserved) interactions, e.g., regarding market creation. In an endeavor to balance the strengths and weaknesses of input and output measures, we propose to proxy demand-pull policies with an integrated approach that combines battery electric vehicle market volume with the quality of the demand-pull policy mix for battery electric vehicles.

For this purpose, we use new registrations of BEVs (output) and multiply them with a qualitative assessment of demand-pull (DP) policy mix quality (input): [15]

$$Demand - pull\ policies_{c,t} = New\ registrations\ of\ BEVs_{c,t} * DP\ policy\ mix\ quality_{c,t}, \quad (4)$$

where c = country and t = year.

We capture the quality of the demand-pull policy mix for battery electric vehicles by the average score of a five-item coding scheme (see Table 1), [16] which is based on the policy mix concept (Rogge and Reichardt, 2016).[17] The policy mix concept comprises three building blocks: (1) elements, i.e., the policy strategy with its objectives and the instrument mix, (2) policy processes, and (3) characteristics such as consistency, coherence, credibility, comprehensiveness, and stability (Reichardt and Rogge, 2016; Rogge and Reichardt, 2016).[18] While this concept is an analytical tool for a holistic policy mix, much of it can be applied to a

[15] The indicator limits the scope of demand-pull policies to 47 OECD, EU, and BRICS countries. Costa Rica is not included due to missing data on BEV registrations.
[16] Data to calculate the score for technology infrastructure provision are not available for all countries and years; when data are missing, demand-pull policy quality is calculated as the average of the remaining four items.
[17] This approach is inspired by the work of Schmidt and Sewerin (2019). However, we differ from their approach by building on the policy mix concept rather than the index of climate policy activity (Schaffrin et al., 2014).
[18] Policy processes and related coherence are beyond the scope of this study and, as such, are not discussed further. The credibility of the policy is difficult to capture and depends, e.g., on other policy mix characteristics such as consistency and coherence (Rogge and Dütschke, 2018). We do not explicitly include this characteristic.

subcomponent of the policy mix, in our case, the demand-pull policy mix. To assess the quality of the demand-pull policy mix, we consider the characteristics, as these are important determinants of the effectiveness of a policy mix (Costantini et al., 2017; Reichardt and Rogge, 2016; Rogge and Schleich, 2018). Additionally, we include insights on the role of specificity of policy mixes and instruments for their effectiveness (Bergek and Berggren, 2014; Schmidt and Sewerin, 2019).

First, a comprehensive policy entails two elements: a policy strategy, e.g., long-term targets, along with instruments to operationalize the strategy (Reichardt and Rogge, 2016). Long-term targets are important for policy mix effectiveness (Rogge et al., 2011; Schmidt et al., 2012a), and a more extensive instrument mix can increase policy mix performance (Costantini et al., 2017). We capture the comprehensiveness of the demand-pull policy mix and its instruments by two items: (1) *objective for deployment* and (2) *extensiveness of the instrument mix*.

Second, consistency describes the alignment of policy mix elements towards a policy objective (Rogge and Reichardt, 2016). We argue that for a demand-pull policy mix, inconsistency could arise at the instrument level. The diffusion of a technology hinges on the deployment of its complementary ecosystem (Adner and Kapoor, 2016). If deployment instruments are not aligned with the emergence of the ecosystem, such as the uptake of infrastructure, a detrimental effect is likely. Similarly, Reichardt and Rogge (2016) find that inconsistencies between deployment instruments and grid access were detrimental in an off-shore wind energy case. We capture consistency at the instrument level by *technology infrastructure provision*.

Table 1: Demand-pull policy mix quality - coding scheme[19]

Characteristic or design feature	Element	Item	Coding question	Measurement
Comprehensiveness of the demand-pull policy mix	Policy strategy	Objective for deployment	Are deployment objectives for electric vehicles stated?	**Coding:** 0 = no deployment objectives stated 1 = deployment objective stated
	Instrument mix	Extensiveness of the instrument mix	Do instruments include branches of (1) purchase, (2) ownership, (3) company incentives, and (4) public procurement?	**Coding:** 0 = 0 categories covered 0.25 = 1 category covered 0.5 = 2 categories covered 0.75 = 3 categories covered 1 = 4 categories covered Policy instrument categories include: Purchase, e.g., subsidies or registration tax allowances Ownership, e.g., annual circulation tax allowances Company, e.g., special deduction or benefit-in-kind regulations Public procurements, e.g., programs or quotas for EV purchases
Consistency of the instrument mix	Instrument mix	Technology infrastructure provision	Does charging infrastructure provision match electrical vehicle uptake?	**Calculation:** Public charging stations per electric vehicle against the European Union's Alternative Fuels Infrastructure Directive recommendation* as the benchmark, with a maximum score of 1: $Infrastructure_t = \frac{number\ of\ publicly\ accessible\ charging\ stations_t}{electric\ vehicle\ stock_t} \div \frac{1}{10}$, where t = year * *1 publicly accessible charging station per 10 EVs (including battery electric and plug-in hybrid electric cars and vans)*
Stability of instrument mix	Instrument mix	Stability of deployment instruments	Are deployment instruments continued over four consecutive years?	**Coding of deployment instrument categories i:** 0 = not continued over four consecutive years 1 = continued over four consecutive years **Calculation of stability of instrument mix:** $Stability_t = \frac{1}{n} * \sum_{i}^{n} stability_{i,t}$, where i = deployment instrument category, t = year
Specificity of the demand-pull policy mix	Policy strategy and instrument mix	Technology specificity of the policy strategy and the instrument mix	Do the demand-pull policy mix elements include hybrid or fuel-efficient conventional technologies?	**Coding of policy strategy and deployment instrument categories i:** 0 = including conventional technologies, e.g., more fuel-efficient conventional vehicles 0.5 = including hybrid or non-electric alternative fuel technologies 1 = only including for zero-emission vehicles **Calculation specificity:** $Specifity_t = \frac{1}{2} * specificity\ of\ policy\ strategy_t + \frac{1}{2} * \left(\frac{1}{n} * \sum_{i}^{n} specificity\ of\ policy\ instrument\ category_{i,t}\right)$, where i = deployment instrument category, t = year

[19] Including national and supranational policies, thus quality might be underestimated due to additional policies implemented on the state level.

Third, the stability of the policy mix, for example, the absence of ad hoc changes, may provide planning certainty for relevant actors (Rogge and Reichardt, 2013). On the contrary, frequent changes in deployment support lead to volatile demand, which can increase uncertainty about market developments (Nemet, 2009). Especially in capital-intensive industries, such as the automotive industry, the stability of policy instruments is highly important (Bergek and Berggren, 2014). We account for this by incorporating the *stability of deployment instruments.*

Lastly, a policy mix can be designed differently regarding its technology specificity. Neutrally designed policy instruments and policy mixes favor more mature technologies or technologies that can be more easily integrated into the current socio-technical regime, which is why higher specificity is important to steer technological change towards more radical trajectories (Bergek and Berggren, 2014; Schmidt et al., 2012b; Schmidt and Sewerin, 2019). Therefore, we account for the *technology specificity of the policy strategy and the instrument mix* in our coding scheme.[20]

Firm-Level Weights of Country-Level Demand-Pull Policies

Previous literature shows that innovation activity is driven by both domestic and foreign demand-pull policies (Dechezleprêtre and Glachant, 2014; Peters et al., 2012). Accordingly, both need to be considered when analyzing the firm-level innovation effects of demand-pull policies. Particularly in the automotive industry with large multinational companies, it is not reasonable to consider only domestic policies. At the same time, however, OEMs are heterogeneous in their market coverage and thus may not benefit equally from policies in all markets, so considering global demand-pull policies for all firms is also not ideal.

To link demand-pull policies at the country level to each company and its market coverage, we apply firm-specific weights. Following the idea that foreign demand-pull policies have a smaller marginal effect than domestic policies due to trade barriers (Dechezleprêtre and Glachant, 2014), we argue that it is more difficult for firms to benefit from demand-pull incentives in markets where they do not hold production sites and, as such as, subject to trade-barriers. Hence, we account for access to demand-pull policies based on production locations, where 1 is assigned if a firm operates a production location in a market and 0 otherwise.

[20] Note that technology specificity is relevant when analyzing a demand-pull policy mix for a radical technology, e.g., BEV, but may not be applicable for technologies that are easier to integrate into the socio-technical regime, e.g., hybrid electric vehicles, which would instead benefit from a more neutral policy design (Schmidt and Sewerin, 2019).

Markets are not always limited by national borders. Therefore, we aggregate demand-pull for major geographically clustered free trade areas.[21] Moreover, because firms' choice of production locations might be endogenous to the innovation strategy, we keep the weight matrix constant over time,[22] in line with former work (Costantini et al., 2017). These firm-specific weights are then used to construct firm-level demand-pull variables by weighting and aggregating the country-level demand-pull policy variables.

Moderating Variables

Beyond demand-pull policies, our hypotheses imply the test of the influence of three moderating variables, namely *technological capabilities, firm performance,* and *commitment to incumbent technology.*

Technological capabilities are measured by R&D intensity, calculated as the share of R&D expenditures on sales. Technological capabilities, as well as the underlying organizational knowledge, are intangible assets that cannot be measured directly (Schoenecker and Swanson, 2002). Therefore, we use R&D intensity, one of the most common approximations that reflects the weight that a firm gives to R&D and is also associated with the grade of capabilities (Schoenecker and Swanson, 2002).[23]

Firm performance is captured by a firm's profitability,[24] measured as return on assets relative to competitors. To this end, we compute quartiles of incumbents' return on assets and assign values ranging from 0 (25% quartile, low performance) to 3 (above 75% quartile, high performance). In Hypothesis 2, we propose that the relative position of incumbents leads to different innovation responses, e.g., lower performance than competitors, incentivizes first- or early-mover strategies. Hence, to capture the mechanism proposed in our hypothesis, we prefer a relative to an absolute performance measure. In addition, the arguments build on a strategic

[21] We use the term "free trade area" and do not distinguish between different forms. We account for the two main free trade areas of OECD countries: NAFTA and EEA.
[22] The weight matrix is constructed based on production locations in 2009, which incorporates important market changes (e.g., the Chinese automotive market uptake) and precedes EV market uptake in 2010.
[23] The arguments in Hypothesis 1 on the path dependence of technological capabilities imply that our measure of technological capabilities should be positively related to innovation activity in incumbent technologies. To test this assumption, we regress (FEP with year and firm fixed effects) the innovation activity in internal combustion engine vehicles (scaled patent count_t) on technological capabilities (R&D intensity_{t-1}). In line with our assumption, we find a positive and significant effect ($\beta = 0.0706$, $p < 0.05$); see Table A.2.
[24] Eco-innovation might impact firms' economic performance (Zheng and Iatridis, 2022), which could lead to endogeneity. However, because BEV sales on total production numbers were small, with an average of less than 1% in 2017, this is of minor concern in this study. This calculation is based on total production numbers (OICA) and EV sales data (IHS Markit).

perspective, which is why we use a discrete measure that is less volatile and, thus, better reflects strategic drivers.

Lastly, we measure *commitment to incumbent technology* as the percentage of incumbent technology-related patents on all car-related patents. Commitments are diverse and highly related to stakeholders and their interests (Sull et al., 1997). For instance, a business unit developing internal combustion engine technology arguably has a high interest in commitments to the incumbent technology to maintain its relevance and resources, while EV units likely have the opposite. Therefore, a proxy for the outcome of the internal negotiation of the interests of firms is required. We argue that the allocation of resources to innovation reflects how much emphasis is placed on a specific technology, as innovation expenditures are upfront investments amortized over time. In engineering-intensive industries, investment-allocation decisions can be captured by patenting (Kaplan, 2008). Therefore, we use the share of patents in incumbent technologies as a proxy for firms' commitment, whereby a higher share of incumbent technology-related patents signals a stronger commitment and vice versa.

4.2.3 Control Variables

To separate focal effects from other influences and to rule out alternative explanations, we control for innovation determinants implied by the literature.

First, prior research has provided convincing evidence that *domestic technology-push policies* drive innovation (Costantini et al., 2017; Dechezleprêtre and Glachant, 2014; Peters et al., 2012). The most common measure of technology-push policies is public R&D funding for the focal technology field, sourced from the IEA. However, in the case of electric vehicle technology, this data is subject to substantial data gaps. Therefore, we use an alternative approach and proxy for technology-push policies using national science activity in BEVs, measured by articles recorded in the SCIE (e.g., Schmoch, 2007). We use fractional counts of the number of institutional addresses to account for increasing international collaboration and in order not to overestimate total publications (Persson and Danell, 2005). Publication dates are deferred by one year to account for publication processes (Schmoch, 2007).

Second, firm performance may have innovation effects beyond being a moderator of demand-pull policy effectiveness, as argued in Hypothesis 2. In particular, former work shows that *profitability* can positively impact innovation activity, e.g., via available resources for investments in innovation (Audretsch, 1995; Hojnik and Ruzzier, 2016). Interestingly, this effect would be opposite to the one suggested in Hypothesis 2. Thus, to separate and control for possible additional effects of firm performance, we include the absolute value of return on assets next to the relative measure of firm performance described above.

Third, we control for additional time-variant firm-level variables that are identified as determinants of firms' innovation in environmentally benign technologies, investments, or adaptation to technological change, namely *firm size, slack resources, R&D cooperation,* and *environmental uncertainty* (Audretsch, 1995; De Marchi, 2012; Eggers and Park, 2018; Hoffmann et al., 2009; Hojnik and Ruzzier, 2016; Kiefer et al., 2019). *Firm size* is measured by the standard measure of the natural logarithm of total assets in USD_{2015}. *Slack resources* are calculated as a firm's ratio of cash to long-term debt (Hoppmann et al., 2021). The level of *R&D cooperation* on BEVs is incorporated as the number of distinct firms and institutions with which a firm jointly signed BEV patents in a focal year, restricted to assignees with unique Derwent standard codes to avoid double counting. Due to this restriction, we mainly cover collaborations with other large companies. Moreover, we control for *environmental uncertainty* captured by the coefficient of variation of a firm's sales calculated over five periods, following Ghosh and Olsen (2009).

Fourth, demand for new technology may be driven not only by demand-pull policies but also by lifestyle purchases, particularly in our case, as cars are consumer goods. We partly account for this in our measure of demand-pull policies, as the share of lifestyle purchases is likely to be lower when the quality of the demand-pull policy mix is higher. Nonetheless, we include an explicit control for lifestyle purchases captured by Tesla's market share of new BEV registrations.[25] Tesla is well-suited to account for lifestyle purchases because the brand is associated with related positive attributes (Long et al., 2019). Furthermore, we include *year-fixed effects* that absorb macro-level time-related effects, such as macroeconomic developments or changes in crude oil prices, which might exert a non-policy-induced demand-pull (Peters et al., 2012).

4.3 Econometric Methodology

To test our hypotheses and for all subsequent robustness checks, we employ a fixed effects Poisson (FEP) model with robust standard errors. This choice is based on the characteristics of our panel data set. First of all, our dependent variable has a count data format for which fixed

[25] Not included are Japan and Mexico, as Tesla registration data were unavailable.

effects negative binomial and FEP models are suitable options (Cameron and Trivedi, 2013; Hausman et al., 1984). As we analyze firms' patenting, it is important to control for firm-fixed effects to prevent any omitted variable bias due to unobservable time-constant heterogeneity. To this end, the fixed effects negative binomial model has some shortcomings and fully controls for individual specific effects only under specific conditions (Allison and Waterman, 2002; Guimarães, 2008). Hence, we prefer the FEP approach and use robust standard errors on the firm level to account for the correlation of errors over time (Cameron and Trivedi, 2013).

Table 2: Test for dynamic endogeneity of demand-pull policy variable (FEP with demand-pull policies as dependent variable)

VARIABLES	(S1) Demand-pull policies
Scaled patents$_{(t-1)}$	2.21e-05
	(0.000113)
Year fixed effects	Yes
Firm fixed effects	Yes
Observations	561
Number of firms	28
AIC	2.300e+06

Note. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Moreover, endogeneity is a common concern in econometrical assessments of causal relationships. To mitigate endogeneity due to omitted variables, we use a fixed effects model to control for unobserved time-constant heterogeneity, include time-variant firm-level controls implied by former work, and add year-fixed effects. To explore endogeneity due to potential measurement errors, we run robustness tests in which we replace all independent variables with alternative measures. Furthermore, potential reverse causality and simultaneity are mitigated by lagging all explanatory variables by one year. Still, our demand-pull policy variable might be endogenous if firms' BEV patenting exerts an influence on demand-pull policies in subsequent periods. It is reasonable to assume that this condition might be fulfilled, e.g., if increasing technology maturity leads to a higher use of purchase grants. Therefore, we adjusted our research design and tested for the risk of dynamic endogeneity, following Li et al. (2021). Hence, we measure our independent demand-pull variable on a higher level than our dependent variable, i.e., we use firm-weighted national-level registrations instead of firm-level data. Then, we assess the likelihood of dynamic endogeneity by regressing current demand-pull policies on lagged values of BEV technology patenting using an FEP model. The ß coefficient is statistically insignificant ($p > 0.1$) and, thus, does not lead to the rejection of the low-risk assumption (Table 2).

5 Results

In the following, we present the results of our econometric analysis regarding Hypotheses 1 to 3 (Table 3). Initially, we estimated a model without interaction terms (Model 1), finding that the effect of demand-pull policies on patenting for incumbent OEMs in the automotive industry is statistically insignificant at the 10% significance level. This suggests that the policy effect might be highly subject to firms' characteristics. In the subsequent models (Models 2 to 8), we stepwise include the moderations implied by our hypotheses. Model 8 includes the full set of variables, and the Akaike information criterion (AIC) indicates that it best describes our data. Therefore, we use this specification to test our hypotheses. In this model, the effect of demand-pull policies on incumbent patenting in BEV technology is positive (β = 2.27e-06) and statistically significant at the 5% level ($p < 0.05$). The coefficient can be interpreted as a semi-elasticity. Hence, an increase of demand-pull policies by 1 unit would lead to an increase of a firm's patents in BEV technology of 0.000227%, or an increase of 100,000 units to an increase of 22.7%, respectively, under the condition that all moderators are 0. How the moderators impact the semi-elasticity is described below, along with the hypothesis tests.

Hypothesis 1 suggests that a firm's technological capabilities counteract the innovation-inducing effect of demand-pull policies. The moderation coefficient is negative and significant at the 5% level (β = -2.57e-07, $p < 0.05$). Hence, the impact of an increase in demand-pull policies is reduced by 11.32% per unit of technological capability, which equates to 1 percentage point in R&D intensity. At the mean of technological capabilities, this amounts to 34.89%. Taken together, our empirical analysis supports Hypothesis 1, and the moderation effect is of a relevant magnitude.

Hypothesis 2 proposes that firms' performance relative to their competitors negatively moderates incumbents' response to demand-pull policies. Model 8 shows that firm performance negatively moderates the demand-pull impact (β = -2.54e-07, $p < 0.1$). An increase in performance quartiles by 1 would lead to a decrease in demand-pull policies' innovation inducement by 11.19%. The coefficient is of a relevant magnitude but statistically significant only at the 10% level. Therefore, Model 8 provides only weak support for Hypothesis 2. In an extension of these results, the coefficient on profitability, which captures the impact of changes in absolute performance, shows a highly significant ($p < 0.01$) and positive coefficient ($\beta = 0.00653$). This suggests that the effect of firm performance may not be unidirectional but that there may be two opposing effects of performance.

Finally, Hypothesis 3 suggests that the *commitment to incumbent technology* negatively moderates the relationship between demand-pull policies and innovation in BEV technology. The coefficient of the interaction term is statistically highly significant and negative (β =-7.92e-08, $p < 0.01$). Accordingly, an increase of 1 percentage point in commitment would lead to a 3.49% lower effect of demand-pull policies on incumbents' innovation activity. Accordingly, our main analysis provides strong support for Hypothesis 3 and shows a relevant magnitude of the interaction effect.

For comprehensibility and brevity, we limited our hypothesis test to Model 8. However, the results are robust in the case not all moderations are included simultaneously (Models 2 to 7). The only exception is the moderation coefficient for firm performance, where the sign is constant, but the coefficient is not statistically significant in Models 3, 5, and 7. Moreover, our estimates show a significant impact of demand-pull policies on innovation activity only when the interaction with commitments is included, suggesting that this moderator may be a key determinant of policy influence. Another noteworthy result is that cooperation on BEV with other large innovators has a negative and, in most models, statistically significant ($p < 0.1$) coefficient.

Table 3: Results of the main models (FEP with scaled BEV patent count as dependent variable)

VARIABLES	(1) Scaled patent count	(2) Scaled patent count	(3) Scaled patent count	(4) Scaled patent count	(5) Scaled patent count	(6) Scaled patent count	(7) Scaled patent count	(8) Scaled patent count
Profitability$_{(t-1)}$	0.0109***	0.00957***	0.00940***	0.00973***	0.00761***	0.00884***	0.00772***	0.00653***
	(0.00260)	(0.00232)	(0.00267)	(0.00216)	(0.00213)	(0.00212)	(0.00250)	(0.00217)
Firm size$_{(t-1)}$	0.230	0.215	0.256	0.0745	0.245	0.0700	0.0996	0.0973
	(0.349)	(0.324)	(0.353)	(0.305)	(0.324)	(0.290)	(0.303)	(0.285)
Slack resources$_{(t-1)}$	-0.00131	-0.00213	-0.00139	-0.00226*	-0.00254	-0.00287	-0.00250*	-0.00342*
	(0.00139)	(0.00202)	(0.00138)	(0.00133)	(0.00202)	(0.00182)	(0.00130)	(0.00182)
Cooperation$_{(t-1)}$	-0.0279**	-0.0315***	-0.0251**	-0.0233**	-0.0285***	-0.0259**	-0.0197	-0.0222**
	(0.0113)	(0.0105)	(0.0120)	(0.0112)	(0.0108)	(0.0105)	(0.0121)	(0.0112)
Environmental uncertainty$_{(t-1)}$	-0.462	-0.164	-0.585	-0.322	-0.289	-0.116	-0.488	-0.278
	(0.742)	(0.686)	(0.749)	(0.647)	(0.687)	(0.650)	(0.656)	(0.657)
Lifestyle purchases$_{(t-1)}$	-0.669	-0.0504	-0.872	-0.581	-0.259	-0.130	-0.832	-0.373
	(0.781)	(1.033)	(0.774)	(0.819)	(1.010)	(0.982)	(0.789)	(0.958)
Technology-push policies$_{(t-1)}$	0.00121*	0.00152*	0.000999	0.00108	0.00126*	0.00132	0.000800	0.00101
	(0.000702)	(0.000814)	(0.000655)	(0.000736)	(0.000715)	(0.000837)	(0.000659)	(0.000726)
Technological capabilities$_{(t-1)}$	-0.00566	0.0539	-0.00102	0.00446	0.0655	0.0510	0.0113	0.0639
	(0.0489)	(0.0836)	(0.0496)	(0.0437)	(0.0858)	(0.0692)	(0.0441)	(0.0688)
Firm performance$_{(t-1)}$	-0.0201	-0.0360	0.0411	-0.0272	0.0387	-0.0372	0.0514	0.0493
	(0.0552)	(0.0539)	(0.0813)	(0.0493)	(0.0751)	(0.0492)	(0.0771)	(0.0716)
Commitment to incumbent technology$_{(t-1)}$	-0.0199	-0.0241	-0.0205	-0.00515	-0.0254*	-0.00942	-0.00589	-0.0109
	(0.0162)	(0.0155)	(0.0158)	(0.0144)	(0.0148)	(0.0142)	(0.0131)	(0.0127)
Demand-pull policies$_{(t-1)}$	-4.17e-07	1.17e-06	-2.20e-07	6.44e-07	1.58e-06	1.80e-06*	9.51e-07	2.27e-06**
	(4.25e-07)	(1.16e-06)	(4.98e-07)	(5.84e-07)	(1.24e-06)	(1.08e-06)	(6.80e-07)	(1.11e-06)
Demand-pull policies$_{(t-1)}$ *		-3.00e-07*			-3.30e-07*	-2.30e-07*		-2.57e-07**
Technological capabilities$_{(t-1)}$		(1.81e-07)			(1.85e-07)	(1.38e-07)		(1.30e-07)
Demand-pull policies$_{(t-1)}$ *			-1.70e-07		-2.18e-07		-2.23e-07	-2.54e-07*
Firm performance$_{(t-1)}$			(1.68e-07)		(1.67e-07)		(1.44e-07)	(1.42e-07)
Demand-pull policies$_{(t-1)}$ *				-8.00e-08***		-7.57e-08***	-8.38e-08***	-7.92e-08***
Commitment to incumbent technology$_{(t-1)}$				(2.95e-08)		(2.75e-08)	(2.89e-08)	(2.62e-08)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	453	453	453	453	453	453	453	453
Number of firms	29	29	29	29	29	29	29	29
AIC	7,676	7,474	7,609	7,073	7,370	6,958	6,964	6,823

Note. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.1 Robustness Tests

To assess the robustness of our results, we conducted tests using alternative measures of the dependent and independent variables,[26] including fuel economy regulations as an additional control variable, and investigated the impact of multicollinearity on our results. In addition, we conducted an explorative analysis of potential interactions with technology-push policies.[27]

First, to ensure that our findings are not conditional on the novel scaling factor approach, we test their robustness to the measurement of the dependent variable as unscaled patent counts. The qualitative implications of the hypothesis tests remain unchanged. However, the significance levels of the coefficients of moderation slightly worsen or improve (Table 4, Model 9).

Second, two points in our operationalization of the demand-pull policies variable might affect the results. First, we presumed that firms only respond to demand-pull policies in markets to which they have access without trade barriers. However, firms may consider global demand-pull policies (e.g., Hoppmann et al., 2021). Therefore, we estimated the main model with demand-pull policies aggregated at the global level as a robustness test.[28] In this model, we use a time trend instead of year-fixed effects. The hypothesis tests are robust, with improvements in significance levels for the coefficients of the moderation terms with technological capabilities and firm performance (Table 4, Model 10). This suggests that firms may consider market opportunities created by demand-pull policies even if not established in a market, possibly as they may consider entry with the new technology (Fabrizio et al., 2017). Second, we proposed a new approach to measure demand-pull policies integrating input and output measures. To test the robustness of our results, we estimated our model using the output measure, new registrations of BEVs (Table 4, Model 11), and the input measure demand-pull

[26] In addition to the robustness tests reported below, we tested the robustness of our results to alternative measures of the moderators. (1) As an alternative to R&D intensity, we operationalized technological capabilities as knowledge stocks in incumbent technologies measured by the depreciated sum of related patents using depreciation rates of 10, 15, and 25%. (2) We calculated firm performance using return on capital employed instead of return on assets. (3) We calculated firms' commitment to incumbent technology using a broad patent search that includes only firm identifiers and IPCs, as keywords may exclude relevant patents (Bruns and Kalthaus, 2020). In all robustness tests, the hypothesis tests are robust. Regression tables are available upon request.
[27] Tesla as a new entrant is excluded from the regression analysis. However, when Tesla is included, all focal coefficients are robust. Regression tables are available upon request.
[28] Aggregation of demand-pull policy measures of 47 of 48 countries in our dataset, Costa Rica not included due to missing data.

policy quality (Table 4, Model 12).[29] The hypothesis tests are robust, with some changes in the significance levels. However, the coefficient of demand-pull policies, while robust in Model 11, remains positive but is not statistically significant ($p > 0.1$) when using the input measure (Model 12). One possible explanation is that the effectiveness of demand-pull policies in creating markets, as emphasized by output measures, might be the key determinant of the innovation effects of demand-pull policies.

Third, our main analysis suggests that there may be two opposing effects of incumbents' performance. On the one hand, *firm performance*, the relative position of incumbents, is indicated to be an inhibiting factor for the effectiveness of demand-pull policies. On the other hand, *profitability*, the absolute level of performance, is found to be a positive determinant of innovation activity. While the simultaneous inclusion of the two variables reflects different mechanisms (see Section 4.2), the high correlation between firm performance and profitability (see Table A.4) may bias coefficients and inflate standard errors (Kalnins, 2018). Therefore, we conduct additional tests to investigate their robustness (Table 5). (1) We estimate our main model without the control for profitability (Model 13) to emphasize the strategic mechanisms proposed in Hypothesis 2. Indeed, the significance level of the coefficient of the negative interaction term improves to be statistically significant at the 5%-level. However, the results do not indicate a counter-directional positive effect from performance, which is not unexpected given that the discrete operationalization cancels out much of the volatility in performance. (2) Therefore, we additionally test the robustness of the results using alternative continuous operationalizations: a continuous relative measure constructed as the difference between the incumbent's return on assets and the average return on assets in Model 14 and profitability as a continuous and absolute measure in Model 15. In both models, the counter-directional effects of performance – a positive, highly significant coefficient on the performance variable and a negative, weakly significant coefficient on the interaction with demand-pull policies – are robust.

[29] The quality indicator is multiplied by the country's GDP in million US$ in 2009 to take into account different market sizes. For consistency, all demand-pull measures cover OECD, EU, and BRICS countries.

Table 4: Robustness tests to unscaled patent counts and alternative measures of demand-pull policies (FEP model with scaled or unscaled BEV patent count as dependent variable)

VARIABLES	(9) Patent count	(10) Scaled patent count	(11) Scaled patent count	(12) Scaled patent count
Technological capabilities$_{(t-1)}$	0.0611 (0.0556)	0.0371 (0.0487)	0.0652 (0.0697)	0.277 (0.204)
Firm performance$_{(t-1)}$	0.0919 (0.0618)	0.0604 (0.0773)	0.0503 (0.0719)	0.417** (0.179)
Commitment to incumbent technology$_{(t-1)}$	-0.00175 (0.0118)	-0.00258 (0.0146)	-0.0106 (0.0127)	0.0361 (0.0296)
Demand-pull policies$_{(t-1)}$	1.74e-06* (9.51e-07)			
Demand-pull policies$_{(t-1)}$ * Technological capabilities$_{(t-1)}$	-2.16e-07* (1.16e-07)			
Demand-pull policies$_{(t-1)}$ * Firm performance$_{(t-1)}$	-2.93e-07** (1.16e-07)			
Demand-pull policies$_{(t-1)}$ * Commitment to incumbent technology$_{(t-1)}$	-5.86e-08** (2.82e-08)			
Global demand-pull policies$_{(t-1)}$		1.43e-06** (6.61e-07)		
Global demand-pull policies$_{(t-1)}$ * Technological capabilities$_{(t-1)}$		-2.18e-07*** (7.59e-08)		
Global demand-pull policies$_{(t-1)}$ * Firm performance$_{(t-1)}$		-2.13e-07** (1.08e-07)		
Global demand-pull policies$_{(t-1)}$ * Commitment to incumbent technology$_{(t-1)}$		-6.72e-08*** (2.27e-08)		
Demand-pull policies - registrations$_{(t-1)}$			2.00e-06** (9.86e-07)	
Demand-pull policies - registrations$_{(t-1)}$ * Technological capabilities$_{(t-1)}$			-2.25e-07* (1.16e-07)	
Demand-pull policies - registrations$_{(t-1)}$ * Firm performance$_{(t-1)}$			-2.23e-07* (1.24e-07)	
Demand-pull policies - registrations$_{(t-1)}$ * Commitment to incumbent technology$_{(t-1)}$			-6.99e-08*** (2.32e-08)	
Demand-pull policies - quality$_{(t-1)}$				2.01e-08 (6.66e-08)
Demand-pull policies - quality$_{(t-1)}$ * Technological capabilities$_{(t-1)}$				-1.09e-08* (5.84e-09)
Demand-pull policies - quality$_{(t-1)}$ * Firm performance$_{(t-1)}$				-1.48e-08** (5.74e-09)
Demand-pull policies - quality$_{(t-1)}$ * Commitment to incumbent technology$_{(t-1)}$				-2.47e-09* (1.26e-09)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	Yes
Time trend	No	Yes	No	No
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	453	453	453	453
Number of firms	29	29	29	29
AIC	7,413	7,753	6,818	6,665

Note. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Fourth, non-market-based regulatory policies, such as fleet-wide fuel economy standards, e.g., CAFE in the US, could either spur incremental innovation to meet stricter requirements (Nemet, 2014) or a shift to alternative technologies, such as electric vehicles (Sen et al., 2017). In both cases, this is an alternative explanation for changes in innovation activity in BEV technology, either by tying up resources in the incumbent technology or by stimulating a reallocation of resources. The stringency of the *fuel economy* regulations is measured by the inverse of the average fuel consumption of new light-duty vehicles, such that higher levels represent higher stringency.[30] Data for this variable are only available from 2005 onwards, resulting in a loss of five periods or more than 20% of observations, so we only use it as a robustness check (Table 5, Model 16). The tests of Hypothesis 1 and Hypothesis 3 are robust, while the coefficient for the interaction between demand policy and firm performance is constant in sign but not statistically significant ($p > 0.1$).

Fifth, multicollinearity might bias model estimations. To assess the vulnerability of our results, we follow Kalnins (2018) and provide estimations in Table A.5 without controls (Model 17), without all controls that have a correlation coefficient larger than +/- 0.3 with a focal variable (Model 18) and singly excluding correlated controls (Models 19 to 23). For comparison, we also report the results of our main specification (Model 8). Neither a change in signs nor an inflation of coefficient sizes is observed. The only differences are minor changes in significance levels in some models.

[30] Country-level fuel economy variables are weighted by the firm's production share in the respective country. Firms' production shares are relative to their aggregated production shares in the countries covered (China, EU27, Japan, USA, Argentina, Brazil, Chile, Egypt, Malaysia, Mexico, Peru, Philippines, Russia, and Ukraine) to not assume that other countries are unregulated. Weights are based on 2009 production shares and are kept constant to avoid the endogeneity of weights.

Table 5: Robustness tests to alternative operationalizations of firm performance and the inclusion of fuel economy regulation (FEP with scaled BEV patent count as dependent variable)

VARIABLES	(13) Scaled patent count	(14) Scaled patent count	(15) Scaled patent count	(16) Scaled patent count
Profitability$_{(t-1)}$			0.00838***	0.00645***
			(0.00272)	(0.00233)
Technological capabilities$_{(t-1)}$	0.0699	0.0543	0.0608	0.0474
	(0.0667)	(0.0677)	(0.0640)	(0.0646)
Firm performance$_{(t-1)}$	0.0815			0.0227
	(0.0652)			(0.0545)
Firm performance - continuous$_{(t-1)}$		0.00847***		
		(0.00271)		
Commitment to incumbent technology$_{(t-1)}$	-0.0113	-0.0105	-0.0107	-0.0167
	(0.0131)	(0.0138)	(0.0137)	(0.0121)
Demand-pull policies$_{(t-1)}$	2.38e-06**	1.89e-06*	2.07e-06*	1.98e-06*
	(1.10e-06)	(1.11e-06)	(1.12e-06)	(1.01e-06)
Demand-pull policies$_{(t-1)}$ *	-2.69e-07**	-2.31e-07*	-2.45e-07*	-2.55e-07**
Technological capabilities$_{(t-1)}$	(1.31e-07)	(1.39e-07)	(1.35e-07)	(1.22e-07)
Demand-pull policies$_{(t-1)}$ *	-2.82e-07**			-1.73e-07
Firm performance$_{(t-1)}$	(1.35e-07)			(1.32e-07)
Demand-pull policies$_{(t-1)}$ *		-5.32e-08*		
Firm performance - continuous$_{(t-1)}$		(3.06e-08)		
Demand-pull policies$_{(t-1)}$ *			-5.21e-08*	
Profitability$_{(t-1)}$			(3.08e-08)	
Demand-pull policies$_{(t-1)}$ *	-8.02e-08***	-7.97e-08***	-7.79e-08***	-6.06e-08**
Commitment to incumbent technology$_{(t-1)}$	(2.63e-08)	(2.86e-08)	(2.87e-08)	(2.50e-08)
Fuel economy regulations$_{(t-1)}$				-9.248
				(17.85)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	453	453	454	359
Number of firms	29	29	29	29
AIC	6,864	6,921	6,952	5,365

Note. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Sixth, the research on policy mixes emphasizes that policies are not independent of each other but interact and may create synergies or trade-offs (Flanagan et al., 2011; Rogge and Reichardt, 2016). With regard to demand-pull policies, the simultaneous implementation of demand-pull and technology-push policies is shown to increase the effectiveness of policies on innovation expenditure (Guerzoni and Raiteri, 2015) and the formation of innovation networks (Cantner et al., 2016). Still, Costantini et al. (2017) find that it is a more balanced use of demand-pull and technology-push policies that strengthens the innovation effect, suggesting that the interaction effect is complex and not unidirectionally positive. Taking into account these previous findings, we test for a possible interaction effect between demand-pull and technology-push policies by including an interaction term (Table 6, Model 24).[31] The hypothesis tests are robust, but we do not find support for a (unidirectional) interaction effect.

Although we find no evidence of an interaction between demand-pull and technology-push policies, the firm-level barriers to the effectiveness of demand-pull policies identified in our results may be overcome by technology-push policies in two ways: by (1) helping incumbents to build up technological capabilities in the fostered technology area (Plank and Doblinger, 2018) and (2) by incentivizing more distant knowledge search beyond the firm's current technological orientation (Hoppmann et al., 2021). In an exploratory analysis, we test if and how technology-push policies shape the moderation effects by introducing three-way interactions between demand-pull policies, respective firm-level moderators, and technology-push policies (Table 6, Models 25 to 28).

The exploratory analysis yields two highly interesting findings. First, demand-pull policies interact with technology-push policies, but the magnitude and direction of the interaction effect depend on the firm-level factors of firm performance (Model 26) or commitment to the incumbent technology (Model 27). This is an indication of the complex role that firm-level factors can play in interactions between policies, in addition to their role in the effectiveness of demand-pull policies. Second, in terms of the focus of the paper, the results indicate that technology-push policies can counteract the negative moderating effects of firm performance (Model 26; β = 1.20e-09, $p < 0.05$) and commitment to incumbent technology (Model 27; β = 1.78e-10, $p < 0.1$) but not of technological capabilities (Model 25; β = 3.77e-10, $p > 0.1$). Accordingly, technology-push policies appear to be an effective means of encouraging both better-performing firms and those with a stronger commitment to incumbent technology to invest more in sustainable innovation in response to demand-pull policies.

[31] Demand-pull and technology-push policies are measured in different units, so we test a unidirectional effect and cannot test the balance between policy types.

Table 6: Explorative analysis of interactions with technology-push policies (FEP with scaled BEV patent count as dependent variable)

VARIABLES	(24) Scaled patent count	(25) Scaled patent count	(26) Scaled patent count	(27) Scaled patent count
Technology-push policies$_{(t-1)}$	0.00217	0.00185	0.00284*	0.00273*
	(0.00219)	(0.00171)	(0.00172)	(0.00140)
Technological capabilities$_{(t-1)}$	0.0528	0.0506	0.0517	0.0578
	(0.0687)	(0.0949)	(0.0693)	(0.0697)
Firm performance$_{(t-1)}$	0.0550	0.0439	0.116	0.0437
	(0.0700)	(0.0664)	(0.0753)	(0.0637)
Commitment to incumbent technology$_{(t-1)}$	-0.0136	-0.0119	-0.0130	-0.00925
	(0.0147)	(0.0139)	(0.0135)	(0.0196)
Demand-pull policies$_{(t-1)}$	2.21e-06**	2.67e-06**	2.27e-06**	2.52e-06**
	(1.11e-06)	(1.24e-06)	(1.11e-06)	(1.07e-06)
Demand-pull policies$_{(t-1)}$ * Technological capabilities$_{(t-1)}$	-2.01e-07	-3.15e-07**	-1.80e-07	-2.59e-07**
	(1.23e-07)	(1.55e-07)	(1.22e-07)	(1.15e-07)
Demand-pull policies$_{(t-1)}$ * Firm performance$_{(t-1)}$	-2.91e-07*	-2.57e-07*	-4.47e-07***	-2.24e-07*
	(1.58e-07)	(1.47e-07)	(1.67e-07)	(1.18e-07)
Demand-pull policies$_{(t-1)}$ * Commitment to incumbent technology$_{(t-1)}$	-7.34e-08**	-7.66e-08**	-7.23e-08**	-1.00e-07***
	(2.99e-08)	(3.04e-08)	(2.99e-08)	(3.50e-08)
Demand-pull policies$_{(t-1)}$ * Technology-push policies$_{(t-1)}$	-1.37e-09	-3.04e-09	-2.80e-09**	-3.61e-09*
	(1.95e-09)	(2.11e-09)	(1.31e-09)	(2.07e-09)
Technological capabilities$_{(t-1)}$ * Technology-push policies$_{(t-1)}$		0.000170		
		(0.000566)		
Demand-pull policies$_{(t-1)}$ * Technological capabilities$_{(t-1)}$ * Technology-push policies$_{(t-1)}$		3.77e-10		
		(5.80e-10)		
Firm performance$_{(t-1)}$ * Technology-push policies$_{(t-1)}$			-0.000699**	
			(0.000306)	
Demand-pull policies$_{(t-1)}$ * Firm performance$_{(t-1)}$ * Technology-push policies$_{(t-1)}$			1.20e-09**	
			(5.25e-10)	
Commitment to incumbent technology$_{(t-1)}$ * Technology-push policies$_{(t-1)}$				7.02e-06
				(0.000109)
Demand-pull policies$_{(t-1)}$ * Commitment to incumbent technology$_{(t-1)}$ * Technology-push policies$_{(t-1)}$				1.78e-10*
				(1.06e-10)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	453	453	453	453
Number of firms	29	29	29	29
AIC	6,780	6,722	6,719	6,686

Note. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6 Discussion

This study investigated how incumbent carmakers' characteristics shape demand-pull policies' impact on their innovation activity. Our findings add robust empirical evidence to the growing literature on firms' diverse responses to public policies (Garcia Hernández et al., 2021; Rogge et al., 2011; Schmidt et al., 2012a; Wesseling et al., 2015) and advance our understanding of firm-level moderators. To the best of our knowledge, this study is the first to combine insights from innovation studies focusing on policy with the literature on incumbent adaptation to technological change to quantitatively assess the influence of firm characteristics on demand-pull policy effects. Our empirical results show that the innovation response of incumbents in the automotive industry is lowered by firms' technological capabilities, performance, and commitment to incumbent technology. Thereby, the results for technological capabilities and commitment to incumbent technology are highly robust, while firm performance is not significant in all models and to the inclusion of a control for fuel efficiency regulations. Our findings not only entail important insights for innovation policy research and the literature on incumbents' adaptation to technological change but also have practical implications for policymakers and managers alike. In the following, we discuss our contributions and reflect on the limitations of our study, which suggest avenues for future research.

6.1 Innovation Studies and Policy Implications

This study makes important contributions to innovation studies and yields valuable implications for policymaking. In the most general terms, our results show that the magnitude of the innovation-inducing effects of demand-pull policies is conditional on incumbent characteristics and, as such, cannot be generalized.

At the aggregate country level, the different responses of heterogeneous incumbents to demand-pull policies translate into different policy effects depending on the population of incumbents in a country. This finding has important implications for the debate on the extent to which domestic firms innovate in response to demand-pull policies or foreign firms' knowledge is transferred to the domestic market, as it extends previous findings on demand-policy spillovers (Dechezleprêtre and Glachant, 2014; Fabrizio et al., 2017; Peters et al., 2012) by showing that the characteristics of domestic incumbents are a relevant determinant of innovation activity in response to demand-pull policies. Comparing the three established export-oriented automotive industries of Europe, the US, and Japan over the period of demand-pull policies and market uptake (2010 to 2019), the European incumbent carmakers scored the lowest on the mean of all inhibiting moderators, i.e., technological capabilities, firm performance and commitment to incumbent technology, and thus demand-pull policies have been more effective in stimulating innovation activity.[32] The Chinese firms in our sample scored even lower on the mean for inhibiting technological capability and commitment to incumbent technology. Still, because of their domestic orientation, they were arguably also more dependent on domestic demand-pull policies. However, this is only a coarse representation of policy effects at the country level because the population of incumbents within countries is highly heterogeneous, as indicated by high standard deviations from the means, and it does not include new entrants such as Tesla or Nio, nor upstream industry actors.

At a more granular level, identifying inhibitory firm-level factors highlights opportunities to enhance the effectiveness and possibly efficiency of demand-pull policies to spur incumbents' innovation activity by complementary policy instruments. Such interactions of policy instruments are an integral part of the policy mix concept and research (Flanagan et al., 2011; Kern and Rogge, 2018; Reichardt and Rogge, 2016). In the following, we discuss our findings with the policy-mix literature on innovation and sustainability transitions.

First, the prior literature shows that technology-push policies, such as R&D funding, and demand-pull policies can create positive synergies for innovation (Cantner et al., 2016; Guerzoni and Raiteri, 2015), especially when they are used in a balanced way (Costantini et al., 2017). Moreover, at the firm level, technology-push policies have been shown to spur innovation activity (Plank and Doblinger, 2018), in particular, radical innovation (Beck et al., 2016), and to incentivize more distant knowledge searches beyond the firms' current technological direction (Hoppmann et al., 2021). In light of these findings, we conducted an exploratory analysis to test whether technology-push policies can counteract the negative moderating effects of firms' technological capabilities, performance, and commitment to the incumbent technology. The results suggest that technology-push policies can mitigate the effects of the latter two but not of technological capabilities. These results are somewhat surprising as, based on the previous work, one might expect technology-push policies to be particularly relevant in addressing the path dependency of technological capabilities. One

[32] Mean scores of the incumbents over the time horizon 2010 to 2019, standard deviations in parentheses, with respect to their headquarters. Technological capabilities: EU = 3.18 (1.43), US = 4.75 (0.43), Japan = 3.94 (1.09), China = 2.25 (1.17); Firm performance: EU = 1.18 (0.89), US = 1.35 (0.93), Japan = 1.65 (1.09), China = 1.67 (1.26); Commitment to incumbent technology: EU = 16.42 (4.53), US = 24.71 (7.31), Japan = 27.53 (10.97), China = 13.81 (8.81). Due to one-year lags for independent variables, 2019 is the last year considered.

possible explanation is that we captured technology-push policies through academic articles, that is, indirect R&D funding, and thus the missing link may be the highly relevant collaboration of firms with universities (De Marchi, 2012; De Marchi and Grandinetti, 2013; Jiang et al., 2011; Szücs, 2018). To strengthen this link, policymakers can design R&D funding programs to encourage industry-university collaboration (Szücs, 2018). Beyond this, our exploratory analysis underscores previous findings of positive synergies between demand-pull and technology-push policies for innovation, suggesting higher innovation activity by high-performing or stronger incumbent technology-committed firms as one mechanism for synergies. The simultaneous use of technology-push and demand-pull policies is therefore particularly promising for encouraging incumbents that are successful in old technologies to explore new ones. Since the innovation effects of technology-push policies do not spill over (Peters et al., 2012), this mechanism can be exploited by countries with an established industry to increase innovation in sustainable technologies, in the case of battery electric vehicles, e.g., the US, Japan, China, India, France, and Germany.

Second, the literature on sustainability transitions argues that the addition of policies that destabilize the dominance of incumbent technologies, e.g., control policies such as taxes and regulations, or the withdrawal of subsidies and R&D funding for incumbent technologies, is an important means of accelerating change (Geels, 2014; Kivimaa and Kern, 2016). Our finding that firms' deep roots and success in incumbent technologies lead to reduced responsiveness to demand-pull policies provides empirical support for this notion. At the same time, however, our results also highlight two constraints on positive synergies between innovation policies and potentially destabilizing policies: (1) While we find that firm performance acts as a negative moderator of demand-pull policy effects on innovation, we also find that firm performance has an opposing positive effect, e.g., due to available resources for innovation (Audretsch, 1995). Thus, implementing policies that intentionally or unintentionally impair the performance of incumbents may not only incentivize increased innovation in emerging technologies but may also inhibit innovation efforts. (2) Since our results suggest that commitment to incumbent technology is an inhibiting factor for the effectiveness of demand-pull policies, policies that induce stronger commitment appear to be detrimental to innovation in new technologies. In particular, this may be the case for policies that require innovation in the legacy technology, e.g., to comply with stricter environmental regulations, as these investments have to be amortized over time, which is likely to strengthen the commitment of incumbents to the technology. In sum, destabilizing policies that impair the performance of incumbents or lead to increased innovation in incumbent technologies could, therefore, be considered a *double-edged sword*, and policymakers should be wary of possible adverse effects on the innovation activities of incumbents. This may be the case for technology standards that require investment in the currently dominant technology, such as the recently controversial Euro 7 emissions standard (Samaras et al., 2023). In this context, it is worth noting that the primary objective of this specific policy is to achieve short-term environmental benefits. In contrast, demand-pull policies are often used to stimulate longer-term technological change. This further points to a potential source of inconsistency at the level of policy strategies (Rogge and Reichardt, 2016), as there may be trade-offs between short-term and longer-term environmental goals.

Despite these caveats, our findings support the idea of including destabilizing measures in the policy mix to address the inhibitory characteristics of incumbents. To this end, gradual or prospective technology bans, i.e., phase-out policies, appear promising (Trencher et al., 2022). Although such policies constitute demand-pull policies in terms of shaping market expectations for new technologies, they differ from the more commonly used deployment-based demand-pull policies, such as subsidies or public procurement, in that they have an additional role as destabilizing policies (Kivimaa and Kern, 2016; Rogge and Johnstone, 2017). Importantly, phase-out policies differ from immediate policy interventions in allowing time for adaptation (Howarth and Rosenow, 2014; Trencher et al., 2022). As a result, the constraints described above on positive synergies between (deployment-based) demand-pull and destabilization policies are less prevalent. On the one hand, a future technology ban limits the commercialization opportunities of the incumbent technology, which is likely to provide additional incentives for firms with a good market position in the currently dominant technology to adapt as cannibalization of their own products becomes a regulatory requirement. On the other hand, phase-out policies have been shown to be highly beneficial for the credibility of the overall policy mix for a sustainability transition (Rogge and Dütschke, 2018; Rogge and Johnstone, 2017). In this way, they might offset the inhibitory effects of previous commitments to incumbent technologies. Given the low (administrative) cost to governments of regulation compared to government support for technology deployment, a regulatory deadline for technological change could increase the efficiency of costly deployment incentives. Yet, a regulatory phase-out approach seems better suited to complement rather than replace deployment incentives to avoid strong headwinds from (powerful) incumbents, as happened with California's zero-emission vehicle mandate in the 2000s (Sierzchula et al., 2012), as well as not to lose public acceptance (Rinscheid et al., 2020). As they work through a demand-pull mechanism, phase-out policies are available to all governments to encourage innovation activity (Dechezleprêtre and Glachant, 2014; Peters et al., 2012), but so far it is mainly countries with a domestic automotive industry that have signaled such ambitions (Meckling and Nahm, 2019). The recent implementation of a regulatory phase-out of non-zero emission vehicles in the EU from 2035 is, considering our results, likely to increase incumbents' innovation activities in battery electric vehicles. However, it appears that other markets will have to follow to overcome the commitments of the multinational incumbent car manufacturers. To give an illustrative example, the Renault Group expects up to 50% of passenger car sales to be hybrid or pure internal combustion engine vehicles, concluding that "developing efficient technologies in that field remains key for the future of any global OEM" (Renault Group, 2022, p. 4).

6.2 Incumbent Adaptation to Technological Change and Managerial Implications

Beyond the policy perspective, our findings contribute to the literature on incumbent adaptation to technological change and have important implications for corporate managers facing policy-driven technological change. Traditionally, the technology adaptation literature is concerned with the adaptation of firms to technological discontinuities due to the technical superiority of emerging technologies, such as generations of disk drives or digital photography (Eggers and Park, 2018). In this setting, the literature has identified various inertial mechanisms that can lead to the failure of incumbents to adapt to a new technology and, ultimately, to the downturn of incumbents. In particular, firms may be trapped by the path dependence of their capabilities, fear of cannibalizing their own profitable sales, and commitment to their legacy technology. Our study shows that those firm characteristics that are known to inhibit incumbents' adaptation in more general, i.e., technological capabilities, firm performance, and commitment to incumbent technology (e.g., Cohen and Levinthal, 1990; Eggers and Park, 2018; Kaplan, 2008; Rosenbloom, 2000; Sull et al., 1997; Zhou and Wu, 2010), also lead to a lower innovation response by incumbents to political market support. This finding is important since public policies are designed to incentivize firms to speed up their adoption of novel technologies by reducing uncertainty about technological trajectories and increasing the returns to marketable innovations (Di Stefano et al., 2012; Nemet, 2009; Peters et al., 2012). Interestingly, however, our findings indicate that those firms that would need policy support most (since they experience the greatest extent of inertia) are also those that respond to demand-pull policies the least. As a result, incumbents might get caught in a *double-trap.*

This finding also has important implications for firms as they choose between a first-mover and a follower strategy. Being a follower helps avoid premature cannibalization of one's own products (Conner, 1988) or profit from the explorative investments of pioneers (Lieberman and Montgomery, 2013; Zachary et al., 2015). However, the failure to take advantage of early policy support increases the barriers to later adaptation when demand-pull policies are reduced and increases the extent of necessary change when regulatory pressures for technological change increase, such as the recent EU regulation to phase out internal combustion engine vehicles by 2035. As, at the same time, competitors tend to seize the opportunities of demand-pull policies, late movers may face higher technological barriers to entry due to the learning and scale of competitors, combined with decreasing deployment support and increasing regulatory pressure, which may significantly reduce their likelihood of successful adaptation to new technology. Thus, early engagement appears to be highly important for incumbents when technological change is driven by public policy. If corporate managers find it challenging to explore the new technology because of the organization's strong commitment to their legacy technology, e.g., due to routines (Gilbert, 2005) or corporate identity (Tripsas, 2009), they may adopt an approach of structural ambidexterity, separating business units to simultaneously exploit the old technology and explore the new without being constrained by existing commitments (e.g., Burgers et al., 2009).

6.3 Limitations and Future Research

Our study has limitations that open avenues for future research. First, we analyzed the moderating role of incumbent characteristics on the impact of demand-pull policies on the innovation activities of incumbent car manufacturers. This research setting is well suited to our analysis, but our results are context-specific to the type of technological change and some characteristics of the firm sample. On the one hand, the type of technological change impairs the generalizability of our results because firms' behavior might be different if, for instance, not only core knowledge but also complementary assets are devalued (Eggers and Park, 2018). On the other hand, innovation patterns may be different for incumbent firms at upstream positions in the value chain (Rogge et al., 2011; Schmidt et al., 2012a; Wang et al., 2020). Future research might test the generalizability of our results in these regards or identify deviating firm-internal factors that shape the impact of demand-pull policies on innovation in different contexts. To this end, one future avenue of research is to analyze automotive suppliers, not only because they are upstream in the supply chain but also because the nature of technological change may differ depending on their technology portfolio.

Second, this study focused on demand-pull policies to generate valuable granular insights. We hope this work inspires more researchers to broaden our knowledge of the role of firm-level factors in various contexts regarding other innovation policies, such as technology-push policies or policy mixes (e.g., Garcia Hernández et al., 2021). Our exploratory analyses of the interactions between demand-pull and technology-push policies suggest that firm-level factors may be important determinants of the interaction, also suggested by Schmidt et al. (2012a). Still, robust empirical evidence is needed to draw reliable conclusions. This provides a promising avenue for future studies to explore the determinants of policy instrument interactions, e.g., between demand-pull and technology-push policies beyond the balance of instruments (Costantini et al., 2017).

Third, while our analysis provides evidence that firm characteristics moderate the impact of demand-pull policies on innovation, we could, by design, explore neither the detailed mechanisms that lead to our findings nor the factors shaping the firm-level determinants. We believe that determinants of the firm characteristics in this study, for instance, the commitment to incumbent technology, are very specific to the context and different firms. As such, in-depth analyses of respective cases are well-needed and could generate valuable insights that allow granular policy recommendations beyond this study's. In addition, we argued that phase-out policies can be beneficial in addressing inhibiting mechanisms. Recent policy developments in the automotive industry allow the study of a contemporary case, which may add to the scant empirical evidence on the impact of phase-out policies (Trencher et al., 2022).

Fourth, our results for the control of cooperation on battery electric vehicle technology with other large innovators show a negative effect on the corresponding innovation activity, suggesting that incumbent carmakers may substitute internal innovation activity by cooperation with other firms, e.g., suppliers or coopetitors. Previous findings on the role of cooperation in environmental innovation show that cooperation, especially with suppliers, is important but also that a (partial) substitution between internal and external innovation investments might take place (Cainelli et al., 2015; De Marchi, 2012; De Marchi and Grandinetti, 2013). Indeed, firms may purposefully use supplier innovation to introduce innovative products with low levels of internal R&D (Pihlajamaa et al., 2017). Future research could explore the different cooperation strategies incumbents adopt in the face of technological change, their motives, and their success. In addition, it would be exciting to see how these evolve, given the recent trend in the automotive industry towards insourcing key components for battery electric vehicles.

Lastly, our study treated the transition toward electric vehicles as a standalone technological change in the automotive industry. In fact, the automotive industry is challenged by the so-called CASE trends (i.e., the interconnected technological trajectories of connected, autonomous, shared, and electrified vehicles). Accordingly, incumbents are confronted with multiple technological discontinuities at once. Future research might investigate how incumbents juggle these multiple transitions and assess the respective role of public policies. Policy support for the electrification of vehicles might be found to channel firms' attention in this direction while slowing down developments in other fields.

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Appendix A

Table A.1: R&D investment to patent ratios and scaling factors, 2000-2020

Firm	Geographical area	R&D investment to patent ratio in PPP-adjusted USD_{2015}	Average R&D investment to patent ratio in PPP-adjusted USD_{2015}	Scaling factor
BYD	Mainland China and Hong Kong	357,774	2,375,418	0.151
GAC	Mainland China and Hong Kong	252,863	2,375,418	0.106
GREAT WALL	Mainland China and Hong Kong	699,882	2,375,418	0.295
JAC	Mainland China and Hong Kong	156,863	2,375,418	0.066
LIFAN	Mainland China and Hong Kong	204,841	2,375,418	0.086
SAIC	Mainland China and Hong Kong	1,102,041	2,375,418	0.464
HONDA	Japan	1,650,351	2,375,418	0.695
ISUZU	Japan	1,463,691	2,375,418	0.616
MAZDA	Japan	1,267,458	2,375,418	0.534
MITSUBISHI	Japan	1,080,569	2,375,418	0.455
NISSAN	Japan	1,839,348	2,375,418	0.774
SUBARU	Japan	1,065,643	2,375,418	0.449
SUZUKI	Japan	1,646,517	2,375,418	0.693
TOYOTA	Japan	901,391	2,375,418	0.379
HYUNDAI	Korea	333,476	2,375,418	0.140
KIA	Korea	724,455	2,375,418	0.305
SSANGYONG	Korea	2,498,058	2,375,418	1.052
AVTOVAZ	Russia	2,554,540	2,375,418	1.075
MAHINDRA & MAHINDRA	India	2,628,941	2,375,418	1.107
TATA	India	4,008,537	2,375,418	1.688
BMW	Europe	3,667,896	2,375,418	1.544
DAIMLER	Europe	3,705,981	2,375,418	1.560
PORSCHE	Europe	2,185,638	2,375,418	0.920
PSA	Europe	2,157,279	2,375,418	0.908
RENAULT	Europe	3,253,456	2,375,418	1.370
VW	Europe	3,839,091	2,375,418	1.616
FCA	Europe (United States)	7,521,645	2,375,418	3.166
FORD	United States	5,830,960	2,375,418	2.455
GM	United States	5,600,788	2,375,418	2.358
TESLA	United States	7,062,574	2,375.418	2.973

Table A.2: The effect of technological capabilities measured by R&D intensity on innovation activity in internal combustion engine vehicles (FEP with scaled patents in internal combustion engine technologies)

VARIABLES	(S2) Scaled patent count - internal combustion engine vehicles
Technological capabilities$_{(t-1)}$	0.0706**
	(0.0311)
Year fixed effects	Yes
Firm fixed effects	Yes
Observations	501
Number of firms	29
AIC	14,601

Note. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.3: Descriptive statistics, 2001-2020

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
(1) Scaled patent count$_{(t)}$	544	52.945	98.042	0	724
(2) Patent count$_{(t)}$	544	67.513	136.66	0	1101
(3) Demand-pull policies$_{(t-1)}$	544	137,628.13	286,078.49	0	1,248,890.6
(4) Demand-pull policies - registrations$_{(t-1)}$	544	158,554.15	325,699.23	0	1,423,260
(5) Demand-pull policies - quality$_{(t-1)}$	544	13,984,402	12,405,292	0	41,206,468
(6) Global demand-pull policies$_{(t-1)}$	544	201,131.94	362,710.6	662.85	1,276,510.1
(7) Technological capabilities$_{(t-1)}$	486	3.082	1.521	0	9.964
(8) Firm performance$_{(t-1)}$	526	1.511	1.104	0	3
(9) Firm performance - continuous$_{(t-1)}$	526	.689	7.596	-56.981	76.955
(10) Commitment to incumbent technology$_{(t-1)}$	522	21.249	11.572	0	100
(11) Profitability$_{(t-1)}$	527	3.03	7.646	-55.191	77.227
(12) Firm size$_{(t-1)}$	527	17.287	1.75	11.593	20.179
(13) Slack resources$_{(t-1)}$	491	2.58	11.916	.002	184.311
(14) Cooperation$_{(t-1)}$	544	2.204	5.602	0	42
(15) Environmental uncertainty$_{(t-1)}$	501	.188	.166	.015	1.394
(16) Lifestyle purchases$_{(t-1)}$	544	.054	.094	0	.744
(17) Technology-push policies$_{(t-1)}$	544	98.015	225.157	0	1,371.005
(18) Fuel economy regulation	404	.127	.043	0	.183

Table A.4: Pairwise correlations, 2001-2020

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Scaled patent count$_{(t)}$	1.000																	
(2) Patent count$_{(t)}$	0.697	1.000																
(3) Demand-pull policies$_{(t-1)}$	0.414	0.348	1.000															
(4) Demand-pull policies - registrations$_{(t-1)}$	0.419	0.352	1.000	1.000														
(5) Demand-pull policies - quality$_{(t-1)}$	0.629	0.514	0.567	0.576	1.000													
(6) Global demand-pull policies$_{(t-1)}$	0.289	0.258	0.891	0.889	0.410	1.000												
(7) Technological capabilities$_{(t-1)}$	0.364	0.223	0.134	0.138	0.395	0.051	1.000											
(8) Firm performance$_{(t-1)}$	-0.092	-0.051	-0.030	-0.031	-0.108	0.005	-0.131	1.000										
(9) Firm performance - continuous$_{(t-1)}$	0.033	0.023	-0.012	-0.012	-0.004	-0.019	-0.020	0.598	1.000									
(10) Commitment to incumbent technology$_{(t-1)}$	-0.079	-0.062	-0.164	-0.162	0.042	-0.159	0.145	0.008	0.018	1.000								
(11) Profitability$_{(t-1)}$	0.030	0.021	0.001	0.001	0.017	-0.004	-0.019	0.593	0.957	0.003	1.000							
(12) Firm size$_{(t-1)}$	0.545	0.434	0.249	0.255	0.635	0.167	0.464	-0.280	-0.074	0.025	-0.073	1.000						
(13) Slack resources$_{(t-1)}$	-0.067	-0.036	0.139	0.140	0.065	0.131	-0.014	0.127	0.044	-0.041	0.054	-0.126	1.000					
(14) Cooperation$_{(t-1)}$	0.453	0.871	0.206	0.210	0.434	0.123	0.219	-0.047	0.005	0.022	0.006	0.376	-0.067	1.000				
(15) Environmental uncertainty$_{(t-1)}$	-0.265	-0.205	-0.246	-0.249	-0.433	-0.231	-0.409	0.338	0.191	-0.190	0.169	-0.485	0.069	-0.202	1.000			
(16) Lifestyle purchases$_{(t-1)}$	0.357	0.271	0.512	0.519	0.572	0.558	0.114	0.000	-0.046	-0.032	-0.042	0.252	0.093	0.180	-0.243	1.000		
(17) Technology-push policies$_{(t-1)}$	0.043	0.073	0.401	0.391	-0.016	0.530	-0.050	-0.039	-0.018	-0.225	-0.006	-0.044	0.068	-0.064	0.014	0.062	1.000	
(18) Fuel economy regulation	0.267	0.217	0.328	0.330	0.490	0.223	0.402	-0.090	0.012	0.045	0.039	0.376	0.089	0.161	-0.330	0.306	0.076	1.000

Table A.5: Robustness test to a multicollinearity bias (FEP with scaled BEV patent count as dependent variable)

VARIABLES	(8) Scaled patent count	(17) Scaled patent count	(18) Scaled patent count	(19) Scaled patent count	(20) Scaled patent count	(21) Scaled patent count	(22) Scaled patent count	(23) Scaled patent count
Profitability$_{(t-1)}$	0.00653***				0.00675***	0.00631***	0.00653***	0.00636***
	(0.00217)				(0.00197)	(0.00197)	(0.00217)	(0.00215)
Firm size$_{(t-1)}$	0.0973			0.114		0.104	0.0986	0.0573
	(0.285)			(0.273)		(0.276)	(0.285)	(0.304)
Slack resources$_{(t-1)}$	-0.00342*		-0.00535***	-0.00357*	-0.00372*	-0.00337*	-0.00349**	-0.00441**
	(0.00182)		(0.00174)	(0.00195)	(0.00193)	(0.00181)	(0.00173)	(0.00189)
Cooperation$_{(t-1)}$	-0.0222**		-0.0211*	-0.0207*	-0.0209*	-0.0212*	-0.0224**	-0.0250**
	(0.0112)		(0.0122)	(0.0112)	(0.0110)	(0.0110)	(0.0111)	(0.0123)
Environmental uncertainty$_{(t-1)}$	-0.278			-0.126	-0.327		-0.318	-0.672
	(0.657)			(0.646)	(0.633)		(0.618)	(0.743)
Lifestyle purchases$_{(t-1)}$	-0.373			-0.363	-0.395	-0.434		-1.135
	(0.958)			(0.949)	(0.984)	(0.882)		(0.825)
Technology-push policies$_{(t-1)}$	0.00101			0.00100	0.000964	0.00106	0.00106	
	(0.000726)			(0.000721)	(0.000749)	(0.000751)	(0.000668)	
Technological capabilities$_{(t-1)}$	0.0639	0.0648	0.0790	0.0699	0.0642	0.0625	0.0650	0.0715
	(0.0688)	(0.0601)	(0.0624)	(0.0667)	(0.0709)	(0.0685)	(0.0686)	(0.0647)
Firm performance$_{(t-1)}$	0.0493	0.101**	0.0714	0.0815	0.0434	0.0457	0.0482	0.0624
	(0.0716)	(0.0515)	(0.0622)	(0.0652)	(0.0725)	(0.0678)	(0.0717)	(0.0718)
Commitment to incumbent technology$_{(t-1)}$	-0.0109	-0.00833	-0.0119	-0.0113	-0.0106	-0.0107	-0.0110	-0.0122
	(0.0127)	(0.0148)	(0.0149)	(0.0131)	(0.0133)	(0.0125)	(0.0126)	(0.0138)
Demand-pull policies$_{(t-1)}$	2.27e-06**	2.24e-06**	2.37e-06**	2.38e-06**	2.26e-06**	2.27e-06**	2.37e-06**	1.98e-06*
	(1.11e-06)	(1.02e-06)	(1.05e-06)	(1.10e-06)	(1.10e-06)	(1.10e-06)	(1.02e-06)	(1.10e-06)
Demand-pull policies$_{(t-1)}$ *	-2.57e-07**	-2.32e-07*	-2.64e-07**	-2.69e-07**	-2.57e-07*	-2.62e-07**	-2.62e-07**	-2.25e-07*
Technological capabilities$_{(t-1)}$	(1.30e-07)	(1.22e-07)	(1.30e-07)	(1.31e-07)	(1.32e-07)	(1.32e-07)	(1.24e-07)	(1.28e-07)
Demand-pull policies$_{(t-1)}$ *	-2.54e-07*	-3.40e-07***	-3.17e-07**	-2.82e-07**	-2.50e-07*	-2.51e-07*	-2.52e-07*	-3.03e-07**
Firm performance$_{(t-1)}$	(1.42e-07)	(1.24e-07)	(1.28e-07)	(1.35e-07)	(1.36e-07)	(1.40e-07)	(1.41e-07)	(1.39e-07)
Demand-pull policies$_{(t-1)}$ *	-7.92e-08***	-8.71e-08***	-8.53e-08***	-8.02e-08***	-8.12e-08***	-7.89e-08***	-7.91e-08***	-8.18e-08***
Commitment to incumbent technology$_{(t-1)}$	(2.62e-08)	(2.69e-08)	(2.76e-08)	(2.63e-08)	(2.83e-08)	(2.63e-08)	(2.63e-08)	(2.55e-08)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	453	479	463	453	453	463	453	453
Number of firms	29	29	29	29	29	29	29	29
AIC	6,823	7,261	7,034	6,864	6,829	6,858	6,823	6,907

Note. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix B

Supplementary material for patent identification strategies for battery electric vehicles (BEV), hybrid electric vehicles (HEV), fuel cell electric vehicles (FCEV), and internal combustion engine vehicles (ICEV) to extract patent data from Derwent Innovation Index. In the submission to *Research Policy* included as e-component (Excel file).

Table B.1: Full search string for technology field - BEV

Search string part	Derwent Innovation Index search string	Supplementary
Firm identifiers	(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")))	*firm identifiers*, see Table B.3
BEV key term search string and BEV components search string	AND ((*BEV key term search string)* OR (*BEV components search string)*)	*BEV key terms search string*, see Table B.4; *BEV components search string*, see Table B.5
IPC codes included	AND IP=(B60K-001* or B60L-003* or B60L-007/1* or B60L-011* or B60L-015* or B60L-050/30 or B60L-050/40 or B60L-050/6* or B60L-053/2* or B60L-058/1* or B60L-058/2* or B60W-010/08 or B60W-010/24 or B60W-010/26 or H01G-011* or H01M-002* or H01M-004* or H01M-010* or H01M-050* or H02K-00* or H02k-01* or H02K-021* or H02M-003* or H02M-007* or H02P-007* or H02P-027*)	*IPC codes included*, see Table B.9
IPC codes excluded	NOT IP=(B01J-023* or B01J-035* or B60K-006* or B60K-013* or B60K-015* or B60L-007/20 or B60L-050/1* or B60L-050/7* or B60L-058/3* or B60L-058/40 or B60W-010/06 or B60W-010/28 or B60W-020* 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 F17C* or H01M-008* or H01M-012* or B61* or B62B* or B62C* or B62H* or B62J* or B62K* or B62L* or B62M* or B63* or B64*))	*IPC excluded*, see Table B.9

Note. For brevity, the *BEV key term search string* and the *BEV component search string* are not shown because they contain 240 BEV key terms and 464 HEV or FCEV key terms, respectively.

Table B.2: Full search string for technology field - ICEV

Search string part	Derwent Innovation Index search string	Supplementary
Firm identifiers	(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")))	*firm identifiers*, see Table B.3
ICEV key term search string	AND TS=(vehicle* or car or cars or automobil* or automotive)	
IPC codes included	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*)	*IPC codes included*, see Table B.9
IPC codes excluded	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*)	*IPC codes excluded*, see Table B.9

Table B.3: Firm identifiers and names, including consolidated subsidiaries

Firm	DII Code	DII codes of consolidated subsidiaries	Source(s): Refinitiv Eikon - M&A database & firms' annual reports
AVTOVAZ	ATVZ-C (until 2017)	none	Groupe Renault, 2016
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)	Daimler Chrysler AG, 1998; Daimler AG, 2007
FCA	FIAT-C	COUA-C; ITMA-C (until 2017); AUTV-C (2001–2017); CHRY-C (since 2011)	FIAT Group, 2001a; FIAT Group, 2001b; Fiat Chrysler Automobiles, 2014; Fiat Chrysler Automobiles, 2018; Stellantis, 2020
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)	General Motors Company, 2009; General Motors Company, 2010; General Motors Company, 2017
GREAT WALL	GRWA-C	none	
HONDA	HOND-C	YACH-C (since 2006)	
HYUNDAI	HYMR-C	KIAK-C (1999–2010)	Hyundai Motor Company, 2002; Hyundai Motor Company, 2011; Kia Motors, 2017
ISUZU	ISUZ-C	none	
JAC	JIAN-C	none	
KIA	KIAK-C (consolidated by Hyundai 1998-2010)	none	Hyundai Motor Company, 2002; Hyundai Motor Company, 2011; Kia Motors, 2017
LIFAN	LIFG-C	none	
MAHINDRA & MAHINDRA	MAHI-C	SSAN-C (since 2011)	Mahindra & Mahindra, 2011
MAZDA	MAZD-C	none	
MITSUBISHI	MITM-C	none	
NISSAN	NSMO-C	JATC-C	Nissan Motor Company, 2001
PORSCHE	PORS-C (until 2011)	none	Porsche SE, 2007; Porsche SE, 2008; Porsche SE, 2009; Volkswagen AG, 2012
PSA	CITR-C	FAUR-C (1998–2014)	PSA Groupe, 2017; Stellantis, 2020
RENAULT	RENA-C	ATVZ-C (since 2017)	
SAIC	SAMO-C		
SSANGYONG	SSAN-C (until 2010)	none	Mahindra & Mahindra, 2011
SUBARU	FUJH-C	none	
SUZUKI	SUZM-C	none	

Table B.3: Firm identifiers and names, including consolidated subsidiaries (ctd.)

Firm	DII Code	DII codes of consolidated subsidiaries	Source(s): Refinitiv Eikon - M&A database & Annual Reports
TATA	TTTA-C AND AN=("Tata Motors Ltd" OR "Jaguar Land Rover" OR "Jaguar Cars")	none	
TESLA	TESM-C	MAXW-C (2019–2020)	
TOYOTA	TOYT-C	DAHM-C (since 1998); HINM-C (since 2001); MSWA-C (since 2017)	Toyota Motor Corporation, 2001; Toyota Motor Corporation, 2002
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)	Volkswagen AG, 1994; Volkswagen AG, 2008; Volkswagen AG, 2011; Volkswagen AG, 2012

Table B.4: Key terms search string for technology field – BEV

BEV key terms search string

TS=("*BEV key term 1*" *OR* "*BEV key term 1*" *OR … OR* "*BEV key term 240*")

Generation BEV key terms

240 BEV key terms are generated by combining the keywords below as follows:
Start-End; Start-Add1-End; Start-Add2-End; Start-Add1-Add2-End

Start	Add1	Add2	End
"electr*	driv*	automotive	vehicle*"
"electr* or hybrid	powered	passenger	car"
"electr* and hybrid	operated	motor	cars"
	propelled		automobile*"

Table B.5: Component search string for technology field – BEV

Search string part	Derwent Innovation Index search string	Supplementary
Automotive key words	(TS=((vehicle* or car or cars or automobil* or automotive)	
BEV component keywords	AND (batter* or "electr* motor*" or "induction motor*" or "electr* driv*" or "on-board charg*"))	
Exclusion of patents identified as HEV or FCEV paten	NOT (*HEV search string*) NOT (*FCEV search string*))	*HEV search string*, see Table B.6; *FCEV search string*, see Table B.7

Note. For brevity, the *HEV key term search string* and the *FCEV key term search string* are not shown because they contain 240 HEV key terms and 224 FCEV key terms, respectively.

Table B.6: Search string for technology field – HEV

HEV key terms search string

(TS=("*HEV key term 1*" OR "*HEV key term 1*" OR … OR "*HEV key term 240*") OR (TS=((vehicle* or car or cars or automobil* or automotive) AND ("hybrid propulsion*" or "hybrid power*" or "hybrid transmission*" or "hybrid driv*" or "regenerat* brak*" or "energy recover*" or "recuperat*"))))

Generation HEV key terms

240 HEV key terms are generated by combining the keywords below as follows:
Start-End; Start-Add1-End; Start-Add2-End; Start-Add1-Add2-End

Start	Add1	Add2	End
"hybrid	driv*	automotive	vehicle*"
"hybrid electr*	powered	passenger	car"
"hybrid or electr*	operated	motor	cars"
"hybrid and electri*	propelled		automobile*"

Table B.7: Search string for technology field – FCEV

FCEV key terms search string

(TS=("*FCEV key term 1*" OR "*FCEV key term 1*" OR … OR "*FCEV key term 224*") OR (TS=((vehicle* or car or cars or automobil* or automotive) AND ("fuel cell*" or "hydrogen tank*"))))

Generation FCEV key terms

224 FCEV key terms are generated by combining keywords below as follows:
Start-End; Start-Add1-End; Start-Add2-End; Start-Add1-Add2-End

Start	Add1	Add2	End
"hydrogen	driv*	automotive	vehicle*"
"fuel cell	powered	passenger	car"
	operated	motor	cars"
	propelled		automobile*"
	fuel$ed		
	electr*		

Table B.8: Derwent manual codes to test the comprehensiveness of search strings

Technology field	Derwent Manual Code
BEV	MAN=(X21-A01F and (X16-B01A1 or X16-B01A3 or X16-B01F1 or X16-F06A or X21-B01B or X21-A07 or X21-B05 or X21-B01B1 or X21-B01A1A)
HEV	MAN=(X21-A01D or X21-A01D3)
FCEV	MAN=(X21-A01J)
ICEV	MAN=(Q17-E* or Q51* or X22-A*)

Table B.9: Overview of IPC codes excluded (0), neutral (1), or included (2) per technology

IPC	Description according to the IPC handbook	BEV	ICEV	HEV	FCEV
B01D-046*	Filters or filtering processes specially modified for separating dispersed particles from gases or vapours (filtering elements B01D 24/00-B01D 35/00; filtering material B01D 39/00; their regeneration outside the filters B01D 41/00) [2006.01]	1	2	2	1
B01D-053*	Separation of gases or vapours; Recovering vapours of volatile solvents from gases; Chemical or biological purification of waste gases, e.g. Engine exhaust gases, smoke, fumes, flue gases or aerosols (recovery of volatile solvents by condensation B01D 5/00; sublimation B01D 7/00; cold traps, cold baffles B01D 8/00; separation of difficult-to-condense gases or air by liquefaction F25J 3/00) [2006.01]	1	2	2	1
B01J-023*	Catalysts comprising metals or metal oxides or hydroxides, not provided for in group B01J 21/00 (B01J 21/16 takes precedence) [2006.01]	0	2	2	1
B01J-035*	Catalysts, in general, characterised by their form or physical properties [2006.01]	0	2	2	1
B60K-001*	Arrangement or mounting of electrical propulsion units	2	0	2	2
B60k-005*	Arrangement or mounting of internal-combustion or jet-propulsion units (B60K 7/00 takes precedence; arrangement or mounting of plural diverse prime-movers for mutual or common propulsion B60K 6/00) [2006.01]	1	2	2	1
B60K-006*	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. Hybrid propulsion systems comprising electric motors and internal combustion engines **[2007.10]**	0	0	2	2
B60K-013*	Arrangement in connection with combustion air intake or gas exhaust of propulsion units (extensions for melting snow or ice on roads or like surfaces E01H 5/00, E01H 6/00; forming part of the engine F01N; supplying combustion engines with combustible mixtures or constituents F02M) **[2006.01]**	0	2	2	1
B60K-015*	Arrangement in connection with fuel supply of combustion engines; Mounting or construction of fuel tanks (tanks in general B65D, F17C; supplying combustion engines with combustible mixtures or constituents F02M) [2006.01]	0	2	2	1
B60L-003*	Electric devices on electrically-propelled vehicles for safety purposes; Monitoring operating variables, e.g. Speed, deceleration or energy consumption (methods or circuit arrangements for monitoring or controlling batteries or fuel cells B60L 58/00) [2019.01]	2	0	2	2
B60L-007/1*	Electrodynamic brake systems for vehicles in general [2006.01] Dynamic electric regenerative braking (B60L 7/22 takes precedence) [2006.01]	2	0	2	2
B60L-007/20	Electrodynamic brake systems for vehicles in general [2006.01] Braking by supplying regenerated power to the prime mover of vehicles comprising engine-driven generators [2006.01]	0	0	2	1
B60L-011*	Electric propulsion with power supplied within the vehicle (B60L 8/00, B60L 13/00 take precedence; arrangements or mounting of prime-movers consisting of electric motors and internal combustion engines for mutual or common propulsion B60K 6/20) [2006.01]	2	0	2	2
B60L-015*	Methods, circuits or devices for controlling the propulsion of electrically-propelled vehicles, e.g. Their traction-motor speed, to achieve a desired performance; Adaptation of control equipment on electrically-propelled vehicles for remote actuation from a stationary place, from alternative parts of the vehicle or from alternative vehicles of the same vehicle train [2006.01]	2	0	2	2

Table B.9: Overview of IPC codes excluded (0), neutral (1), or included (2) per technology (ctd.)

IPC	Description according to IPC handbook	BEV	ICEV	HEV	FCEV
B60L-050/1*	Electric propulsion with power supplied within the vehicle (with power supply from forces of nature, e.g. Sun or wind, B60L 8/00; for monorail vehicles, suspension vehicles or rack railways B60L 13/00) [2019.01] using propulsion power supplied by engine-driven generators, e.g. Generators driven by combustion engines [2019.01]	0	0	2	1
B60L-050/30	Electric propulsion with power supplied within the vehicle (with power supply from forces of nature, e.g. Sun or wind, B60L 8/00; for monorail vehicles, suspension vehicles or rack railways B60L 13/00) [2019.01] using propulsion power stored mechanically, e.g. In fly-wheels [2019.01]	2	0	2	2
B60L-050/40	Electric propulsion with power supplied within the vehicle using propulsion power supplied by capacitors [2019.01]	2	0	2	2
B60L-050/6*	Electric propulsion with power supplied within the vehicle using power supplied by batteries (in combination with fuel cells B60L 50/75) [2019.01]	2	0	2	2
B60L-050/7*	Electric propulsion with power supplied within the vehicle using power supplied by fuel cells (in combination with batteries B60L 50/75) [2019.01]	0	0	0	2
B60L-053/2*	Methods of charging batteries, specially adapted for electric vehicles; Charging stations or on-board charging equipment therefore; Exchange of energy storage elements in electric vehicles [2019.01] characterised by converters located in the vehicle [2019.01]	2	0	2	1
B60L-058/1*	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles [2019.01] for monitoring or controlling batteries [2019.01]	2	0	2	2
B60L-058/2*	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles [2019.01]for monitoring or controlling batteries [2019.01] (continued)	2	0	2	2
B60L-058/3*	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles **[2019.01]** for monitoring or controlling fuel cells [2019.01]	0	0	0	2
B60L-058/40	Methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles [2019.01] for controlling a combination of batteries and fuel cells [2019.01]	0	0	0	2
B60W-010/06	Conjoint control of vehicle sub-units of different type or different function including control of propulsion units including control of combustion engines [2006.01]	0	2	2	1
B60W-010/08	Conjoint control of vehicle sub-units of different type or different function including control of electric propulsion units, e.g. Motors or generators [2006.01] including control of electric propulsion units, e.g. Motors or generators [2006.01]	2	0	2	2
B60W-010/24	Conjoint control of vehicle sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle B60L 50/00-B60L 58/00) [2006.01] including control of energy storage means [2006.01]	2	0	2	2
B60W-010/26	Conjoint control of vehicle sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle B60L 50/00-B60L 58/00) [2006.01] including control of energy storage means [2006.01] for electrical energy, e.g. Batteries or capacitors [2006.01]	2	0	2	2
B60W-010/28	Conjoint control of vehicle sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle B60L 50/00-B60L 58/00) [2006.01] including control of fuel cells [2006.01]	0	0	0	2

Table B.9: Overview of IPC codes excluded (0), neutral (1), or included (2) per technology (ctd.)

IPC	Description according to IPC handbook	BEV	ICEV	HEV	FCEV
B60W-020*	Control systems specially adapted for hybrid vehicles [2016.01]	0	0	2	2
F01L-001*	Valve-gear or valve arrangements, e.g. Lift-valve gear (lift valve and valve seat assemblies per se F01L 3/00; slide-valve gear F01L 5/00; actuated non-mechanically F01L 9/00; valve arrangements in working piston or piston-rod F01L 11/00; modifications of valve-gear to facilitate reversing, braking, starting, changing compression ratio, or other specific operations F01L 13/00) [2006.01]	0	2	2	1
F01L-013*	Modifications of valve-gear to facilitate reversing, braking, starting, changing compression ratio, or other specific operations [2006.01]	0	2	2	1
F01M-013/02	Crankcase ventilating or breathing [2006.01] by means of additional source of positive or negative pressure [2006.01]	0	2	2	1
F01M-013/04	Crankcase ventilating or breathing [2006.01] having means for purifying air before leaving crankcase, e.g. Removing oil [2006.01]	0	2	2	1
F01N*	GAS-FLOW SILENCERS OR EXHAUST APPARATUS FOR MACHINES OR ENGINES IN GENERAL; GAS-FLOW SILENCERS OR EXHAUST APPARATUS FOR INTERNAL-COMBUSTION ENGINES (arrangements in connection with gas exhaust of propulsion units in vehicles B60K 13/00; combustion-air intake silencers specially adapted for, or arranged on, internal-combustion engines F02M 35/00; protecting against, or damping, noise in general G10K 11/16)	0	2	2	1
F01P*	COOLING OF MACHINES OR ENGINES IN GENERAL; COOLING OF INTERNAL-COMBUSTION ENGINES (arrangements in connection with cooling of propulsion units in vehicles B60K 11/00; heat-transfer, heat-exchange or heat-storage materials C09K 5/00; heat-exchange in general, radiators F28)	0	2	2	1
F02B*	INTERNAL-COMBUSTION PISTON ENGINES; COMBUSTION ENGINES IN GENERAL (cyclically operating valves therefor F01L; lubricating internal-combustion engines F01M; gas-flow silencers or exhaust apparatus therefor F01N; cooling of internal-combustion engines F01P; internal-combustion turbines F02C; plants in which engines use combustion products F02C, F02G)	0	2	2	1
F02D*	CONTROLLING COMBUSTION ENGINES (vehicle fittings, acting on a single sub-unit only, for automatically controlling vehicle speed B60K 31/00; conjoint control of vehicle sub-units of different type or different function, road vehicle drive control systems for purposes other than the control of a single sub-unit B60W; cyclically operating valves for combustion engines F01L; controlling combustion engine lubrication F01M; cooling internal-combustion engines F01P; supplying combustion engines with combustible mixtures or constituents thereof, e.g. Carburettors, injection pumps, F02M; starting of combustion engines F02N; controlling of ignition F02P; controlling gas-turbine plants, jet-propulsion plants, or combustion-product engine plants, see the relevant subclasses for these plants) [2006.01]	0	2	2	1
F02F*	CYLINDERS, PISTONS, OR CASINGS FOR COMBUSTION ENGINES; ARRANGEMENTS OF SEALINGS IN COMBUSTION ENGINES (specially adapted for rotary-piston or oscillating-piston internal-combustion engines F02B; specially adapted for gas-turbine plants F02C; specially adapted for jet-propulsion plants F02K) [2]	0	2	2	1
F02M*	SUPPLYING COMBUSTION ENGINES IN GENERAL WITH COMBUSTIBLE MIXTURES OR CONSTITUENTS THEREOF (charging such engines F02B)	0	2	2	1

Table B.9: Overview of IPC codes excluded (0), neutral (1), or included (2) per technology (ctd.)

IPC	Description according to IPC handbook	BEV	ICEV	HEV	FCEV
F02N*	STARTING OF COMBUSTION ENGINES (starting of free-piston combustion-engines F02B 71/02; starting of gas-turbine plants F02C 7/26); STARTING AIDS FOR SUCH ENGINES, NOT OTHERWISE PROVIDED FOR	0	2	2	1
F02P*	IGNITION, OTHER THAN COMPRESSION IGNITION, FOR INTERNAL-COMBUSTION ENGINES; TESTING OF IGNITION TIMING IN COMPRESSION-IGNITION ENGINES (specially adapted for rotary-piston or oscillating-piston engines F02B 53/12; ignition of combustion apparatus in general, glowing plugs F23Q; measuring of physical variables in general G01; controlling in general G05; data processing in general G06; electrical components in general, see section H; sparking plugs H01T)	0	2	2	1
F16H*	Gearing	1	2	2	1
F17C*	Vessels for containing or storing compressed, liquefied, or solidified gases; fixed-capacity gas-holders; filling vessels with, or discharging from vessels, compressed, liquefied, or solidified gases	0	0	0	2
H01G-011*	Hybrid capacitors, i.e. Capacitors having different positive and negative electrodes; Electric double-layer [EDL] capacitors; Processes for the manufacture thereof or of parts thereof **[2013.01]**	2	0	2	2
H01M-002*	PROCESSES OR MEANS, e.g. BATTERIES, FOR THE DIRECT CONVERSION OF CHEMICAL ENERGY INTO ELECTRICAL ENERGY [2] Constructional details, or processes of manufacture, of the non-active parts [2006.01]	2	0	2	2
H01M-004*	PROCESSES OR MEANS, e.g. BATTERIES, FOR THE DIRECT CONVERSION OF CHEMICAL ENERGY INTO ELECTRICAL ENERGY [2] Electrodes [2006.01]	2	0	2	2
H01M-008*	Fuel cells; Manufacture thereof [2016.01]	0	0	0	2
H01M-010*	PROCESSES OR MEANS, e.g. BATTERIES, FOR THE DIRECT CONVERSION OF CHEMICAL ENERGY INTO ELECTRICAL ENERGY [2] Secondary cells; Manufacture thereof [2006.01]	2	0	2	2
H01M-012*	Hybrid cells; Manufacture thereof (hybrid capacitors H01G 11/00) [2006.01]	0	0	0	2
H01M-050*	PROCESSES OR MEANS, e.g. BATTERIES, FOR THE DIRECT CONVERSION OF CHEMICAL ENERGY INTO ELECTRICAL ENERGY [2] Constructional details or processes of manufacture of the non-active parts of electrochemical cells other than fuel cells, e.g. Hybrid cells [2021.01]	2	0	2	2
H02K-00*	DYNAMO-ELECTRIC MACHINES (dynamo-electric relays H01H 53/00; conversion of DC or AC input power into surge output power H02M 9/00): DETAILS	2	1	2	2
H02k-01*	DYNAMO-ELECTRIC MACHINES (dynamo-electric relays H01H 53/00; conversion of DC or AC input power into surge output power H02M 9/00): DETAILS, Continuously rotating and Manufacture	2	1	2	2
H02K-021*	Synchronous motors having permanent magnets; Synchronous generators having permanent magnets [2006.01] DYNAMO-ELECTRIC MACHINES (dynamo-electric relays H01H 53/00; conversion of DC or AC input power into surge output power H02M 9/00)	2	1	2	2
H02M-003*	Conversion of dc power input into dc power output [2006.01]	2	1	2	2

Table B.9: Overview of IPC codes excluded (0), neutral (1), or included (2) per technology (ctd.)

IPC	Description according to IPC handbook	BEV	ICEV	HEV	FCEV
H02M-007*	Conversion of ac power input into dc power output; Conversion of dc power input into ac power output [2006.01]	2	1	2	2
H02P-007*	Arrangements for regulating or controlling the speed or torque of electric DC motors **[2016.01]**	2	1	2	2
H02P-027*	Arrangements or methods for the control of AC motors characterised by the kind of supply voltage (of two or more motors H02P 5/00; of synchronous motors with electronic commutators H02P 6/00; of DC motors H02P 7/00; of stepping motors H02P 8/00) [2006.01]	2	1	2	2
B61*	Railways	0	0	0	0
B62B*	HAND-PROPELLED VEHICLES, e.g. HAND CARTS OR PERAMBULATORS; SLEDGES (characterised by animal propulsion B62C; propulsion of sledges by driver or engine B62M)	0	0	0	0
B62C*	Vehicles drawn by animals	0	0	0	0
B62H*	Cycle stands; supports or holders for parking or storing cycles; appliances preventing or indicating unauthorised use or theft of cycles; locks integral with cycles; devices for learning to ride cycles	0	0	0	0
B62J*	CYCLE SADDLES OR SEATS; AUXILIARY DEVICES OR ACCESSORIES SPECIALLY ADAPTED TO CYCLES AND NOT OTHERWISE PROVIDED FOR, e.g. ARTICLE CARRIERS OR CYCLE PROTECTORS	0	0	0	0
B62K*	Cycles; cycle frames; cycle steering devices; rider-operated terminal controls specially adapted for cycles; cycle axle suspensions; cycle sidecars, forecars, or the like	0	0	0	0
B62L*	Brakes specially adapted for cycles	0	0	0	0
B62M*	RIDER PROPULSION OF WHEELED VEHICLES OR SLEDGES; POWERED PROPULSION OF SLEDGES OR CYCLES; TRANSMISSIONS SPECIALLY ADAPTED FOR SUCH VEHICLES (arrangements or mounting of transmissions in vehicles in general B60K; transmission elements per sef16)	0	0	0	0
B63*	Ships or other waterborne vessels; related equipment	0	0	0	0
B64*	Aircraft; aviation; cosmonautics	0	0	0	0

0	excluded
1	neutral
2	included

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