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Good design is good business:

How industry interests affect technology policy designs

Exploring the evolution of battery storage policies in the United States between 1999 and 2020

Master Thesis

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Abstract

Battery storage technology is one of the key technologies to facilitate the energy transition, decarbonise the mobility sector, and spread renewable energies. In order to speed up battery storage innovation, policy interventions are essential. When shaping policy designs to foster the technologies and technological applications needed for change, policy-makers do not act in a vacuum, but are influenced by industry interests. This master thesis adds insights from innovation studies to the debate on policy designs by exploring *how industry interests affect policy-makers' technology policy design preferences*. Based on the concept of design coalitions, I hypothesise that the battery producing sector forms "technology-specific design coalitions" with policy-makers to foster their favoured technology. Correspondingly, the battery using sector forms "application-specific design coalitions" with policy-makers to promote their favoured technological application. Industries can thereby influence decision-makers indirectly, through pressure on the level of the constituency, or directly, through lobbying activities. The present analysis is based on a newly developed dataset on battery storage policies in the United States between 1999 and 2020. Using multinomial logistic regression models and descriptive empirical methods, it could be shown that policy-makers are affected by the economic circumstances of their constituencies when designing technology policies. Policy-makers representing a state with a larger battery producing sector are more likely to support technology-specific policy designs; policy-makers representing a constituency with a larger battery using sector are more likely to support application-specific policy designs. More research will be necessary to explore the direct link between industries and policy-makers to uncover the causal mechanism of the direct influence of industries on policy-makers' policy design preferences and, eventually, on technology policy designs. In conclusion, I wish to contribute with this thesis to the policy design literature to better understand the politics behind policy-making in the understudied field of battery storage policies. Ultimately, I want to explore how designing good policy is good business for industry sectors and policy-makers – and contributes to the technological innovation necessary to govern the energy transition.

Keywords

Policy design, technology specificity, application specificity, design coalitions, industry interests

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1 Introduction

The decarbonisation of the mobility sector and the increase of renewable energies are essential for the energy transition and necessary to achieve an average global warming of no more than 1.5 degrees by 2050 (United Nations, 2015). Battery storage is one of the key technologies facilitating this transition process. Battery storage technologies are the centrepiece of electric vehicles, gradually replacing internal combustion engines. Speeding up their innovation decreases the costs of electric transportation and increases their market penetration. Furthermore, with the increasing deployment of renewable energies, energy storage is inevitable to support grid stability and power reliability, as supply and demand change throughout the day and during the cycle of a year. In turn, storing energy can save costs for consumers by enabling them to store cheap energy and use it during peak hours (Energy Storage Association, 2021). Thus, facilitating innovation in energy storage is fundamental to achieving a diversified, safe, economically and environmentally sustainable energy supply and to decarbonising the mobility sector. However, the challenge remains how these goals can be attained.

The past has shown that major societal challenges have commonly urged political responses. Therefore, to face climate change and govern the energy transition, policy interventions are essential to foster and speed up battery technology innovation and set the framework to direct the necessary change (Mazzucato, 2016; Stern, 2008; Torvanger and Meadowcroft, 2011; Unruh, 2000). In this context, the policy design literature has recognised the importance of technology policy designs in picking technological winners and avoiding technological lock-ins of emerging technologies. Technology-specificity has for a long time been the determinant factor in influencing technological innovation or lock-in. However, multi-purpose technologies are used in multiple applications, and therefore, recognising the importance of the application-specificity of a policy is crucial (Battke and Schmidt, 2015). Besides that, there is a consensus that industries are among the primary addressees of technology policies. These target actors are not only passive recipients of policy interventions but actively influence the policy-making process by fostering or blocking it (Meckling, 2011; Mildenberger, 2020). Nonetheless, whereas the policy literature recognises the importance of industry actors in influencing the policy-making process, it remains unclear how these industries affect the policy design preferences of policy-makers, and ultimately the policy design of technology policies.

The present master thesis aims at filling this gap in the policy design literature by investigating how industry interests affect technology policy designs. Drawing on innovation studies literature provides a deeper insight into how different industries are involved in upstream and downstream manufacturing processes of technologies through their knowledge and experience (Stephan et al., 2017). Integrating these insights into the debate around policy designs will set the basis for exploring a new facet of the politics behind policy-making. Therefore, this thesis explores what drives policy-makers to support specific policy designs and how industry interests influence this process. The following research question will be investigated: *How do industry interests affect policy-makers' technology policy design preferences?*

To study this research question, I will explore battery storage policy designs in the United States between 1999 and 2020. Understanding battery storage policies is crucial to set a policy framework within which battery innovation can take place, and ultimately, the decarbonisation of the energy sector and the reliable deployment of renewable energies can happen. Based on innovation literature, I will go beyond current policy design literature and investigate whether different industry sectors along the value-chain of a lithium-ion battery have different and unique policy design preferences. I hypothesise that the battery producing sector forms "technology-specific design coalitions" with policy-makers to foster their favoured technology. Correspondingly, I assume that the battery using sector forms "application-specific design coalitions" with policy-makers to promote their favoured technological application. Industries can thereby influence decision-makers indirectly, through pressure on the level of the constituency, or directly, through lobbying activities.

To empirically analyse the research question, I created a dataset on battery storage bills and laws in the United States over the past 20 years. The dataset contains information on 363 battery storage bills and their technology- and application-specificity. Moreover, on the bill level, the dataset contains information on whether a policy attracted lobbying by a firm from the battery producing and/or the battery using sector. Additionally, the dataset includes information on each bill's sponsor and co-sponsors, allowing for better understanding policy-makers' technology policy design preferences. Finally, there is data on the economic circumstances in each state, namely the employment shares in the battery producing and the battery using sector, and the number of firms per industry sector along the value-chain of a lithium-ion battery. The data frame contains 4'885 entries of policy-makers and bills.

To evaluate how the battery producing and the battery using sector influence policy-makers' technology policy design preferences, and eventually the design of a technology policy, I will, in a first step, use multinomial logistic regression models. I will test how the economic situation in a state affects policy-makers' technology policy preferences. I will scrutinize how the battery producing sector affects policy-makers' design choice regarding the technology-specificity of a policy; and how the battery using sector affects policy-makers' design choice regarding the application-specificity of a policy. Moreover, I will split the data into two time periods to investigate whether the indirect influence of industries on policy-makers changes over time. In a second step, I will descriptively explore the subset of bills that attracted lobbying by the battery producing and the battery using sector to shed light on the direct link between industry interests and policy designs.

The results of the first step of the analysis confirm that policy-makers are affected by the economic circumstances of their constituencies. Policy-makers representing a state with a larger battery producing sector are more likely to support technology-specific policies; policy-makers representing a constituency with a larger battery using sector are more likely to favour application-specific policies. However, time matters. Whereas higher economic activities in the battery producing sector were mostly relevant until around 2010, economic circumstances of the battery producing sector only started affecting policy-makers' policy-design preferences in recent years. The second step of the analysis that serves to explore the direct links between industries and firms through lobbying was only possible in a descriptive way due to the limited availability of data on direct lobbying activities. Therefore, further research will be needed to investigate the causal mechanism linking industry interests and technology policy designs.

Understanding how battery storage policies are designed, why they are designed that way, and how industries affect policy-makers' technology policy design preferences is of far-reaching relevance: Battery storage policies have long been ignored among policy design scholars (Schmidt et al., 2016; Sewerin et al., 2020). However, focusing on storage batteries is vital because batteries are one of the key technologies necessary to decarbonise our mobility sector, spread renewable energies, and ultimately govern the energy transition (Battke and Schmidt, 2015; Beuse et al., 2018; Energy Storage Association, 2021). In this context, technology policies are the inevitable basis to transform our energy system and foster the necessary technological innovation (Mazzucato, 2018). Better understanding how battery storage policies are designed, both in terms of the designing process and the product, is therefore a necessary first step (Schneider and Ingram, 1988). Moreover, it is essential to better understand the politics behind policy-making. As the primary target group of most technology policies, industry groups are closely linked to the political system and actively influence the policy-making process (Ingold et al., 2016; Meckling, 2011; Mildenberger, 2020). Thus, for the transition towards decarbonising our society, it is crucial to understand how industry actors foster and block this process by influencing policy-makers, their technology policy design preferences, and ultimately the design of technology policies. Finally, studying the case of the United States gives insights into one of the largest economies urged to face a major energy transition in the upcoming years. To remain competitive and increase its independence on the energy market, the United States must draft "smart" policies that provide the necessary framework to increase battery storage capacity to be well-prepared to govern the energy transition.

With this master thesis, I wish to contribute to the policy design literature to better understand the politics behind policy-making in the understudied field of battery storage policies. Consequently, I want to explore how designing good policy is good business for industry sectors and policy-makers – and contributes to the technological innovation necessary to govern the energy transition.

2 Literature and Theory

The past has shown that major societal problems have commonly urged political responses – and that innovation and technology policy have the potential to address those challenges and set the direction of change (Mazzucato, 2016). Therefore, government support and policy interventions are inevitable to speed up the innovation and diffusion of technologies, such as battery storage technologies, that are necessary to govern the energy transition successfully (Jacobsson and Lauber, 2006; Mazzucato, 2018; Schmidt and Sewerin, 2017; Stern, 2008; Torvanger and Meadowcroft, 2011).

Compared to private investors, governments have the advantage that they can take bigger risks and make larger investments by pooling the risks associated with large-scale investments. In contrast, private firms are more dependent on single investments and are therefore more risk-averse regarding investments in new technologies with an uncertain future (Arrow and Lind, 1970; Mazzucato, 2016; Stern, 2008; Torvanger and Meadowcroft, 2011; Unruh, 2000). Moreover, firms' profit maximising behaviour often ignores the positive spillovers associated with innovations in climate-friendly technologies (Smolny, 2000). One example are knowledge spillovers, which are positive externalities that come with the innovation of new technologies. Based on diversifying and spreading knowledge, learning within and across technologies can take place (Battke et al., 2016). Neglecting such positive externalities leads to market outcomes below the social optimum (Seto et al., 2016). Therefore, particularly for novel technologies, initial policy support is essential to give them the chance to drive down their learning curve and benefit from economies of scale, which affects their future competitiveness. (Azar and Sandén, 2011; Hoppmann et al., 2013). In short, policy interventions are inevitable to set a framework within which technologies can develop and technological innovation can happen (Jaffe et al., 2005; Smolny, 2000).

Despite the consensus in the literature that government intervention is necessary to foster and speed up technological innovation, two research gaps remain to be investigated more closely: First, there is a wide debate on how and to what extent governments can and should influence the choice of technologies, commonly phrased as "pick technological winners". As a result, it is contested what policy design best serves to foster technological innovation and what dimensions of policy design must be considered to avoid technological lock-ins. The risk of a technological lock-in is that an economy gets "trapped" in a particular technology (Unruh, 2000). In turn, other technologies are locked out because they are more cost-intensive in the short run, despite they might be superior in the long run (del Río González, 2008; Azar and Sandén, 2011). Such kind of inertia is the result of path-dependency, long investment periods and random events influencing technological outcomes (Seto et al., 2016).

Second, there is a consensus that policy-makers are embedded in social, political, and economic networks that influence their policy choices. Relevant actors in the network around policy-makers are industries. They are one of the primary addressees of technology policies (Ingold et al., 2016). Industries are interested in shaping and influencing political processes and outcomes because they can directly benefit (Meckling, 2011; Mildenberger, 2020; Torvanger and Meadowcroft, 2011). However, it remains understudied what drives policy-makers to support different technology policy design elements, and how the network of industries influences policy-makers' policy design preferences (Schmidt et al., 2016). The research question underlying this master thesis combines these two debates by asking: *How do industry interests affect policy-makers' technology policy design preferences?*

In the following, I will introduce the debate around policy designs and industry interests in the policy-making process. I will combine the two strands of literature and introduce a new framework for studying technology policy-design preferences. Thereby, I will distinguish between two different industry sectors, the *battery producing* and the *battery using* sector, and between different policy design elements, focusing on the *technology specificity* and the *application specificity* of a policy. I will derive four exploratory hypotheses to test how industry sector interests affect policy-makers' technology policy design preferences and, eventually, the designs of the drafted bills and laws.

2.1 The debate on policy designs – or how governments should pick technological winners

The debate on policy designs has emerged in the 1980s (e.g. Linder and Peters, 1987; Schneider and Ingram, 1988). To better understand policy outcomes, it was recognised that the focus had to shift away from studying mere policy implementation and to acknowledging the importance of designing policies in accordance with the aspired political goals. In the following, the studies of policy design focused on the process of formulating and drafting policy alternatives (design as a verb) and on the content of the policies (design as a noun) (Schneider and Ingram, 1988). Around the latter, more recent branches of research have evolved on policy instruments and policy mixes (e.g. del Río González, 2008; Del Río, 2014; Schmidt and Sewerin, 2019b), and on specific policy designs (Azar and Sandén, 2011; Howlett, 2014; Sandén and Azar, 2005; Schmidt et al., 2016; Schmidt and Sewerin, 2019b; Sewerin et al., 2020). The debate concerning specific policy designs and their influence on technological innovation will subsequently be outlined.

Opponents of extensive government support argue that "[g]overnments are not good at picking [technological] winners; that should be left to the market" (Azar and Sandén, 2011, p. 135). Advocates of this school of thought argue in favour of "technology-neutral" policy designs. Taking for example policies targeting carbon emissions, technology-neutral policies aim at reducing emissions without specifying by which technology to achieve this reduction (Sandén and Azar, 2005). Such technology-neutral policies include carbon taxes and cap-and-trade schemes that allow the market to decide, based on price signals, how to reduce carbon emissions without further specifying what technology should be used to attain this goal (Jaffe et al., 2005). Nonetheless, due to path-dependent processes, technologies that bring a high return to scale in their initial phase of deployment can become locked-in and outperform technologies that would be superior in the long run (Arthur, 1989; del Río González, 2008; Jaffe et al., 2005; Seto et al., 2016; Unruh, 2002). Thus, while short-term costs may be reduced, sub-optimal solutions can be the result (Unruh, 2000). Consequently, making political choices on technologies is unavoidable (Azar and Sandén, 2011; Howlett, 2014; Meadowcroft, 2009; Schmidt et al., 2016).

In comparison, proponents of "technology-specific" policy designs claim that technology-neutral policies lock out promising technologies because only the currently most competitive technologies benefit from the introduced policy (Schmidt et al., 2016). They argue that well-designed policies have the potential to foster current innovations that influence subsequent innovations through learning spillovers, learning-by-doing and learning-by-using processes (Gawel et al., 2017). Moreover, they argue that the private sector neglects investments in capital-intensive technologies due to long payback periods, but that specific policy support can remedy this problem (Neuhoff and De Vries, 2004). Finally, while technology-neutral policies do not internalise external costs and benefits, policy-makers can internalise market failures by designing technology-specific policies (Gawel et al., 2017). To avoid premature technological lock-ins of established technologies in the short run and to benefit from new technologies in the long run, great care should therefore be taken when designing technology policies (Hoppmann et al., 2013; Sandén and Azar, 2005; Schmidt et al., 2016; Seto et al., 2016).

More recent perspectives on policy designs as drivers for political action or inertia state that the mere distinction between "more market" vs "more state" is flawed and outdated (Beuse et al., 2018; Howlett, 2014; Mazzucato, 2018). The debate should be complemented with a profound discussion on "the direction of change so that such [state] investments will lead to growth that is not only 'smarter' (innovation-led) but also more 'inclusive' and 'sustainable' " (Mazzucato, 2018, p. 2). "Technology-smart" policies should be the basis for the emergence of new technologies by providing a fertile ground for the decarbonisation of the mobility sector and the deployment of renewable energy technologies to the point where they are competitive, affordable, reliable, and suitable for mass use (Beuse et al., 2018; Sandén and Azar, 2005). Such policies should foster collaboration between companies, create space for technological learning and innovation, provide planning security for firms and contribute to an inclusive and innovation-led growth (Beuse et al., 2018; Mazzucato, 2018). A mere distinction between "technology-neutral" and "technology-specific" policy designs is therefore not expedient.

Consequently, the question should not be whether a policy is designed technology-neutral or technology-specific, but rather *how* specific a policy should be formulated in order to reach an intended goal (Azar and Sandén, 2011). The specificity level targeted by a policy depends on the degree of competition among technologies on diverse hierarchy levels. Hence, the policy design determines the likelihood of diffusion of a promoted technology or its technological lock-in (Azar and Sandén, 2011; Schmidt et al., 2016). Technologies addressed by deployment policies are often multi-purpose technologies that serve multiple applications, compete in more than one market, and create economic value for different specific user groups (Battke and Schmidt, 2015). Selecting an application is closely associated with selecting a technology (Schmidt et al., 2016). Therefore, Schmidt et al. (2016) and

Sewerin et al. (2020) have introduced two new dimensions to the debate on policy designs: Firstly, they propose a more gradual distinction between different technology hierarchy levels, from neutral to very specific. Secondly, they have developed a set of applications of multi-purpose technologies, ranging from economy-wide to very specific applications. Both design elements can appear in a technology policy. The two frameworks allow the distinction between different technology specificity levels and between different application specificity levels, from neutral to specific:

- On the *Technology Specificity* dimension of a technology policy design, five levels are defined. A policy can be formulated on the *Economy, Field, Technology, Subtechnology* or the technological *Design* level. These levels distinguish how specific a legislative proposal is designed in terms of the technology targeting battery storage, ranging from neutral (Economy) to very specific (Design).
- On the *Application Specificity* dimension of a technology policy design, four levels are defined. A policy can be formulated on the *Economy, Industry, Application* and *Subapplication* level. These levels distinguish how specific a legislative proposal is designed in regard to energy storage applications, ranging from neutral (Economy) to very application specific (Subapplication).

2.2 Industry interests shape technology policy – or about the dependence of policy-makers

Political outcomes are not only determined by classical power considerations of policy-makers but are the result of a plurality of actors who build coalitions in social networks and change their beliefs based on interactions and learning (Heikkila and Gerlak, 2013; Mattli and Woods, 2009; Meckling, 2011; Sabatier and Weibel, 2007). In these networks, industries and their advocacy groups are closely linked to the political system (Ingold et al., 2016). Industries are the primary target group addressed by technology policies. Consequently, it is in their interest to influence the policy-making process and the policy outcome (Meckling, 2011; Mildenberger, 2020; Torvanger and Meadowcroft, 2011). In turn, policies provide valuable incentives and resources for industry actors, which leverages their material power and produces winners and losers (Pierson, 1993; Schmid et al., 2019). Classical political economy literature thus argues that industry sectors support regulatory policies if they can benefit economically. However, not all firms are endowed with the same amount of resources. Therefore, the industrial structures of the industry sectors matter (Bernauer and Caduff, 2004).

Whereas there is a wide consensus that industries influence the *policy-making process*, the influence of industries on *policy designs* remains understudied (Schmidt and Huenteler, 2016). However, precisely this is important to understand the emergence of technology policy designs better. In this subchapter, I will theorise how different industry sectors, namely the battery using and the battery producing sector, influence the technology policy designs of battery storage policies in terms of their technology specificity and application specificity.

2.2.1 Decision-making behaviour of policy-makers

When studying the decision-making behaviour of policy-makers, the complexity and uncertainty under which policy-makers develop new ideas, make decisions, and learn over time must be considered (Pierson, 1993). Complexity, uncertainty and political desirability set constraints on political feasibility; therefore, rational considerations based on maximising benefits such as power, status, money, and the prospects of re-election fall too short (Dye, 2017; Howlett Rayner, 2013; Meadowcroft, 2011; Sapru, 2020). Instead, decision-making often happens based on trial and error, under time and resource constraints and by relying on cognitive shortcuts and heuristics (Cohen et al., 1972; Geddes, 2020; Kahneman, 2012; Lindblom, 1959; Simon, 1959). Policy-makers do not act in a vacuum, but are embedded in and influenced by social structure. Together with interest groups, they form dynamic and strategic design coalitions in social networks around different policy design preferences. Depending on the goals of the actors, positions and coalitions form and change in the wake of the policy-making process (Haelg et al., 2020). As a result, policy-makers adapt, learn, and change their beliefs, and eventually translate them into actual policy designs (Granovetter, 1985; Sabatier and Weibel, 2007).

The Advocacy Coalition Framework provides a systematic approach to analyse the arrangements and developments of coalitions advocating for (or against) a policy change (Sabatier and Jenkins-Smith, 1988; Sabatier and Weibel, 2007). The framework assumes an interaction between advocacy coalitions, i.e. groups that share common beliefs and aim at translating them into policy through coordinated action (Béland and Haelg, 2020; Ingold et al., 2016). Over an extended period of time, and influenced by external factors and competition within a policy subsystem, policy-makers can learn and increase the technical and scientific knowledge necessary to design new policies (Bennett and Howlett, 1992; Gerlak et al., 2019; Heikkila and Gerlak, 2019, 2013; Ingold et al., 2016; Sabatier and Weibel, 2007; Yanow, 2004). These learning processes are accompanied by a change of intentions, thoughts, and beliefs that can ultimately be transformed into policy actions and result in policy change (Geddes, 2020; Sabatier and Weibel, 2007; Sager et al., 2017).

2.2.2 "Technology-specific" and "application-specific" design coalitions

Despite the consensus that industry interests influence the political decision-making process, industry interests are not homogenous. Many different actors are involved in the manufacturing of multi-component technologies. The lithium-ion battery represents such a multi-component technology and is one of the most prominent battery storage technologies. For this thesis, industries along the value-chain of a lithium-ion battery will be separated into the *battery producing* and the *battery using* sector. The battery producing sector is engaged in manufacturing core components of the battery, such as the cell system, but also involves the industry sectors linked to the production process along the value chain of the battery. In contrast, the battery using sector integrates the different components into a broader range of applications, such as electric vehicles, energy and electronic application (Battke et al., 2016; Stephan et al., 2017). Given the different foci of manufacturing, it is likely that the interests along the value-chain of a lithium-ion battery diverge and that the battery producing and the battery using sector have different and distinctive interests regarding their preferred policy designs (Schmidt et al., 2016).

Distinctive industry interests have so far not been considered in the study of policy designs. Schmidt et al. (2016) expect that the producing sector affects the technology dimension of a policy, whereas the using sector has an impact on the application dimension. However, from these assumptions, it remains unclear *how* the using and the producing sector translate their interests into policy designs and *what design elements* they favour. These shortcomings will be explored in the following by expanding on the concept of design coalitions and deriving hypotheses that link the battery producing sector to the technology specificity and the battery using sector to the application specificity dimension of a policy design.

Design coalitions are composed of policy-makers and interest groups that form around different policy designs. Collaboration within such coalitions enables them to translate their policy concerns into actual policies during the policy designing process (Haelg et al., 2020). Haelg et al. (2020) introduced the concept of design coalitions and tested on the policy design elements introduced by Howlett (2009), distinguishing policy goals and means at different levels of abstraction. In this subchapter, I build on the concept of design coalitions and show that it is also applicable to studying technology policy designs regarding their *technology* and *application specificity*.

To gain wide recognition and legitimacy among decision-makers, emerging technologies need support from proponents who build "technology-specific coalitions" that engage in the political debate (Jacobsson and Lauber, 2006). To gain political ground for their concerns and needs, these advocacy coalitions need to enlarge their network of supporters within and outside the political sphere. Common visions and objectives and the formation of political networks are therefore necessary to influence and shape the institutional setting needed for their favoured technology to become self-sustained and competitive (Azar and Sandén, 2011; Hoppmann et al., 2013). However, the competitiveness of a technology largely varies across different applications (Schmidt et al., 2016). In consequence, not only coalitions around technologies must be considered, but also what I define as "application-specific coalitions". Application-specific coalitions consist of interest groups and policy-makers forming around particular technological applications. These coalitions jointly translate their policy preferences for their favoured technological application into application-specific policy designs. In consequence, policy-makers can reduce the risk of premature technology lock-in by designing application-specific policies without yet fully specifying the technology, allowing technologies to remain competitive or become profitable through learning feedback (Haelg et al., 2018; Schmidt et al., 2016).

I propose a theoretical mechanism stating that the battery producing sector is in favour of technology-specific policy designs and therefore forms "technology-specific design coalitions" with policy-makers to promote technology-specific policies. In contrast, the battery using sector favours application-specific policy designs and thus forms "application-specific design coalitions" with decision-makers to promote specific technological applications and ultimately application-specific policies. Figure 1 represents an overview of the theoretical framework that will be outlined next.

Theoretical framework linking industry interests to technology policy designs

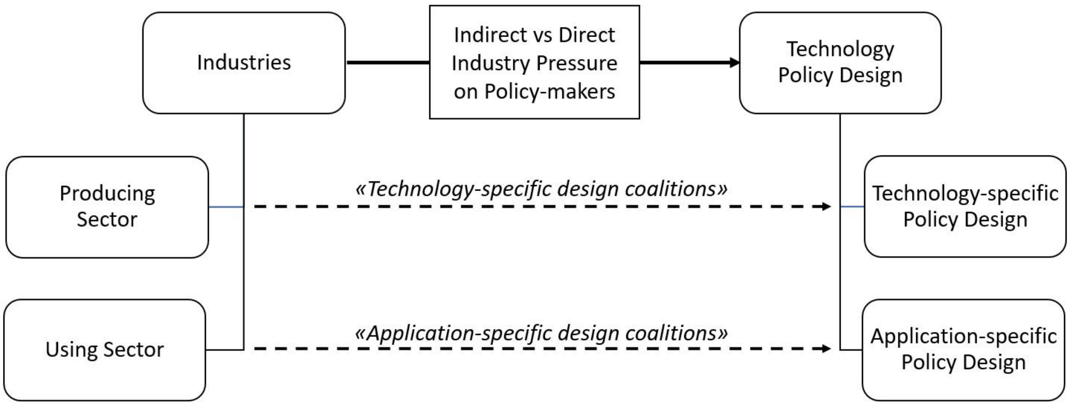

Figure 1: Theoretical mechanism linking industry interests to technology policy designs
Source: Own figure.

Producers of a multi-component technology provide single components for a technology. In the case of the lithium-ion battery, battery producers are engaged in manufacturing the cell system that includes electrodes, electrolytes and separators, but also peripheral parts necessary for a battery such as battery chargers, cooling and casing (Battke et al., 2016; Stephan et al., 2017). Due to their primary focus on technologies, I expect battery producers to be interested in forming "technology-specific design coalitions" with policy-makers to promote their favoured technologies. Moreover, I expect battery producers to benefit most from technology-specific policies that foster *specific technologies* and thereby create the necessary space for technological learning and innovation inevitable for battery producers' commercial success (Beuse et al., 2018; Mazzucato, 2018). Hence, by forming "technology-specific design coalitions", industries receive a venue to influence policy-makers – and ultimately policy-makers' policy design preferences and policy designs. This can either happen indirectly due to the growing presence of technology manufacturing in a state which urges policy-makers to react to their constituencies' needs; or directly through lobbying activities by industries that provide information and share expert knowledge with policy-makers.

In contrast, industries that rely on multi-component technologies, such as storage batteries, are expected to be less concerned about specific technologies. The core of battery users' business is integrating batteries into a broad range of applications, including electric vehicles, energy and electronic applications (Stephan et al., 2017). Due to their primary focus on applications of storage batteries, I expect battery users to be more interested in what applications a technology policy supports and therefore form "application-specific design coalitions" together with policy-makers to promote their favoured technological application. In consequence, I expect industries of the battery using sector to benefit most from policies that target *specific applications*. Such application-specific policy designs incentivise the target actors of that policy, the battery using sector, to foster innovation due to increased planning security that simplifies the production process (Beuse et al., 2018). Consequently, the formation of "application-specific design coalitions" creates a setting of links between firms and policy-makers where firms can impact policy-makers' policy design preferences and, ultimately, the design of a policy. In consequence, industry interests affect policy-makers' technology policy design preferences and, through the interaction with policy-makers in design coalitions, eventually influence the design of technology policies.

Industries can influence the design of a policy indirectly or directly. In the case of *indirect industry pressure*, the economic situation in a state substantively influences the priorities of its representatives. It is widely recognised that policy-makers strive for political power and influential positions, however, being elected into a representative office is associated with responsiveness and with pressure from their constituency (Meckling, 2011; Mildenberger, 2020). The electorate expects policy-makers to represent their interest and be responsive to their needs. Accordingly, industrial firms, which are the primary addressees of technology policies, are particularly interested in being adequately represented by the policy-makers (Meckling, 2011). In turn, states profit from hosting prominent industry sectors in their constituency since they provide jobs, pay taxes and contribute to the reputation of a state (Vatter and Heidelberger, 2014). Correspondingly, when firms grow by increasing their market shares, they are endowed with more financial and other resources, which allows them to pool their resources, particularly legitimacy and money, and build coalitions with policy-makers (Meckling, 2011; Pierson, 1993; Sandén and Azar, 2005). Consequently, industries gain momentum to influence policy instruments and designs needed to develop their favoured technology to the point where they become self-sustained and competitive (Sandén and Azar, 2005). Thus, firms do not only compete in the market for services and goods, but also for influence of the institutional framework and policy designs (Jacobsson and Lauber, 2006; Mildenberger, 2020). I therefore expect:

Hypothesis 1 *Policy-makers representing a constituency with a large battery producing sector are more likely to support technology-specific policy designs.*

Hypothesis 2 *Policy-makers representing a constituency with a large battery using sector are more likely to support application-specific policy designs.*

Complementary industries can influence policy-makers and their policy design choices directly by lobbying for specific bills that are sponsored by policy-makers. The provision of technical and scientific knowledge belongs to the primary endowments of firms necessary to put *direct industry pressure* on policy-makers and can lead to a change in their beliefs. Interest groups and lobbying organisations that provide such specialised knowledge are key players in this process (Sabatier and Weibel, 2007). Through lobbying activities, firms can contribute extensive expertise and specific information into the policy-making process by representing industry interests and trying to influence policy-makers by providing information and arguments favouring their industry (Heaney and Crosson, 2020; Jacobsson and Lauber, 2006). At the same time, firms with access to the political venue achieve competitive advantages. They profit from political protection and support, such as import restrictions, subsidies, or regulations (rent-seeking) (Krueger, 1974; Schöbel and Krämer, 2018). They can influence policy outcomes in their favour by preventing decision-makers from introducing regulations that would harm them, make regulations more business-friendly, and create particular business opportunities, such as the creation of new markets or competitive advantage (Falkner, 2008). Therefore, information, good arguments, and access to the decision-making process are key to winning political battles, legitimating new technologies, arguing against opponents' views, and convincing policy-makers of new ideas (Jacobsson and Lauber, 2006; Sabatier and Weibel, 2007). I, therefore, expect that:

Hypothesis 3 *Bills that attract lobbyism by the battery producing sector are designed more technology specific.*

Hypothesis 4 *Bills that attract lobbyism by the battery using sector are designed more application specific.*

To account for the indirect mechanism, hypotheses 1 and 2 will be tested on the level of policy-makers, their design preferences and the economic situation regarding battery manufacturing in their constituency. In contrast, hypotheses 3 and 4 will be tested on the bill level, comparing policies, namely bills and laws, that attracted lobbying with those that did not.

3 Data and Methods

3.1 Case Selection

Battery storage is one of the critical technologies facilitating the transition towards the decarbonisation of the mobility sector and the increase in renewable energies. Therefore, understanding how battery storage *policies* are designed, why they are designed that way, and how industries affect policy-makers' technology policy design preferences is important for three reasons.

Firstly, battery storage policies have long remained understudied and are only slowly being brought to the fore by policy design scholars (Schmidt et al., 2016; Sewerin et al., 2020). Focusing on battery storage is vital because storage batteries are among the key multi-purpose technologies necessary to govern the energy transition (Battke and Schmidt, 2015; Beuse et al., 2018). To foster their innovation, policies are needed to set the direction of change necessary to transform society and tackle climate change (Mazzucato, 2018). In line with this, there is a necessity to design policies that support the implementation of the Paris Agreement (United Nations, 2015), and help each country fulfil their Nationally Determined Contributions (NDC, 2020). Therefore, a better understanding of national policies contributes to reaching international policy goals and fostering the current energy transition.

Secondly, it is important to better understand the politics behind policy-making. Industries are the primary target group of technology policies and closely linked to the political system (Ingold et al., 2016). However, they are not passive recipients but take over an active role in influencing the policy-making process (Meckling, 2011; Mildenberger, 2020). Thus, for the transition towards decarbonising our society, it is crucial to understand how industry actors foster or block this process by influencing policy-makers, their technology policy design preferences, and ultimately the design of technology policies.

Finally, studying the case of the United States gives insights into one of the largest economies that are urged to face a major energy transition in the upcoming years. Regarding battery storage, the United States held 13 per cent of the world's battery manufacturing capacity by 2018, with a rising tendency. However, compared to the world leaders in battery manufacturing, China and Korea, the United States lag far behind (Energy Storage Association, 2021; Sewerin et al., 2020). Therefore, in order to remain competitive and increase independence regarding their energy use, the United States are urged to increase their storage capacities quickly. To face this challenge, battery storage policies are vital. Consequently, studying how industries affect technology policy designs is of academic, political, economic and social relevance.

3.2 Introducing a new dataset

The creation of a data frame is one major contribution of this master thesis to the existing policy design literature. In this section, I will introduce the new dataset on battery storage policies in the

United States. The data frame contains information on 363 energy storage bills in the United States between 1999 and 2020. Moreover, it has information on the sponsors and co-sponsors of those bills, resulting in a dataset with 4'885 ties between policy-makers and bills. This dataset shall serve as the basis to investigate how industry interests affect policy-makers' technology policy design preferences. It allows me to conduct first exploratory quantitative and qualitative analyses in the understudied field of energy storage policy. However, it is also meant to be used to conduct further analyses and open the black box of what drives policy-makers to support certain technology policy designs more than others and how industry interests influence the politics behind policy-making.

The dataset does not only include laws but also bills in their different implementation stages (cf. Figure 2). Policies in the United States go through multiple implementation phases before they potentially become laws. If a congressperson endorses the content of a bill, she can sponsor it, which is the necessary first step to bring a bill to Congress (*Introduction phase*, cf. Figure 2). Other members of Congress can co-sponsor the bill by adding their names to the bill to signal their support (Palmer, 2020). The members of Congress are either part of the House of Representatives or part of the Senate. In the chamber in which the draft is first introduced, a committee will debate on it and can amend it. If the draft passes a simple majority of the full chamber of Congress, it is forwarded to a committee of the other chamber (*Passed the House/Passed the Senate*). After release, a committee of the second chamber discusses the draft and can make amendments. If the draft passes this second chamber by a simple majority, a conference committee existing of representatives of the House and the Senate works out any differences between the two versions of the bill. Then, the House and the Senate can approve the resulting version. Finally, the President has ten days to sign (*Became Law)* or veto the final bill (Sullivan, 2007). Including the different implementation stages, the data allows the investigation of policy-makers' and industries' policy design preferences during the policy-making process and goes beyond only looking at bills that made it through the legislative process and became law.

The bill-specific information in the dataset contains the following information on the bills: Firstly, the data frame contains information on the specificity level of each bill in terms of the application targeted by the bill (Application Specificity) as well as the level of technology addressed (Technology Specificity) (cf. chapter 3.3.1 The Dependent Variable: Technology Policy Design). Secondly, there is information on whether the bill was lobbied by a firm related to battery storage manufacturing, distinguishing between five different sectors along the value chain of a lithium-ion battery (cf. 3.3.2 The Industry Sectors along the Lithium-Ion Battery Value Chain). Thirdly, it contains information on each policy's implementation phase at the end of the 106th Congress (January 19th, 2021). The distinction between the different implementation phases shows whether a bill was introduced only, passed the House of Representatives, passed the Senate, or became law. Figure 2 shows that most of the 363 battery storage bills were introduced only (n = 323), but then lost steam and did not pass on. Only a minority passed the House (n = 22), passed the Senate (n = 4), or became law (n = 14).

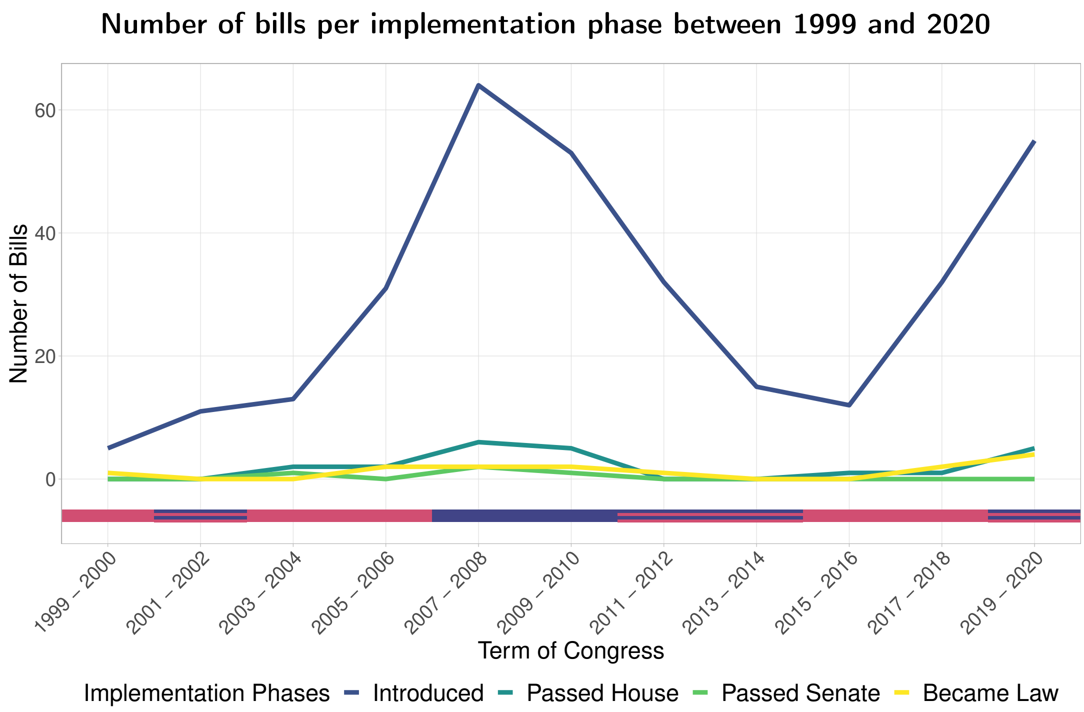

Figure 2: Energy storage policies per implementation phase in the U.S. Congress, 1999–2020

A total of 363 battery storage policies (bills and laws) were introduced in the U.S. Congress between 1999 and 2020. Of these 363 policies, 323 bills were *introduced* in the House of Representatives or the Senate, but then ran out of steam and did not pass on (violet). An additional 22 bills *passed the House* (dark green), and four bills *passed the Senate* (light green). Finally, 14 bills were signed by the President and *became law* (yellow). The blue-red coloured bar represents the majority party in Congress during a given term, the Democrats (blue), the Republicans (red), or when one party had the majority in one chamber and the other party the majority in the other chamber (striped). *Source:* Own figure based on own data.

Furthermore, the data frame contains information on the date the bill was introduced and the length of the bill in number of pages to approximate the complexity of each bill (Clinton and Lapinski, 2006). Finally, additional bill-specific variables were collected, which are not used as part of the present analysis. The full codebook can be found in Appendix A.1.

Besides the bill-specific data, the data frame also contains information on the sponsors and co-sponsors of these bills. The dataset contains the name of each congressperson who sponsored or co-sponsored a battery storage bill, what state they represent, whether they are part of the House or the Senate, and of what Committees they are part. Moreover, the dataset contains information on the economic circumstances related to battery manufacturing in the states represented by the policy-makers. The distinction is made between five different sectors along the value chain of a lithium-ion battery (cf. 3.3.2 The Industry Sectors along the Lithium-Ion Battery Value Chain). The economic circumstances are approximated by two variables: the employment share of battery manufacturing per industry sector in each state; and the number of firms working in each battery-related industry sector.

Table 1 shows the basic structure of the dataset. Each bill can appear in several rows, depending on the number of co-sponsors. The dataset is designed to conduct quantitative and qualitative analyses. Given the detailed information on policy-makers, including their name, their party and the state they represent, the dataset can easily be expanded by adding information on the policy-maker level. Additionally, on the bill-level, the data can be expanded by merging information by number, title, and year of introduction of each bill. Moreover, the structure of the data allows investigating social networks between bills and policy-makers.

Table 1: Simplified structure of the U.S. Battery Storage Dataframe

Bill Number	**Member of Congress**	**Sponsor/Co-sponsor**	**State**
Bill 1	Name 1	Sponsor	State A
Bill 1	Name 2	Co-sponsor	State B
Bill 1	Name 3	Co-sponsor	State C
Bill 2	Name 4	Sponsor	State D
...	...	...	...
Bill 363	Name 5	Sponsor	State B
Bill 363	Name 2	Co-sponsor	State B

Reading example: Bill 1 is sponsored by a sponsor from state A, and co-sponsored by members of Congress of state B and C. Bill 2 only has one sponsor from state D, but no co-sponsors. Bill 363 is sponsored and co-sponsored by two legislators from state B.

3.3 Data collection and measurements

To identify the relevant policies[1], I manually downloaded all bills and laws containing the search terms "energy storage batter*" and "electric vehicle batter*" from the Congress homepage (Congress.gov, 2021) between the 106th Congress (1999-2000) and the 116th Congress (2019-2020), ending on January 19, 2021. I deleted all the bills which included the search terms in a different context and were thus not relevant in the context of battery storage. The result was a dataset containing 363 bills on battery storage in the United States[2]. The following section outlines how I operationalised the different variables on the bill level and on the policy-maker level.

For the subsequent analysis, the outcome variable of interest is the design of a technology policy, namely the *application specificity* and the *technology specificity* of a policy. I will start by introducing how I operationalised these two concepts. Then, I will operationalise the explanatory variable, the

[1]When I refer to policies, I mean specific bills and laws.

[2]More information on the initial data collection process can be found in my Seminar paper, which I wrote in the seminar on "Topics in Public Policy: Governing the Energy Transition" (857-0103-00L), and for which I developed the first version of the "US Battery Storage Dataset 1999–2019". The paper will be made available in the supplementary material of this thesis.

employment share in the battery-related industries, distinguishing between the *battery producing* and the *battery using* sector. In a second step, I will introduce and justify the empirical methods, the multinomial logistic regression and the descriptive analyses.

3.3.1 The dependent variable: Technology policy design dimensions

The design of a technology policy determines the likelihood of the diffusion for a promoted technology and its lock-in, respectively (Azar and Sandén, 2011; Schmidt et al., 2016). The two policy design classifications that I considered are the *technology specificity* and the *application specificity* targeted by a policy. These two dimensions are unique to the study of technology policies and serve to operationalise the two dependent variables. For their operationalisation, I built on previous research (Schmidt et al., 2016; Sewerin et al., 2020) and expanded the coding dictionaries in an iterative process by adding additional relevant labels to the existing categories. More information on my updates and the two dictionaries can be found in Appendix A.2 and A.3.

On the first dimension, the *Technology Specificity* dimension, the five levels of the coding scheme are: *Economy, Field, Technology, Subtechnology* and technological *Design*. They represent whether a legislative proposal was formulated neutrally (Economy) or very specifically (Design) regarding the technology targeting energy storage.

Applied to U.S. energy storage policies, a bill can be formulated very broadly and target the *(1) Economy* at large. Such a policy could, for instance, aim at mitigating climate change or at promoting a sustainable economy, without further specifying with which energy storage technologies these goals should be achieved. In the *(2) Field* of energy storage, policies can address specific storage technologies, such as electrochemical or thermal energy storage. More specifically formulated policies target the energy storage *(3) Technology*, such as thermal energy storage, but also electric vehicles. Alternatively, they target a subset of those technologies, a *(4) Subtechnology*, such as lithium-ion batteries or lead-acid batteries. Finally, on the most specific technology level, a policy can be directed at the *(5) technology Design*, including battery designs such as lithium iron phosphate or zinc-air batteries.

The second dictionary, the one covering *Application Specificity*, is a four-level dictionary with key terms around the application of energy use and storage technology. The dictionary includes the following levels: *Economy, Industry, Application* and *Subapplication*. It represents whether an energy storage related application targeted in a bill or law is formulated generally (Economy) or targets a very specifically (Subapplication). If a policy affects all applications of a technology, and does not distinguish between different applications, it is considered application neutral and targets the *(1) Economy* at large. If it addresses the applications within a distinct industry sector of the economy, the bill is coded on the *(2) Industry* level. These policies target, among others, the automotive sector, the military, or the electric power sector. More specifically, formulated policies address specific *(3) Applications* of an energy storage technology, such as passenger cars, plug-in, plug-in hybrid, and hybrid electric vehicles, power reliability or power quality. On the most specific level of abstraction, the *(4) Subapplication* level, policies are proposing, for instance, the diffusion of "clean school busses" (e.g. H.R. 3973, 2016) or power quality and reliability for end-consumers.

I coded the data on the specificity levels manually. If several levels of technology specificity appeared in the bill's text, I only coded the most specific level. I did so in order to capture the specificity, i.e., the most specific design level targeted by a policy. The same procedure was applied to the application specificity dimension.

In the following subchapter, I will introduce how I identified the industries related to energy storage manufacturing and how I collected the data related to the economic circumstances in the states of the policy-makers who sponsored or co-sponsored an energy storage bill.

3.3.2 The independent variables: Indirect and direct industry pressure

I will first outline how I identified the industries relevant for battery manufacturing by introducing the value chain of a lithium-ion battery. Then, I will present how I operationalised the two mechanisms how industries can affect policy-makers' technology policy design preferences and policy designs.

The industry sectors along the lithium-ion battery value chain

Batteries are multi-component technologies and are the centrepiece of battery storage. Battery storage facilities include, among others, permanently installed batteries used for electricity storage, but also rechargeable batteries that are, for instance, used in electric vehicles (Hawken, 2017). Multiple sectors influence the technological architecture of multi-component technologies with their knowledge and capabilities. They determine their production process. One of the most prominent examples of storage technologies is the lithium-ion battery. Figure 3 illustrates the involved upstream and downstream industry sectors that are linked along the value chain of the lithium-ion battery (Stephan et al., 2017).

The value chain of a lithium-ion battery can be separated into two categories, the *battery producing* sector and the *battery using* sector. The battery producing sector involves the main components of a battery, including electrodes, electrolytes, and separators. In addition, it involves the peripheral components, which are not directly part of the core of a battery system, such as casing, cooling, battery chargers or measurement. Main components and peripheral components make up the core of the cell system of the batteries (Battke et al., 2016). In contrast, the battery using sector displays the integration of the battery into a broad range of applications, including electric vehicles, energy and electronic applications. Additionally, research is conducted along all four sectors of the value chain and influences the development, production and use of the multi-component technology (Porter, 1985; Stephan et al., 2017). Figure 3 graphically shows the sectoral configuration along the technology value chain of a lithium-ion battery.

Along the lithium-ion battery value chain, I identified 109 unique industries, nine as part of the

Main Components sector, 27 as part of the Peripheral Components sector, two as part of the Cell Systems sector, 67 as part of the Battery Integration sector and four as part of the Research sector (Stephan et al., 2017). Overall, this results in 42 industries belonging to the *battery producing* sector, and 67 belonging to the *battery using* sector[3].

Technology value chain of a lithium-ion storage battery

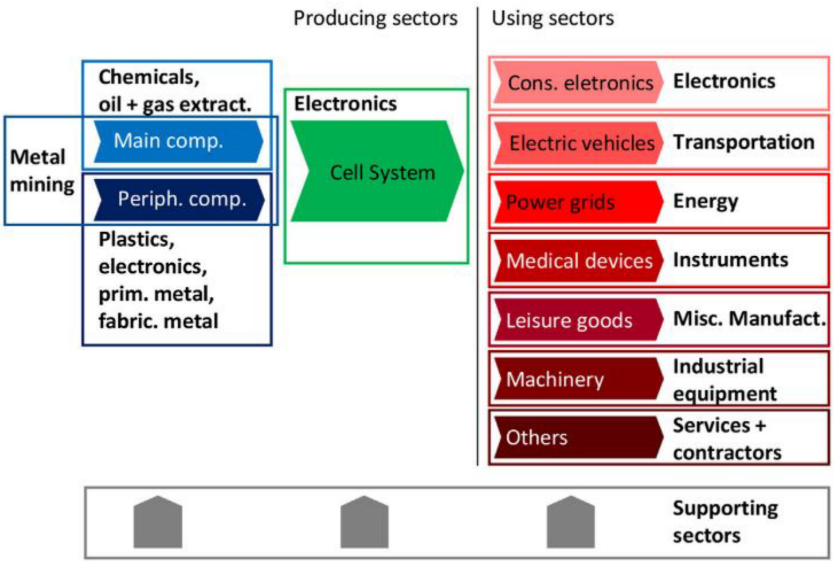

Figure 3: Technology value chain and sectoral configuration of a lithium-ion battery
Source: Stephan et al. (2017)

Indirect industry pressure: Employment shares in the battery producing and the battery using sector

The dependent variable operationalising indirect industry pressure will be the *employment share* in the battery producing and the battery using sector per state. An alternative proxy for indirect industry pressure is the number of firms related to the battery producing and the battery using sector in the constituencies policy-makers represent. The size of firms can vary heavily within and between states and is thus not comparable. Therefore, the use of firms as proxy for the economic situation in a state was rejected in favour of the employment share. This information is merged to the states the sponsors and co-sponsors of battery storage policies represent. The data serves as the basis for the regression analysis to test hypotheses 1 and 2, stating that policy-makers representing a constituency with a large battery producing (using) sector are more likely to support technology-specific (application-specific) policy designs. The employment share data for the years 1999 to 2018 is calculated based on data provided by the United States Census Bureau (for each year, the dataset "Complete State File" was downloaded) (US Census Bureau, 2020).

[3]The list of industries provided by Stephan et al. (2017) bases on 4-digit SIC (Standard Industrial Classification) codes. For the present analysis, I needed to "translate" those codes into 6-digit NAICS (North American Industry Classification System) codes (U.S. Census Bureau, 2021a), using the translation key provided by the NAICS Association (NAICS Association, 2021).

Direct industry pressure: Lobbying by the battery producing and the battery using sector

In order to explore the influence of industries on policy designs more in-depth, a second, more direct way of industry pressure will be considered, namely the occurrence of lobbying on energy storage bills. This data serves as the basis for the descriptive analysis to test hypotheses 3 and 4, stating that bills that attract lobbyism by the battery producing (using) sector are formulated more technology (application) specific.

To identify which bills attracted lobbying by which sector, I used some of the newly published data provided by LobbyView (LobbyView, 2021). LobbyView is a project of the Massachusetts Institute of Technology (MIT) that is currently building a number of databases on lobbying activities in the United States (Kim and Kunisky, 2020).

Lobbying organisations in the United States are obliged to report their activities quarterly. A lobby report contains information on the lobbying activity and the lobbied bill's identification number (e.g. "H.R. 6, The Energy Independence and Security Act of 2007; Clean Air Act Regulatory Issues"[4]). Moreover, it provides information on the *client*, i.e. the firm that initiates the lobbying, and the *registrant*, the lobbying firm, organisation or self-employed individual that conducts the lobbying, including their address and contact details. Additionally, there is information on the quarter of the year in which the lobbying activity took place, including the amount of U.S. dollars spent on the lobbying activity.

Based on these reports, LobbyView provides a dyadic dataset, published under the name "Network Data", on the yearly number of congressional bills lobbied by firms (clients) and sponsored by a legislator (Kim, 2018). The firms' can be linked to the 6-digit NAICS codes of the lobbying firms provided in the "Client Level Data". Moreover, the "Bill Level Data" provides information on what legislator sponsored what bill in what year. Based on this data, I could identify which bills attracted lobbying by which firms (clients) along the lithium-ion battery value chain and who sponsored these bills.

However, there exist some limitations of this data. Firstly, although LobbyView stated that the data is exhaustive, they admit that there are some difficulties in the data collection, which do not guarantee full coverage of all the lobbied bills. One challenge is that the legislative number of each bill is not unique, and therefore they sometimes had difficulties identifying the exact year a lobbying activity took place[5]. Secondly, the data only shows whether a lobbying activity for a specific bill took place. However, it does not account for the direction of lobbying, i.e. whether the lobbying activities favoured a policy proposal or targeted at its decline. Thirdly, the data displays firms' interest in a bill but does not provide information on the direct link between firms and policy-makers. Thus, lobbying of an interest group does not imply a direct link to the sponsor of a bill. It can, however, be assumed that "recurring instances of lobbying that involve the same interest group and sponsor on numerous

[4] https://disclosurespreview.house.gov/ld/ldxmlrelease/2011/4A/300524385.xml

[5] An extract of the email conversation with a researcher at LobbyView outlines the current difficulties (cf. Appendix A.4)

bills do reliably indicate a shared involvement on specific political issues" (Kim and Kunisky, 2020, p. 2). Overall, the LobbyView data sheds light on the black box of lobbying activities and firms' interests. Therefore, to better understand the mechanism, the data must be complemented with more theory and in-depth research.

3.4 Control variables

To test hypotheses 1 and 2, stating that policy-makers representing a constituency with a large battery producing (using) sector are more likely to support technology-specific (application-specific) policy designs, different factors that potentially confound the relationship between industry interests and policy-makers' policy design preferences will subsequently be introduced and justified. The choice of the control variables bases on theoretical considerations but also on multicollinearity concerns.

The first control variable is the *party* of the sponsors and co-sponsors of a battery storage policy. Party membership and political polarisation shape the policy-making process of the United States. Therefore, the majority party in the House of Representatives and the Senate can significantly control the political process (Krutz, 2018). Additionally, as shown in Figure 2, there is evidence for a correlation between the party holding the majority in Congress and the number of battery storage policies introduced in Congress. The number of battery storage policies increases when the Republicans hold the majority in Congress and decreases when Democrats have the majority. In the case of a tie, the number tends to stagnate. Consequently, it should be controlled for the party of the sponsors and co-sponsors of a battery storage policy. Controlling whether each supporter belongs to the Republicans or the Democrats, instead of only controlling for the majority party in Congress, has the advantage to control for the party membership of each Congress member supporting a battery storage bill and simultaneously approximates the majority party conditions in Congress.

The second set of control variables are the *Committee memberships*. The majority of the work around drafting and designing policies is done in Committees. There are twenty standing committees in the House of Representatives and sixteen in the Senate. They are very powerful in the legislative process. They can organize hearings with experts and draft argumentative reports for the entire congress on why a bill should be passed. At the same time, they can stop a bill from going to the full chamber. In consequence, most bills die in these committees (Krutz, 2018). However, not all committees are equally important when it comes to drafting battery storage bills. Figure 4 shows that most of the members of the House who support (sponsor or co-sponsor) one of the 363 energy storage bills are part of the *House Committee on Ways and Means* and the *House Committee on Energy and Commerce*. Figure 5 displays that the majority of the Senate members supporting one of these bills is part of the *Senate Committee on Finance* or the *Senate Committee on Energy and Natural Resources*.

Controlling for policy-makers' co-sitting in these four most influential committees is important to consider for two reasons. From a theoretical point of view, it is crucial to control for collaboration

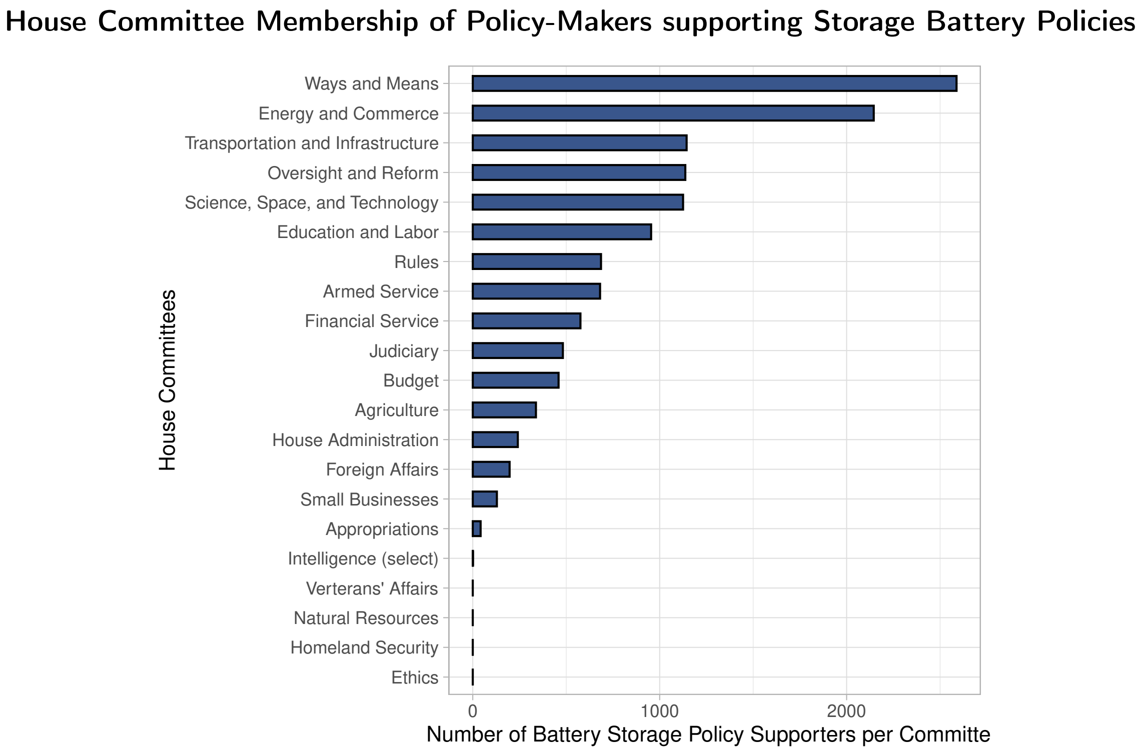

Figure 4: Support for battery storage policies per House Committee

The figure shows the number of members of the House of Representatives who supported (sponsored or co-sponsored) a battery storage policy (bill or law) between 1999 and 2020. Each member can support multiple policies. Most of the supporters were part of the House Committee on Ways and Means and the House Committee on Energy and Commerce. *Source:* Own figure based on data provided by Stewart III and Woon (2017) and the US House of Representatives (2021).

among members of Congress because it is very likely that policy-makers are not only influenced by outside pressure from industries but also bring in their experiences, knowledge and ideas into the committees and influence each other through close collaboration. Moreover, it is important from a statistical point of view. The data structure is likely to violate the first part of the iid-assumption stating that the data must be independent and identically distributed (iid), which is a necessary condition for regression model outputs to be valid. Policy-makers who collaborate with each other are therefore not independent in their policy design choice. Controlling for co-sitting in committees is thus essential to account for the dependence of the longitudinal data.

Thirdly, the *chamber seniority* of the legislators serves as an additional control. It is likely that legislators who have served in Congress for a longer time act differently from those who have only been elected into Congress recently (Campbell, 1982). Policy-makers who serve in Congress for a longer period are more experienced than those who only serve for one or a few terms. Furthermore, more senior Congress members are allowed to choose first in what Committee they want to serve. Among the most prestigious committees in Congress are the House Committee on Ways and Means and the Senate Committee on Finance, two of the most influential committees also regarding battery storage

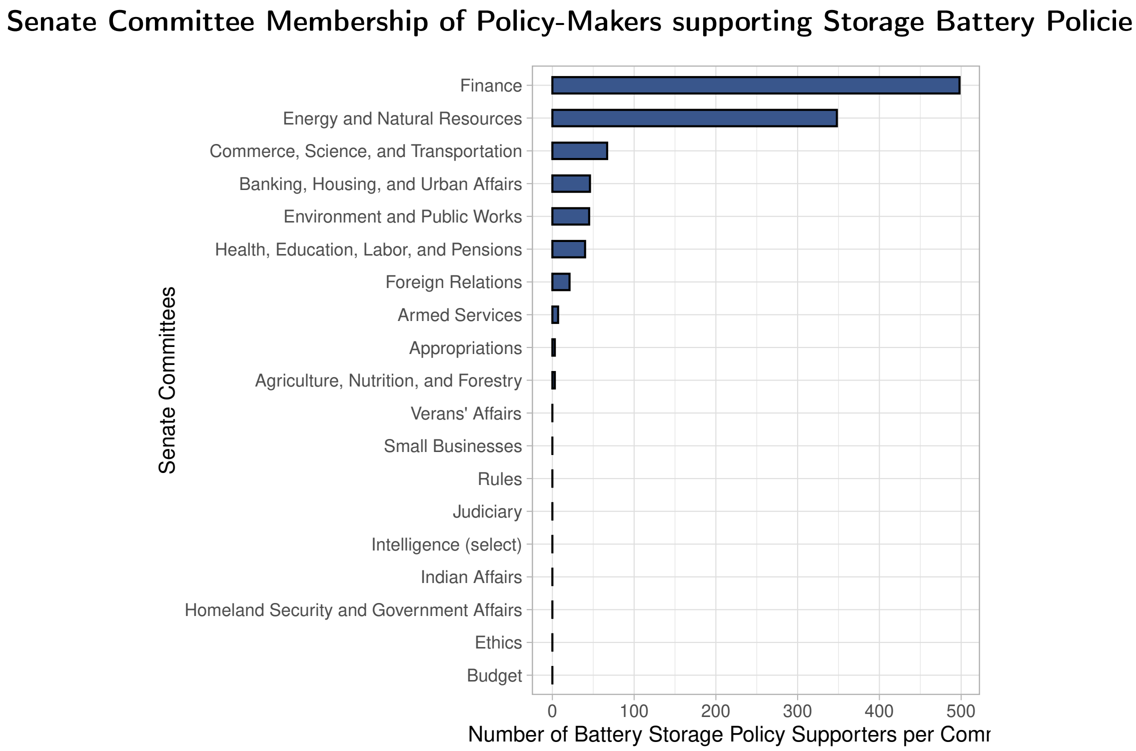

Figure 5: Support for battery storage policies per Senate Committee

The figure shows the number of members of the Senate who supported (sponsored or co-sponsored) a battery storage policy (bill or law) between 1999 and 2020. Each member can support multiple policies. Most of the supporters were part of the Senate Committee of Finance and the Senate Committee on Energy and Natural Resources. *Source:* Own figure based on data provided by Stewart III and Woon (2017) and the Senate of the United States (2021).

(University of Minnesota Libraries, 2016). Thus, controlling for Chamber Seniority allows investigating whether the number of years someone has served in the House or the Senate is associated with their policy design preferences.

The data on committee membership and chamber seniority was provided by Charles Stewart's Congressional Data Page (Stewart III and Woon, 2017), available for the years 1999 to 2017. For the former, I manually updated the missing information up to 2020 using committee membership overviews provided by the House of Representatives (US House of Representatives, 2021) and the Senate (Senate of the United States, 2021). For the latter, I manually updated the missing information up to 2020 with the help of the Congress Library (Congress.gov, 2021).

Fourthly, the number of pages of each bill is considered to control for the complexity of a bill (Clinton and Lapinski, 2006). Longer bills likely touch upon more different design levels regarding technology and application specificity. The number of pages is counted in pdf pages after downloading the full text from the Congress Library (Congress.gov, 2021).

Finally, state and term fixed effects will be considered to additionally counteract the plausible violation of the iid-assumption. Policy-makers are often in office for several terms, thus, there is likely to be some dependence over time. It may also occur that bills formulated in one year show similarity to bills drafted in a subsequent year. Therefore, state and term fixed effects are included. In consequence, there are likely to be factors that vary across states but are constant over time and thus bias the relationship, or that vary over time but not across states (Hanck et al., 2020). For the state fixed effects, the state represented by a Congress member is used. For the term fixed effects, the two year period between two elections is considered. Data are provided by Congress Library (Congress.gov, 2021).

3.5 Empirical strategy

A multinomial logistic regression analysis will be combined with an exploratory, descriptive analysis to investigate what role businesses play in influencing technology policy design preferences of policy-makers and, ultimately, the design of a technology policy. The multinomial logistic regression models will be used to test hypotheses 1 and 2 stating that policy-makers representing a constituency with a large battery producing (using) sector are more likely to support technology-specific (application-specific) policy designs. The descriptive analyses will be used to explore hypotheses 3 and 4 that propose that bills that attract lobbyism by the battery producing (using) sector are formulated more technology (application) specific[6].

3.6 Multinomial logistic regression

Multinomial logistic regression is suitable to model a logistic regression with more than two nominal outcome categories. It will be applied to test hypotheses 1 and 2, stating that policy-makers representing a constituency with a large battery producing (using) sector are more likely to support technology-specific (application-specific) policy designs. The multinomial logistic regression models the log odds of the outcomes as a linear combination of the independent variables (UCLA, 2021b). Splitting the data set into two time periods, 1999-2008 and 2009-2018, allows me to additionally uncover possible shifts in design preferences over time. I will also test for other splits to account for the robustness of the results.

Multiple assumptions need to be met for the multinomial logistic regression model to be valid. Firstly, the maximum likelihood estimation method requires a large sample size. There are 3'024 observations in the first period, and 1'835 in the second period. Tables 2 and 3 show the distribution of policy design support over time. The small numbers for the economy and the design level of the Technology Specificity dimension between 1999 and 2008 indicate that the results for these two levels should be interpreted with caution. Regression outputs based on small sample sizes result in unreliable results (Schlegel, 2016).

[6] The advantages of using a multinomial logistic regression over a logistic regression, an ordinal logistic regression or a Temporal Network Autocorrelation Model (TNAM) is justified in Appendix A.5.

Technology Specificity	1999–2008	2009–2018
Economy	4	60
Field	270	156
Technology	1032	235
Subtechnology	1265	634
Design	5	143

Table 2: Number of policy-makers supporting battery storage bills per Technology Specificity level, 1999-2008 vs 2009–2018

Application Specificity	1999–2008	2009–2018
Economy	98	297
Industry	199	107
Application	1970	348
Subapplication	309	476

Table 3: Number of policy-makers supporting battery storage bills per Application Specificity level, 1999-2008 vs 2009–2018

Secondly, there should be no complete separation and no perfect prediction. The dependent variable should not separate the independent variable completely, which would otherwise lead to a perfect prediction of the outcome by the predictor variable. Thus, no single independent variable must be associated with only one value of the dependent variable. The tabulation of every independent variable with the outcome variable showed no complete separation or perfect prediction. Thirdly, there should not be any empty or small cells. A cross-table between the independent variables and the different categorical predictors shows no empty and almost no small cells. In the one case where there were only a few observations of the independent variable, namely in the category "Independent" members of Congress of the variable party, I deleted these observations, resulting in a dataset that only includes Democrats and Republicans. Finally, there should not be any correlation between the independent variable and the control variables. However, there is a medium correlation (0.519) between the House Committee Ways and Means and the House Committee Energy and Commerce. Nevertheless, I dare to include both variables in the same regression because the correlation shows that parliamentarians collaborating in one committee also often collaborate in the other committee.

The multinomial logistic regression model compares the different outcome categories to the predefined reference category. Thereby, the reference category should be comparably large because it would otherwise result in large standard errors (Schlegel, 2016). For the first dependent variable, the Application Specificity, I chose the design level "Application" as the reference category. For the second dependent variable, the Technology Specificity, I chose the design level "Subtechnology" to be the reference category because they are, overall, the largest categories (cf. Tables 2 and 3).

The formal notation of the multinomial logistic regression is illustrated for the Application Specificity in the formulas 1 to 3. On the left-hand side of the equation are the log-odds. The log-odds are the natural logarithm of the ratio of the probability that a policy-maker supports a bill on the level of interest to the probability that they would support a bill on the application level. On the right-hand side of the equation is the multinomial logistic regression model with the independent variable, the control variables, state and term fixed effects.

$$\ln\left(\frac{P(Applicaton\ Specificity = Economy)}{P(Application\ Specificity = Application)}\right) = b_{10} + b_{11} \cdot (Indep.\ Variable) + CV + FE \quad (1)$$

$$\ln\left(\frac{P(Applicaton\ Specificity = Field)}{P(Application\ Specificity = Application)}\right) = b_{20} + b_{21} \cdot (Indep.\ Variable) + CV + FE \quad (2)$$

$$\ln\left(\frac{P(Applicaton\ Specificity = Subappl.)}{P(Application\ Specificity = Application)}\right) = b_{30} + b_{31} \cdot (Indep.\ Variable) + CV + FE \quad (3)$$

To calculate the model, I used the multinom() function of the nnet package in R. I calculated the fixed effects by including the states and terms into the model, but then did not display them in the output (Angrist and Pischke, 2009). Finally, the Akaike Information Criterion (AIC) serves as a measure to compare the goodness of fit between models with different combinations of variables. The AIC is usually reduced when comparing the full models with the models which only contain the independent variable and the fixed effects, giving evidence that the full models fit the mechanism better. The smaller the AIC, the better the model.

3.7 Qualitative analysis

The multinomial logistic regression analysis will be followed by an in-depth analysis on the subset of bills that attracted lobbying. This second analysis explores hypotheses 3 and 4 proposing that bills that attract lobbyism by the battery producing (using) sector are formulated more technology (application) specific. In a first step, I will compare the distribution of bills that attracted lobbying by the battery using and the battery producing sector. Then, I will investigate which particular battery using and battery producing firms are the ones that most actively lobbied. Finally, I will explore on what Technology and Application Specificity levels the bills that attracted lobbying were designed.

4 Results

In this section, I will systematically present the results of testing hypotheses 1 to 4. I will start with the descriptive analysis of the dependent variable, the Technology Specificity and Application Specificity of battery storage policies over time. Then, I will illustrate the independent variable, the employment share in the battery producing and the battery using sector. In a second step, I will present the multinomial logistic regression results and discuss their implications for hypotheses 1 and 2, stating that policy-makers representing a constituency with a large battery producing (using) sector are more likely to support technology-specific (application-specific) policy designs. To test this first two hypotheses, I will rely on the full dataset containing information on the bills, their sponsors and co-sponsors, and the economic situation in each state. Finally, by testing hypotheses 3 and 4, the last section discusses the direct relationship between firms and specific policy designs and explores whether bills that attract lobbyism by the battery producing (using) sector are designed more technology-specific (application-specific). To test these hypotheses, I will rely on the subset of the bills that attracted lobbying.

4.1 The dependent variable: Policy designs

4.1.1 Technology-specific and application-specific policy designs

Over time, the analysis of the policy design features displays a shift in designs towards more diversity on the Technology Specificity and the Application Specificity dimension. Figures 6 and 7 show the shares of policy designs on the Technology Specificity and the Application Specificity dimension between 1999 and 2020. The top rows show the total number of bills introduced in each term.

Figure 6 displays a gradual shift towards more technology-specific policy designs over time. In the first four years of investigation, only two distinctive design elements are present, policies designed on the Technology and the Designs level. Only from 2003 onwards, technology policy designs become more diverse. Whereas in the first years of observation, bills designed on the Technology level dominate, there is an apparent decrease in those design elements in the subsequent years. Instead, there is an increase in the share of bills designed on the more specific Subtechnology level. In contrast, policies designed on the Economy and the Field level occur only very rarely.

The shift in Technology Specificity over time is supplemented by a gradual shift in the Application Specificity of the investigated policies. Figure 7 shows that up to 2002, most bills were designed on the Application level, with only a few additional bills designed on the Subapplication level. In the subsequent years, the share of bills designed on the Application level gradually decreased; the shares of bills on the Economy and the Subapplication level increased. In conclusion, on the Application Specificity dimension, there has been a shift over time from a majority of bills designed on the Application level towards more specific policies designed on the Subapplication level, but also towards more neutral policies designed on the Economy level.

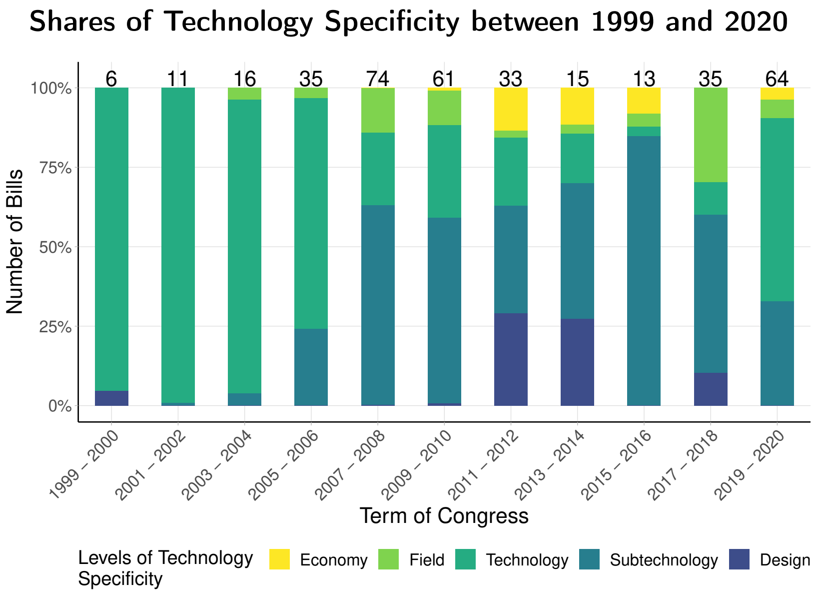

Figure 6: Shares of policies designed on the Technology Specificity dimension, 1999–2020

For each term, the policy design elements on the Technology Specificity dimension are shown as shares of the total number of battery storage policies, ranging from neutrally designed policies designed on the Economy level to very specifically designed policies on the Subtechnology level. *Source:* Own figure based on own data.

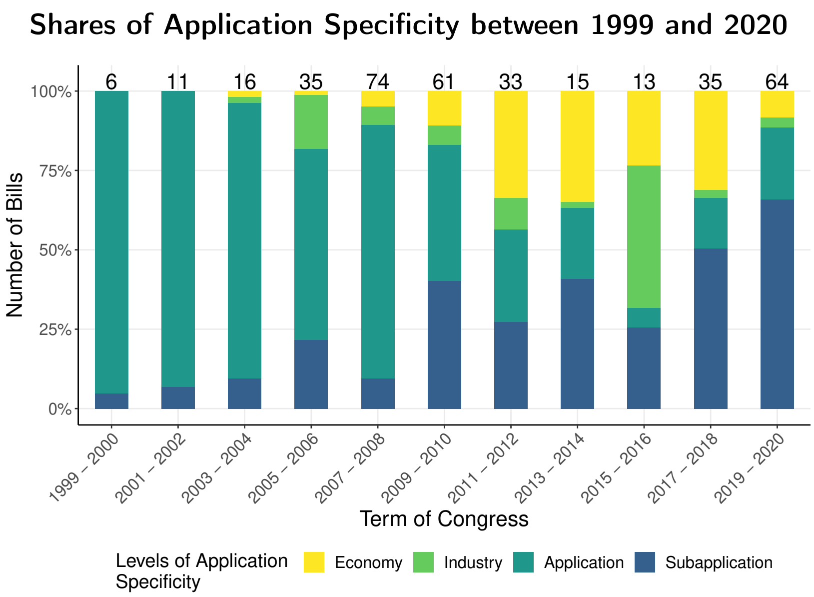

Figure 7: Shares of policies designed on the Application Specificity dimension, 1999–2020

For each term, the policy design elements on the Application Specificity dimension are shown as shares of the total number of battery storage policies, ranging from neutrally designed policies designed on the Economy level to very specifically designed policies on the Subapplication level. *Source:* Own figure based on own data.

Ultimately, the described variation in policy design elements shows that the policy-making process is dynamic, and that policy-makers' preferences change over time. The shares of design preferences shift gradually and tend to become more specific over time, both in terms of Application and Technology Specificity. This incremental shift in design specificities happens independently of the number of bills introduced per term.

In the next section, I will continue with a closer investigation of the independent variable, the employment share in the battery using and battery producing sector, first across the United States, then in each state. Subsequently, I will move on to the results of the multinomial logistic regression models and conclude the results section with an exploration of how industry interests influence policy designs through lobbying.

4.2 The independent variable: Employment shares

4.2.1 Employment shares over time in the United States

The employment shares in the battery producing and the battery using sector across the United States have sharply increased in the past 20 years. Figure 8 shows that the employment share in the battery producing sector roughly doubled between the early 2000s and 2018. Up to 2011, it oscillates around 0.30 per cent, but then strongly rises to 0.65 per cent in the year 2018. At the same time, Figure 9 shows a threefold increase in the battery using sector employment share, rising from 1.49 per cent in 1999 to 4.10 per cent in 2018.There is a sharp increase between 2002 and 2003, from 1.23 per cent to 3.89 per cent. Subsequently, the share fluctuates between 3.16 and 4.10 per cent, with peaks in 2006 and 2018 and a low point in 2011[7].

Employment shares in the battery producing sector in the United States

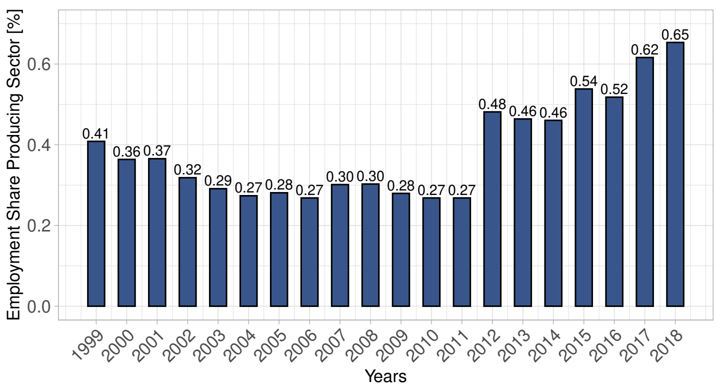

Figure 8: Employment shares in the battery producing sector in the United States, 1999–2018

The employment in the battery producing sector is displayed as a share of total employment in the United States *Souce:* Own figure based on data provided by U.S. Census Bureau (2021b).

[7]This drop in employment in the battery using sector after 2008 is likely to result from the financial crisis. However, with the recovery of the economic situation in the United States, the employment share increases again. This lets me speculate that the financial crisis hit the battery using sector harder than the producing sector.

Employment shares in the battery using sector in the United States

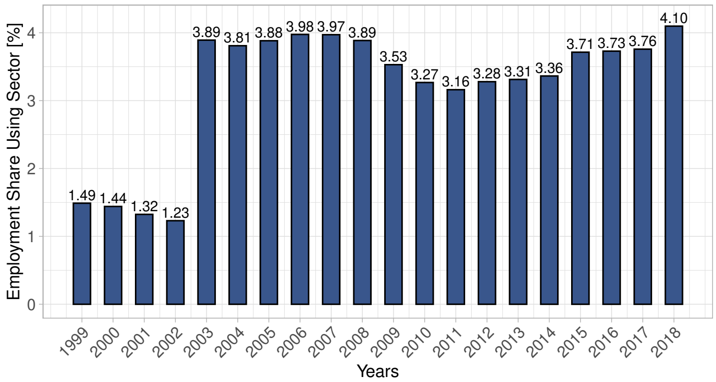

Figure 9: Employment shares in the battery using sector in the United States, 1999–2018

The employment in the battery using sector is displayed as a share of total employment in the United States. *Souce:* Own figure based on data provided by U.S. Census Bureau (2021b)

4.2.2 Employment shares over time and across the different U.S. states

Exploring in more detail the distribution of the employment shares in the battery producing and battery using sector reveals that there is wide variation in both sectors between states and across time. Figures 10 and 11 illustrate the United States, separated by states. The x-axis displays the percentages of the employment shares. The y-axis represents the years from 2000 (yellow) to 2018 (violet) in three-year steps. In Figure 10, the employment share ranges from 0 to 2 per cent; in Figure 11, it ranges from 0 to 6 per cent.

As shown in Figure 10, in 2000, most *battery production* concentrated in the Rust Belt, Northeast and Southeast of the United States, California, and later Nevada, with shares around 0.5 to 1 per cent. Between 2000 and 2010, there was a decrease in the employment share. The shares afterwards started rising again, whereby most states hosting battery producing industries experienced a sharp increase in the employment share to up to 15 per cent, either between 2009 and 2012 or between 2015 and 2018. One example is Nevada, which experienced a sharp increase in battery production between 2015 and 2018, primarily due to the construction of Tesla's Gigafactory. The factory started with 24 employees in 2015 and jumped to around 6'400 employees at the end of 2018 (Damon, 2020). Given that there were 1'221'809 people registered as employees in Nevada in 2018 (U.S. Census Bureau, 2021b), the Gigafactory provided jobs for around 0.52 per cent of the total state employees. Besides, between 2015 and 2018, there was an additional countrywide spread of battery production to states that did not host any battery production manufacturing before, such as Colorado (CO), North Dakota (ND) and Wyoming (WY).

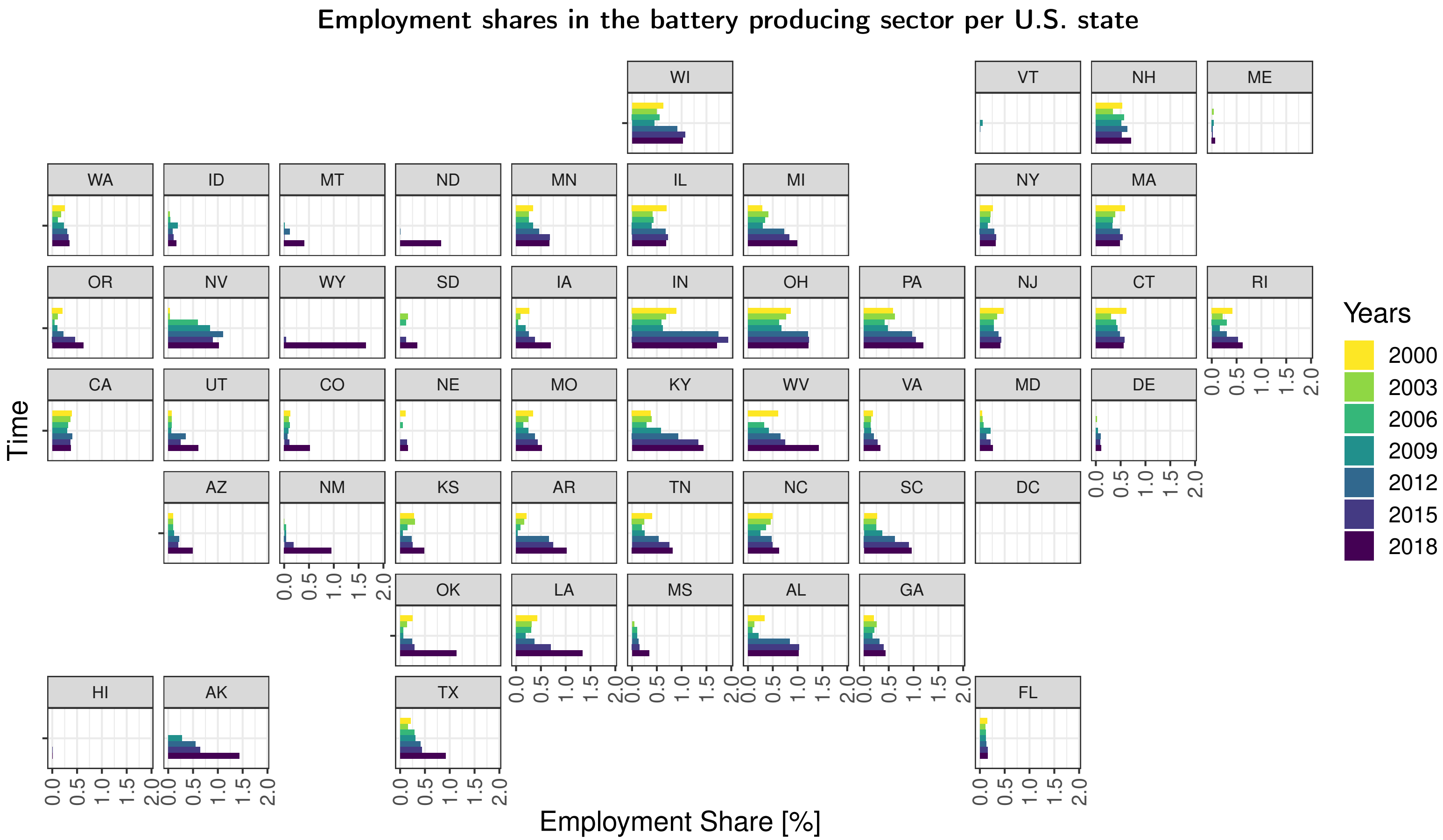

Figure 10: Employment shares in the battery producing sector per U.S. state, 2000–2018

The employment in the battery producing sector is displayed as a share of total employment per U.S. state. *Souce:* Own figure based on data provided by U.S. Census Bureau (2021b).

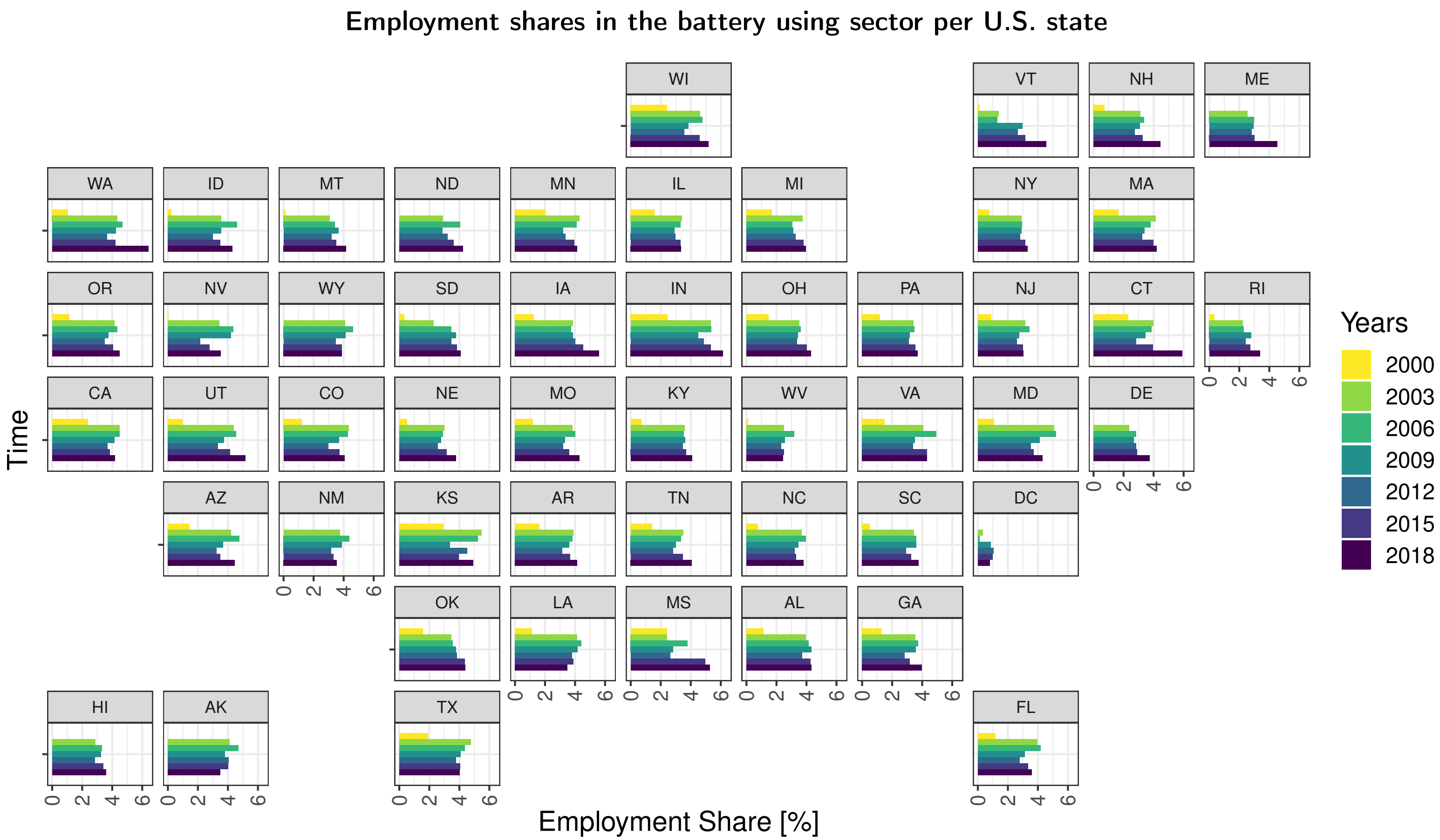

Figure 11: Employment shares in the battery using sector per U.S. state, 2000–2018

The employment in the battery using sector is displayed as a share of total employment per U.S. state. *Souce:* Own figure based on data provided by U.S. Census Bureau (2021b).

Whereas there is a wide variation in employment shares in the battery producing sector between states and across time, Figure 11 shows that this variation is less pronounced in the battery *using sector*. In 2000, there existed a few states without any battery using sector; however, in the succeeding years, production in the battery using sector spread across the entire country, with employment shares peaking around 2010 and 2018 with 4 to 5 per cent. The development in the single states reflects the overall trend in the employment share over time, shown in Figure 9, with a sharp increase between 2000 and 2003, a small decrease around 2012, followed by another increase. Apart from the District of Columbia (DC), Washington DC, the United States capital city that hosts the government but does not host any large industry sectors, all the states host battery using manufacturing.

4.3 Multinomial logistic regression results

Using multinomial logistic regression, I next estimate the relationship between the employment shares in the battery using and the battery producing sector, respectively, and the policy design preferences of the members of the US Congress between 1999 and 2018[8]. Based on these regressions, I will test hypotheses 1 and 2. Hypothesis 1 states that policy-makers representing a constituency with a large battery producing sector are more likely to support technology-specific policy designs. Hypothesis 2 states that Policy-makers representing a constituency with a large battery using sector are more likely to support application-specific policy designs. To get insights into the changes in design preferences over time, I will differentiate the periods 1999 to 2008 and 2009 to 2018. Effect plots that show the predicted probabilities will be used to supplement the multinomial logistic regression outputs. They visualise how the results change when the independent variables are varied (Ford, 2016).

4.3.1 Hypothesis 1: Policy-makers representing a constituency with a large battery producing sector are more likely to support technology-specific policy designs

To test the first hypothesis, a multinomial logistic regression model was calculated with the employment shares in the *battery producing sector* regressed on the *Technology Specificity* policy design dimension (cf. Table 4). The employment shares always refer to the shares present in the constituency of the policy-maker who supports (sponsors or co-sponsors) a battery-related policy. The reference category is the category Subtechnology because it is one of the largest categories. Models 1 to 4 are based on the period 1999 to 2008, and models 5 to 8 on the years 2009 to 2018.

[8]At the point of data collection there was only data on the employment shares available up to 2018 (U.S. Census Bureau, 2021b). The employment share data for the year 2019 is expected to be published in early 2022. (https://www.census.gov/programs-surveys/susb/data/datasets.2018.html)

Table 4: Multinomial logistic regression with employment share in the Battery Producing sector regressed on Technology Specificity

	Dependent Variable: Technology Specificity							
	Economy	Field	Technology	Design	Economy	Field	Technology	Design
	1999 - 2008	1999 - 2008	1999 - 2008	1999 - 2008	2009 - 2018	2009 - 2018	2009 - 2018	2009 - 2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment Share in the Battery Producing Sector	-11.427^{***}	-0.700^{***}	-1.672^{***}	16.581^{***}	0.171	-1.208^{**}	-0.147	-0.291
	(0.480)	(0.260)	(0.210)	(0.600)	(0.437)	(0.516)	(0.408)	(0.541)
Democrats (Ref = Republicans)	14.053^{***}	1.547^{***}	-0.658^{***}	0.861	-0.960^{*}	2.386^{***}	1.891^{***}	-0.687^{*}
	(0.516)	(0.248)	(0.127)	(0.636)	(0.566)	(0.415)	(0.352)	(0.369)
Chamber Seniority	0.008	-0.064^{***}	-0.050^{***}	-0.124	-0.032	-0.016	0.031^{**}	-0.034
	(0.205)	(0.015)	(0.010)	(0.134)	(0.033)	(0.024)	(0.016)	(0.025)
House Committee: Energy and Commerce	-7.345^{***}	-0.678^{***}	-0.092	-5.079^{***}	-7.534^{***}	3.451^{***}	-0.366	2.399^{***}
	(0.712)	(0.193)	(0.141)	(0.003)	(0.002)	(0.663)	(0.292)	(0.439)
Senate Committee: Energy and Natural Resources	-18.569^{***}	-1.738^{***}	-1.361^{***}	1.488^{***}	3.521^{***}	4.983^{***}	-0.987^{***}	4.505^{***}
	(0.00000)	(0.449)	(0.365)	(0.393)	(0.676)	(0.771)	(0.327)	(0.581)
House Committee: Ways and Means	-13.548^{***}	-3.163^{***}	-1.380^{***}	-12.072^{***}	-7.390^{***}	-0.015	-2.019^{***}	1.452^{***}
	(0.002)	(0.240)	(0.194)	(0.003)	(0.002)	(0.354)	(0.296)	(0.352)
Senate Committee: Finances	-9.297^{***}	-0.849^{***}	-0.189	-0.338	0.369	2.793^{***}	-0.747^{**}	4.095^{***}
	(0.013)	(0.324)	(0.243)	(0.656)	(1.148)	(0.797)	(0.315)	(0.529)
Number of Pages	-0.031	-0.009^{***}	-0.002^{***}	0.004	-0.003	-0.003^{***}	-0.009^{***}	0.004^{***}
	(0.026)	(0.001)	(0.0003)	(0.010)	(0.003)	(0.001)	(0.002)	(0.001)
Constant	-9.941^{***}	-34.488^{***}	25.260^{***}	6.721^{***}	-5.320^{***}	-10.832^{***}	-0.977^{**}	-8.627^{***}
	(0.516)	(0.368)	(0.345)	(0.519)	(1.118)	(0.789)	(0.445)	(0.984)
State Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Term Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Akaike Inf. Crit.	3,801.672	3,801.672	3,801.672	3,801.672	2,129.099	2,129.099	2,129.099	2,129.099

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The reference category of the dependent variable is Subtechnology

The number or observations is n = 2576 for models 1-4 and n = 1231 for models 5-8.

In the first period, 1999 to 2008, all regression outputs are significant; however, not all are meaningful. Starting with comparing the Economy level to the reference category Subapplication shows that an increase in the employment share is associated with no increase (e^{-11} = 0) in the odds of a policy-maker to prefer policies designed on the Economy level over policies designed on the Subtechnology level. Comparing policy-makers' preferences of supporting a policy designed on the Field and the Technology level with one designed on the Subtechnology level shows that they favour the latter over the first two design levels. With a one per cent increase in the employment share of the battery producing sector, the odds for a policy-maker to support a policy designed on the Field level decrease by (e^{-7} = 0.5) or by 50 per cent[9], and decrese on the Technology level by ($e^{-1.7}$ = 0.2) or by 80 per cent, compared to the Subtechnology level. In consequence, with an increase in the employment share in the battery producing sector, the odds for a policy-maker to support a policy designed on the Subtechnology level increase. Regarding policies designed on the most specific level, the Design level, compared to those designed on the Subtechnology level, a one unit increase in the employment share of the producing sector is associated with an increase in the odds of e16.5 = 14'650'719. The adjusted McFadden pseudo-R^2 for this model is 0.24, showing that 24 per cent of the total variability can be explained by this model (UCLA, 2021a).

Although all the outputs are significant, the results are problematic for the category Economy and Design. The first assumption underlying the Maximum Likelihood estimation method (cf. 3.5 Empirical Strategy), which requires a large sample size, is not fulfilled for those two categories. There are only four observations of policy-makers supporting a policy designed on the Economy level and five supporting a policy designed on the Design level, making the estimation for those two categories unreliable. The Akaike Information Criterion (AIC) of 3'801, which is quite large compared to the AIC of the estimation for the model post-2008, is another indicator that some of the results should be handled with care. The predicted probability plots, which I will discuss below, account for the number of observations and give a more intuitive picture of the results.

In the second period, 2009 to 2018, only the estimation for the Field level is significant. The odds for the support of a policy designed on the Field level compared to the Subtechnology level decreases by 70 per cent with a one per cent increase in the employment share in the battery producing sector. The AIC for this model estimation is 2'132. The adjusted McFadden pseudo-R^2 is 0.34.

The predicted probabilty plots give a clearer and more intuitive picture of how the support for technology-specific policy design elements changes with an increase in the employment share and over time. The predicted probability plots shown in Figure 12 distinguish between the periods 1999–2008 and 2009–2018 and between the battery producing and the battery using sector. Hypothesis 1 refers to the battery producing sector, the two plots on the left in Figure 12. The two plots on the right show the battery using sector and serve as a reference, although I did not formulate any hypothesis for the link between the battery using sector and the technology specificity of a policy design.

[9] The formula to derive the odds from the log odds provided in the regression output is: $e^{\text{log odds}}$ = odds; to calculated the increase/decrease from the odds in percentages, the following formula is needed: 100*($e^{\text{log odds}} - 1$)%.

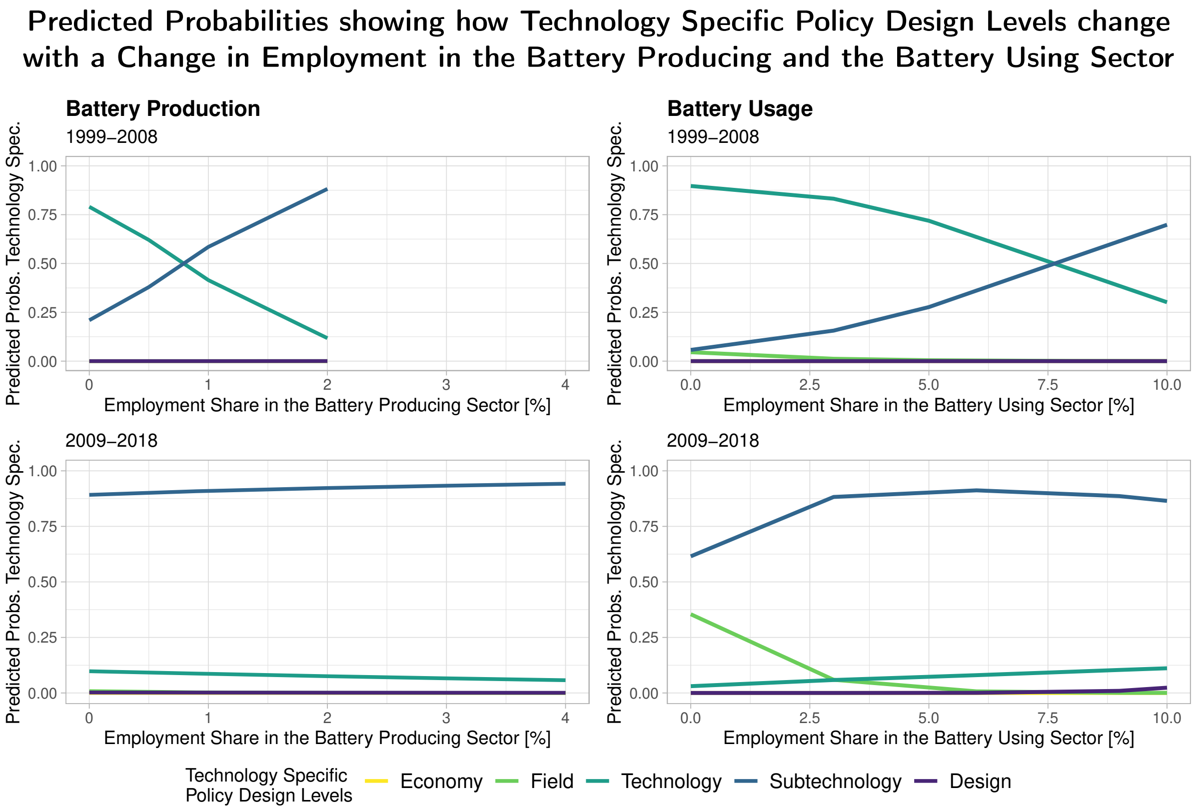

Figure 12: Predicted probability plots for Technology Specific policy design Levels

The predicted probability plots show how the probability that a policy-maker supports a bill designed on a specific Technology Specificity level changes with a change in the employment share of their constituency. *Top left: Battery Production, 1999–2008* With an increase in the employment share of the battery producing sector, the probability that a policy-maker supports a bill designed on the Subtechnology level increases, whereas it decreases for the Technology level. There is no state with employment shares above 2 per cent. *Bottom left: Battery Production, 2009–2018:* With an increase in the employment share in the battery producing sector, there is no change in the predicted probabilities; support for policies designed on the Subtechnology level dominates. *Top right: Battery using sector, 1999–2008:* The trends are comparable to the battery producing sector during the same period. *Bottom right: Battery using sector, 2009–2018:* With an increase in the employment share of the battery using sector, there is a minor increase in the probability for a policy-maker to support a policy designed on the Subtechnology level and a decrase to support a policy designed on the Field level. *Souce:* Own figure.

For the battery producing sector, the above discussed trends are underlined. With an increase in the employment share in the battery producing sector, policy-makers are most likely to support policies designed on the *Subtechnology* level. However, there is a difference between the first and the second period of observation. In the period up to 2008, with an increase in the employment share in the battery producing sector from 0 to 2 per cent, the probability for a policy-maker to support a policy designed on the Subtechnology level increases from around 20 per cent to around 85 per cent. Simultaneously, the probability of supporting a policy designed on the Technology level decreases from around 80 per cent to 12 per cent. In the period after 2008, policies on the Subtechnology level are the most favoured design, almost independent from a change in the employment share in the state represented by the policy-maker. These results are robust when splitting the data between 2010 and 2011, comparing the periods 1999–2010 vs 2011–2018 (cf. Appendix A.6 Multinomial Logisitc Regression Robustness Checks). *In conclusion, the first hypothesis that policy-makers representing a constituency with a large battery producing sector are more likely to support technology-specific policy designs is supported. However, differences over time need to be considered.*

The results for the battery using sector serve as a comparison and should inspire further research. No expectation regarding the design preferences of technology-specific policy designs were formulated for the using sector. What we can see by exploring this data is a similar trend compared to the battery producing sector. With an increase in the employment share of the battery using sector, policy-makers' preferences for technology-specific policy designs increases, whereas those for less policy specific, or more policy-neutral, designs decrease. This trend is more prominent for the early 2000s but can still be observed between 2009 and 2018.

4.3.2 Hypothesis 2: Policy-makers representing a constituency with a large battery using sector are more likely to support application-specific policy designs

To test the second hypothesis stating that policy-makers representing a constituency with a large battery using sector are more likely to support application-specific policy designs, a multinomial logistic regression model is calculated with the employment share in the battery using sector regressed on the policy Application Specificity dimension of the policy design. The category Subapplication serves as the reference category. In Table 5, the models 1 to 3 cover the period between 1999 to 2008, the models 4 to 6 the time between 2009 to 2018.

The model output shows that for 1999 to 2008, with a one per cent increase in the battery using sector employment, the odds for a policy-maker to support a policy designed on the Economy level is $e^{0.7}$ = 2 times higher than for one designed on the Subapplication level. This effect is significant. For 2009 to 2018, there is a significant effect for policies designed on the Industry level compared to the Subapplication level. A one per cent increase in the the battery using sector employment is associated with the odds for a policy-maker to support a policy designed on the Industry level that is $e^{-1.2}$ = 0.3 or 70 per cent lower than the odds for supporting a policy designed on the Subtechnology level. The model accuracy given by the AIC is 2'792 for models 1 to 3 and 2'710 for models 4 to 6. The adjusted McFadden pseudo-R^2 is 0.30 for the former and 0.14 for the latter model.

In the next step, the predicted probabilities for the support of application-specific policy design elements are discussed, once for 1999 to 2008 and once for 2009 to 2018. Additionally, a distinction will be made in Figure 13 between the battery producing and the battery using sector. This allows a comparison between the two sectors, although I only derived a hypothesis for the link between the battery using sector and the application specificity of a policy design.

Table 5: Multinomial logistic regression with employment share in the Battery Using sector regressed on Application Specificity

	Dependent Variable: Application Specificity					
	Economy	Industry	Application	Economy	Industry	Application
	1999 - 2008	1999 - 2008	1999 - 2008	2009 - 2018	2009 - 2018	2009 - 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Employment Share in the Battery Using Sector	0.672***	0.067	−0.006	−0.170	−1.224***	−0.076
	(0.092)	(0.076)	(0.061)	(0.153)	(0.135)	(0.185)
Democrats (Ref = Republicans)	0.289	1.664***	1.154***	0.629***	2.116***	1.067***
	(0.403)	(0.299)	(0.161)	(0.226)	(0.453)	(0.228)
Chamber Seniority	0.088***	0.042**	0.016	0.015	0.015	0.032**
	(0.021)	(0.019)	(0.013)	(0.015)	(0.021)	(0.014)
House Committee: Energy and Commerce	−0.301	1.266***	−0.970***	0.904***	−0.815	0.435*
	(0.473)	(0.400)	(0.243)	(0.245)	(0.507)	(0.250)
Senate Committee: Energy and Natural Resources	0.720	−7.995***	1.749***	−0.614**	−0.479	−1.244***
	(0.565)	(0.0003)	(0.448)	(0.293)	(0.385)	(0.286)
House Committee: Ways and Means	−4.450***	−1.065***	2.169***	−1.718***	−2.779***	−1.073***
	(1.021)	(0.358)	(0.252)	(0.231)	(0.564)	(0.243)
Senate Committee: Finances	−2.149***	2.169***	−0.212	−0.688**	−1.970***	−0.596**
	(0.793)	(0.452)	(0.295)	(0.309)	(0.530)	(0.303)
Number of Pages	−0.021***	−0.017***	−0.002***	0.002***	0.001	−0.004***
	(0.004)	(0.002)	(0.0003)	(0.001)	(0.001)	(0.001)
Constant	−7.959***	−11.118***	2.188***	1.072	1.769**	0.894
	(0.485)	(0.452)	(0.450)	(0.960)	(0.876)	(1.207)
State Fixed Effects	yes	yes	yes	yes	yes	yes
Term Fixed Effects	yes	yes	yes	yes	yes	yes
Akaike Inf. Crit.	2,792.846	2,792.846	2,792.846	2,705.119	2,705.119	2,705.119

Note: *p<0.1; **p<0.05; ***p<0.01
The reference category of the dependent variable is Subapplication
The number or observations is n = 2576 for models 1-3 and n = 1231 for models 4-6.

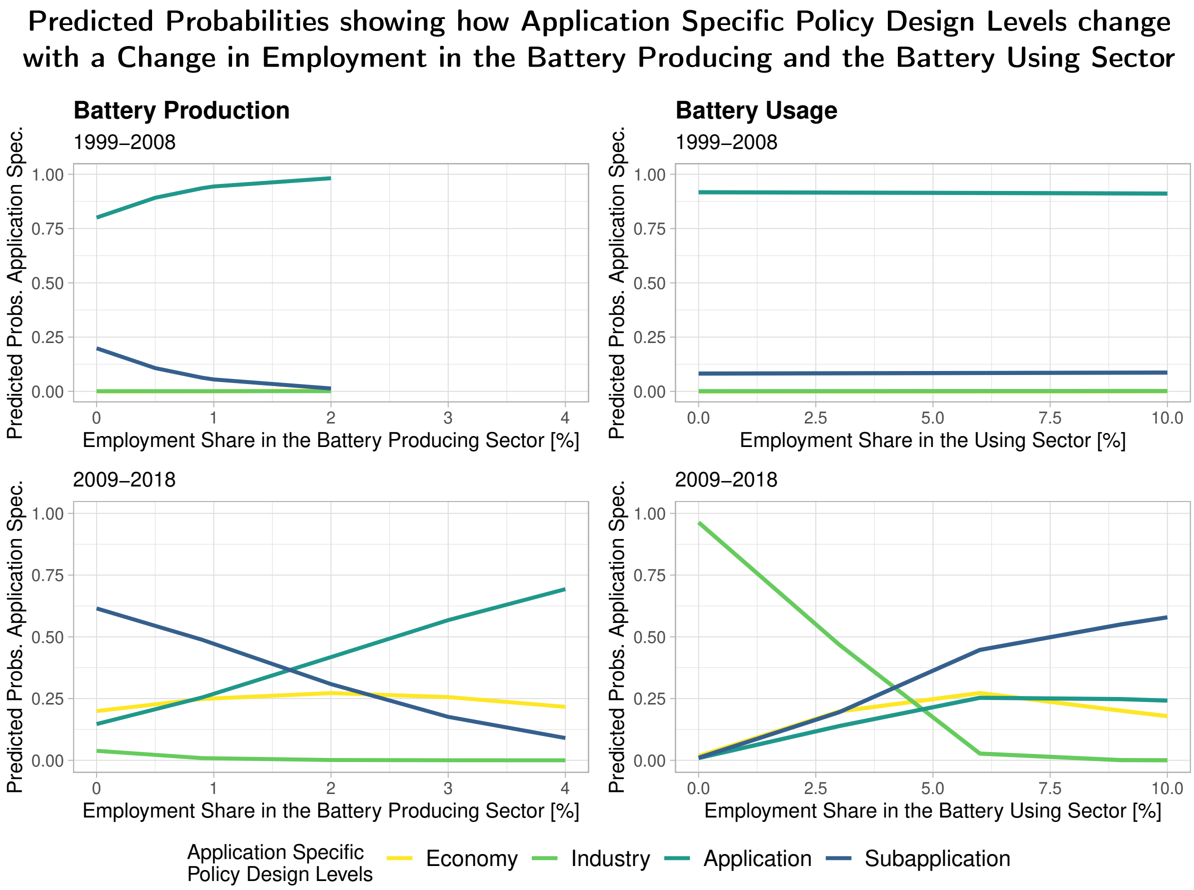

Figure 13: Predicted probability plots for Application Specific policy design levels

The predicted probability plots show how the probability that a policy-maker supports a bill designed on a specific Application Specificity level changes with a change in the employment share of their constituency. *Top left: Battery Production, 1999–2008:* With an increase in the employment share of the battery producing sector, there is a minor increase in the probability for a policy-maker to support a policy designed on the Application level and a minor decrease for supporting a policy designed on the Subapplication level. *Bottom left: Battery Production, 2009–2018:* With an increase in the employment share in the battery producing sector, there is an increase in the probability for policy-makers to support a policy designed on the Application level and a decrease for the support of one designed on the Subapplication level. *Top right: Battery using sector, 1999–2008:* With an increase in the employment share in the battery using sector, there is no change in the predicted probabilities; support for policies designed on the Application level dominates. *Bottom right: Battery using sector, 2009–2018:* With an increase in the employment share of the battery using sector, there is a sharp decrease in support of policies designed on the Field level and a gradual increase in the support for policies designed on the Application and Subapplication level. *Souce:* Own figure.

Starting with the *battery using sector*, for which the second hypothesis is formulated, we see that for the years 1999 to 2008, the probability that policy-makers support a policy design that is formulated on the Application level is almost 90 per cent, independent from the employment share in the battery using sector. Only in the subsequent years up to 2018, some dynamics can be observed with an increase in the employment share. With an increase in the employment share in the battery using sector from 0 to 10 per cent in the state represented by a policy-maker, the probability for them to support a policy designed on the Field level drops from almost 100 per cent to zero. Simultaneously, the probability for policy-makers' preferences for specific policy designs designed on the Application and the Subapplicaiton level increase from 0 to 25 per cent and 60 per cent, respectively. These results are robust when splitting the data between 2010 and 2011, comparing the periods 1999–2010 vs 2011–2018 (cf. Appendix A.6 Multinomial Logisitc Regression Robustness Checks). *In conclusion, the second hypothesis that policy-makers representing a constituency with a large battery using sector are more likely to support application-specific policy designs, is supported. However, differences over time need to be considered.*

The results for the battery producing sector are added for comparative purposes. No expectations regarding the preferences of the producing sector for application-specific designs were formulated. Figure 12 on the right-hand side shows that for the Technology Specificity, the trends for the battery using and battery producing sector were similar; however, for the Application Specificity, this is only the case for the very early 2000s. For the years 2009 to 2018, with an increase in the employment share, the preferences for technology-specific policy designs on the Subapplication level decrease, whereas those for policies designed on the more neutral Application level increase. These findings lead to the speculative assumption that the battery producing sector is more interested in fostering application-neutral policies than the battery using sector favouring technology-specific policy designs. Additional research will be needed to explore this relationship further.

4.4 Lobbying by on Battery Storage Policies

4.4.1 A descriptive analysis of the bills that attracted lobbying

In this thesis, I want to investigate how industries influence policy-makers' policy design preferences and, consequently, the design of technology policies. The multinomial logistic regression results approximate this relationship and show that the economic circumstances in the constituencies of the policy-makers influence their design choices. A large producing sector in the state represented by policy-makers is associated with design preferences targeting technology-specific policies. In contrast, the presence of a large using sector is associated with design preferences for application-specific battery policies.

In the subsequent section, hypotheses 3 and 4 will be explored. Hypothesis 3 states that bills that attract lobbyism by the battery producing sector are designed more technology-specific; whereas hypothesis 4 states that bills that attract lobbyism by the battery using sector are designed more application-specific. Whereas hypotheses 1 and 2 focused on the indirect industry pressure of firms on policy-makers, hypotheses 3 and 4 concentrate on the direct link between industries and battery policies. Thereby, the focus lies on the *subset* of bills that attracted lobbyism. I will start with a general description of lobbying activities over time and introduce the battery storage bills that attracted lobbying. Then I will present the firms within the battery producing and the battery using sector that were most actively lobbying battery storage policies. Finally, I will move on to test the hypotheses as far as the limited data allows.

Figure 14 gives an overview of the number of lobbied bills per industry sector over time. Of the 363 battery storage policies, there are a total of 65 bills that attracted lobbying, some of them by several industry sectors. The producing sector lobbied for 11 bills, 17 bills attracted lobbying by the using sector. Almost all the battery storage bills, 62 of them, additionally attracted lobbying by other sectors outside of the value chain of a lithium-ion battery.

There is a peak of lobbying activities among all the sectors between 2007 and 2010, and a new increase since 2018. The shape of this distribution correlates with the total number of bills introduced (cf. Figure 2 in chapter 3.2 Introducing a new dataset). In total, the using sector lobbied for more bills than the producing sector. However, when comparing the employment shares, the using sector is much larger than the producing sector (cf. Figures 8 and 9); consequently, the relative lobbying activities of the battery producing sector are more intense than those of the battery using sector.

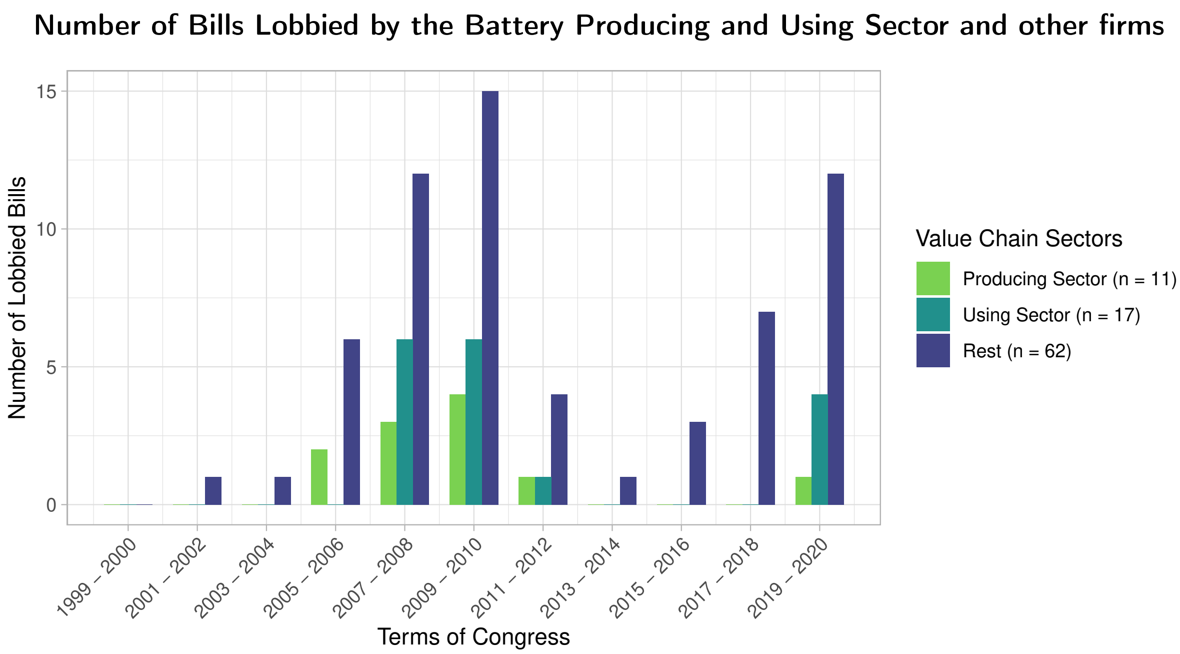

Figure 14: Number of lobbied bills per industry sector

A total of 65 bills of the 363 battery storage bills attracted lobbying. Firms of the battery producing sector lobbied 11 of them, firms among the battery using sector 17. Additionally, other firms not part of the value chain of lithium-ion battery manufacturing lobbied 62 bills. Multiple sectors can lobby a bill. *Source:* Own figure.

A total of 20 bills attracted lobbying by the battery using and/or the battery producing sector. Table 6 gives an overview of these bills, their term of introduction and their legislative number. "H. R." stands for a bill worked on in the House, and "S." for a bill dealt with in the Senate. Additionally, it shows whether the using sector and/or the producing sector lobbied for the respective bill. The last two columns provide information on the *Technology* and *Application Specificity* of each bill.

Regarding their Technology Specificity levels, Table 6 shows that the vast majority of the lobbied bills were designed very specifically on the Subtechnology level. In contrast, the design elements of the Application Specificity dimension vary from neutral to very specific.

Concerning the topics the battery producing and the battery using sector lobby for, an exploratory analysis of the abstracts of each bills revealed that the predominant topics concern the deployment of renewable energies, electric vehicles and energy security. The list in Appendix A.8 shows the parts of each bill's abstract that deal with energy and electricity. Both sectors are equally likely to support bills dealing with renewable energies and electric vehicles. However, according to this small descriptive analysis, the battery using sector is more likely to support policies dealing with energy security. An explanation for this phenomenon is that policies dealing with energy security predominantly target the military and defence (cf. all policies starting with the National Defense Authorisation Act). These military related policies are usually very long and are thus likely to contain a topic interesting for battery using firms.

Finally, taking a look at the 14 bills that became law, shown in Figure 7, reveals that on the Technology Specificity dimension, all the bills that became law were designed very specifically, namely on the Technology, Subtechnology or Design level. On the Application level, these bills were also predominantly designed specifically, mainly on the Application and Subapplication level. Not all of them attracted lobbying by the battery producing or the battery using sector, but most of them did. Finally, Tables 18 and 19 in the Appendix A.7 provides a list of the firms of the battery producing and the battery using sector that most actively lobbied for battery storage policies.

4.4.2 Exploring industries' policy design preferences

The preceding descriptive analysis has revealed that firms of the battery producing and the battery using sector do lobby for battery storage bills. Moreover, there is a tendency that they are in favour of specific policy designs regarding the Technology Specificty of a bill. The picture is more ambiguous regarding their Application Specificity preferences. It remains to explore whether these design preferences remain specific when comparing them to the total number of battery storage policies.

The total number of bills per specificity level is presented in Table 8 for the different Technology Specificity levels, and in Table 9 for the distinctive Application Specificity levels. These tables lead to the assumption that specific bills designed on the Subtechnology level attract more lobbying by the battery producing sector than more neutral bills designed on the Economy and the Field level. These findings support hypothesis 3. There is also some evidence that, regarding the Application Specificity design dimension, bills formulated specifically on the Application dimension attract more lobbying by the battery using sector than more neutral bill designed on the Economy or Industry level. These findings support hypothesis 4. No expectations were formulated regarding lobbying of

Bills Lobbied by the Battery Producing and Using Sector including their Technology and Application Specificity Levels

	Term	Legislation Number	Lobbyed by Producing Sector	Lobbyed by Using Sector	Title	Technology Specificity Levels	Application Specificity Levels
1	109	H.R. 6111	1	0	Tax Relief and Health Care Act of 2006	Subtechnology	Subapplication
2	109	S. 2025	1	0	Vehicle and Fuel Choices for American Security Act	Technology	Industry
3	110	S. 3002	0	1	Department of Defense Authorization Act for Fiscal Year 2009	Subtechnology	Industry
4	110	H.R. 6899	0	1	Comprehensive American Energy Security and Consumer Protection Act	Subtechnology	Application
5	110	H.R. 6049	1	1	Energy Improvement and Extension Act of 2008	Subtechnology	Application
6	110	H.R. 1424	0	1	A bill to provide authority for the Federal Government to purchase and insure certain types of troubled assets for the purposes of providing stability to and preventing disruption in the economy and financial system and protecting taxpayers, to amend the Internal Revenue Code of 1986 to provide incentives for energy production and conservation, to extend certain expiring provisions, to provide individual income tax relief, and for other purposes.	Subtechnology	Application
7	110	S. 357	1	1	Ten-in-Ten Fuel Economy Act	Subtechnology	Industry
8	110	H.R. 6	1	1	Energy Independence and Security Act of 2007	Subtechnology	Application
9	111	S. 3454	0	1	National Defense Authorization Act for Fiscal Year 2011	Subtechnology	Application
10	111	S. 1462	1	1	American Clean Energy Leadership Act of 2009	Technology	Industry
11	111	S. 1390	1	1	National Defense Authorization Act for Fiscal Year 2010	Subtechnology	Application
12	111	H.R. 2647	0	1	National Defense Authorization Act for Fiscal Year 2010	Subtechnology	Economy
13	111	H.R. 2454	1	1	American Clean Energy and Security Act of 2009	Subtechnology	Economy
14	111	S. 774	1	1	NESA of 2009	Economy	Subapplication
15	112	H.R. 658	1	0	FAA Modernization and Reform Act of 2012	Subtechnology	Economy
16	112	S. 298	0	1	Charging America Forward Act	Subtechnology	Subapplication
17	116	H.R. 6395	0	1	National Defense Authorization Act for Fiscal Year 2021	Subtechnology	Application
18	116	S. 2302	0	1	America's Transportation Infrastructure Act of 2019	Subtechnology	Economy
19	116	H.R. 2500	0	1	National Defense Authorization Act for Fiscal Year 2020	Subtechnology	Industry
20	116	H.R. 1865	1	1	Further Consolidated Appropriations Act, 2020	Technology	Subapplication

Table 6: Overview of the 20 bills that attracted lobbying by the battery Using and the Battery Producing sector.

The table shows what bill that attracted lobbying by the battery producing and/or using sector, including their Technology and Application Specificity level. *Source:* Own figure based on own data.

Bills that became Law and their Technology and Application Specificity

	Legislation Number	Term	Title	Technology Specificity Levels	Application Specificity Levels
1	H.R. 2084	106	Department of Transportation and Related Agencies Appropriations Act, 2000	Design	Subapplication
2	H.R. 6111	109	Tax Relief and Health Care Act of 2006	Subtechnology	Subapplication
3	H.R. 3	109	SAFETEA-LU	Technology	Subapplication
4	H.R. 1424	110	A bill to provide authority for the Federal Government to purchase and insure certain types of troubled assets for the purposes of providing stability to and preventing disruption in the economy and financial system and protecting taxpayers, to amend the Internal Revenue Code of 1986 to provide incentives for energy production and conservation, to extend certain expiring provisions, to provide individual income tax relief, and for other purposes.	Subtechnology	Application
5	H.R. 6	110	Energy Independence and Security Act of 2007	Subtechnology	Application
6	H.R. 6523	111	Ike Skelton National Defense Authorization Act for Fiscal Year 2011	Technology	Application
7	H.R. 2647	111	National Defense Authorization Act for Fiscal Year 2010	Subtechnology	Economy
8	H.R. 658	112	FAA Modernization and Reform Act of 2012	Subtechnology	Economy
9	H.R. 302	115	FAA Reauthorization Act of 2018	Subtechnology	Economy
10	H.R. 4318	115	Miscellaneous Tariff Bill Act of 2018	Design	Subapplication
11	H.R. 6395	116	National Defense Authorization Act for Fiscal Year 2021	Subtechnology	Application
12	S. 1790	116	National Defense Authorization Act for Fiscal Year 2020	Subtechnology	Industry
13	H.R. 1865	116	Further Consolidated Appropriations Act, 2020	Technology	Subapplication
14	H.R. 133	116	Consolidated Appropriations Act, 2021	Technology	Application

Table 7: Overview of the 14 bills that became law and their design specificity Levels

TThe table shows the 14 bills among the 363 battery storage bills that became law, including their level of Technology and Applicaiton Specificity. *Source:* Own figure based on own data.

the using sector on the technology specificity of a bill, but the trends are comparable to those in focus. In conclusion, there seems to be some evidence in favour of hypothesis 3 and hypothesis 4.

However, these results must be taken with caution. The results become less explicit when examining the number of lobbied bills on a particular specificity level as a share of the total number of battery storage bills on that level. Regarding the *Technology Specificity*, among the 363 energy storage bills, 12 were formulated on the Economy level, 39 on the Field level, 142 on the Technology level, 152 on the Subtechnology level, and 18 on the Design level. Regarding the *Application*

Technology Specificity	**Producing Sector**	Using Sector
Economy	1	1
Field	0	0
Technology	3	2
Subtechnology	7	14
Design	0	0

Table 8: Total number of battery storage policies lobbied by the battery producing and the battery using sector
The producing sector is highlighted because hypothesis 3 states that bills that attract lobbying by the battery producing sector are designed more technology-specific.

Application Specificity	Producing Sector	**Using Sector**
Economy	2	3
Industry	3	3
Application	3	7
Subapplication	3	3

Table 9: Total number of battery storage policies lobbied by the battery producing and the battery using sector
The using sector is highlighted because hypothesis 4 states that bills that attract lobbying by the battery using sector are designed more application-specific.

Specificity, 71 of the 363 bills were formulated on the Economy level, 45 on the industry, 168 on the Application, and 79 on the Subapplication level. Given these distributions, I will next examine the shares of each design element on the total bills designed on that level.

The shares for the different Technology and Application Specificity levels presented in Tables 10 and 11 lead to the rejection of hypotheses 3 and 4. The shares of each lobbied policy as a share of the total bills designed on the respective specificity level show that regarding their Technology Specificity, of all the bills designed on the Economy level, 8.3 per cent attracted lobbying by the producing sector. This is the highest share, followed by 4.6 per cent of all the bills formulated on the Subapplication level that attracted lobbying. These results do not support hypothesis 3. Furthermore, the using sector, for which no expectations were formulated, displays that 8.3 per cent of all the bills

Technology Specificity	**Producing Sector**	Using Sector
Economy	8.3%	8.3%
Field	0%	0%
Technology	2.2%	1.4%
Subtechnology	4.6%	9.2%
Design	0%	0%

Table 10: Shares of lobbied bills per Technology Specificity level
Share of lobbied bills per Technology Specificity level as the number of bills lobbied on a specificity level divided by the total number of bills designed on that specificity level.

Application Specificity	Producing Sector	**Using Sector**
Economy	2.8%	4.2%
Industry	6.7%	8.9%
Application	1.8%	4.2%
Subapplication	3.8%	3.8%

Table 11: Shares of lobbied bills per Application Specificity level
Share of lobbied bills per Application Specificity level as the number of bills lobbied on a specificity level divided by the total number of bills designed on that specificity level.

formulated on the Economy level attracted lobbying, and 9.2 per cent of all the policies designed on the Subtechnology level. Concerning their Application Specificity and the using sector, for which hypothesis 4 was formulated, the highest shares appear for the Industry level. 8.9 per cent of all the bills formulated on the Industry level attracted lobbying by the using sector. Similarly, for the producing sector, the highest share is also on the Industry level. These results are not in line with the expectations formulated in hypothesis 4.

The rejection of hypotheses 3 and 4 should nonetheless be interpreted with caution. This analysis was laid out as an exploratory analysis to get first insights of the influence of the producing and the using sector on technology policy designs through lobbying. However, the present analysis is based on a minimal number of bills that attracted lobbying, which does not allow for drawing far-reaching conclusions. One or two bills more on a specific policy design level would leverage the results substantively. Therefore, more data on battery storage policies are needed by either including a wider range of search terms in the initial policy search or expanding the search to a broader field of comparable technologies. Overall, based on the limited number of lobbied bills, drawing general conclusions on the policy design preferences of industries is impossible. Furthermore, it remains unclear whether the bills attracted lobbying because of their design or whether industries influenced the policy-making process to shape policies to their advantage, i.e. it remains unclear whether lobbyists lobby for the most promising bills or whether bills become more successful because of the lobbying. To conclude, these first results evoke a plethora of avenues for further research. The list of firms provided in the Tables 18 and 19 of Appendix A.7 and the insights on policy designs of the lobbied bills may set the ground for further research on technology policy design preferences of industries along the value chain of a technology.

5 Discussion

In the subsequent section, I will outline the contributions of this thesis to the policy design literature. Moreover, I will discuss the importance of designing "smart" technology policies in the national and international setting. I will continue with an outlook on the future of battery storage technology and its growing importance. Finally, I will highlight some limitations of this thesis and conclude with avenues for future research.

5.1 Contribution to the policy design literature

So far, the literature on policy designs has discussed the importance of policy designs in picking technological winners. For a long time, technology-specificity seemed to be *the* determinant factor influencing technological innovation or lock-in. However, every technology comes with its applications. Particularly, multi-purpose technologies serving *multiple* applications create economic value for different user groups. Consequently, it is important to consider not only the technology-specificity of a policy design but also its application-specificity. Moreover, although there is a consensus that the primary addressees of technology policy are industries and that these industries are interested in influencing the policy-making process, policy design scholars have often neglected these crucial actors to understand policy-makers' and industries' technology-policy design preferences better.

In contrast, the innovation studies literature has primarily focused on different industry sectors, the diffusion of new multi-purpose technologies, or technological learning through multiple learning processes, such as learning-by-doing or learning-by-using. Moreover, the focus has been on avoiding the negative effects of path dependence and technological lock-ins to spread innovative new technologies. To a lesser extent however, innovation studies have concentrated on the interaction between industries and policy-makers, and the interest of industries to influence, on the one hand, policy-makers' policy-design preferences that are in favour of these industries; and on the other hand, on how industries directly influence technology policy designs through lobbying activities. This thesis draws on insights from the innovation studies literature to explore the politics behind policy-making and analyse *how industry interests affect policy-makers' technology policy design preferences.*

The first contribution of my thesis to the existing policy design literature is the creation and introduction of a new dataset on battery storage policies in the United States between 1999 and 2020 focusing on technology design elements, namely Technology Specificity and Application Specificity. Battery storage technologies are multi-purpose technologies with a wide range of applications that are expected to become inevitable in the upcoming years. It is understudied in political science and therefore serves as a good example to better understanding how industries affect technology policy design preferences. The dataset includes bills and laws to study policy outputs and the design preferences of policy-makers in their different implementation phases during the entire policy-making process. Beyond my thesis, it should serve as a basis for further analyses on what drives policy-makers to support certain technology policy designs more than others and how industry interests influence the politics behind policy-making. Based on this dataset, my second contribution to the policy design literature is the quantitative and qualitative exploration of policy-makers' technology policy design preferences and how industries indirectly and directly influence these policy designs. By relying on innovation studies literature, I distinguish between the *battery producing* and the *battery using sector* and argue why the former is more interested in technology-specific policy designs, whereas the latter favours application-specific policy designs. The findings from the quantitative and qualitative analyses will subsequently be discussed, and it will be outlined why designing "smart" technology policies is inevitable to decarbonise the mobility sector, foster renewable energies, and ultimately reach the 1.5-degree target stated in the Paris Agreement.

5.2 The importance of designing "smart" technology policies

National and international policies affect the future of energy storage technologies. In line with Article 4 of the Paris Agreement, the United States adjusted their Nationally Determined Contributions (NDC) after rejoining the Paris Agreement in 2021. As part of this, they pledged to reduce their greenhouse gas emissions by 50 per cent by 2030 compared to 2005. The transportation and the energy sector are two pillars in which they are determined to become active. For both sectors, energy storage technologies are essential. Decarbonising the mobility and transportation sector requires national policies consisting of "tailpipe emissions and efficiency standards; incentives for zero-emission personal vehicles; [and] funding for charging infrastructure [. . .]" (U.S. NDC, 2021, p. 4). Furthermore, to reach a decarbonised electricity sector by 2030, the "rapid deployment of carbon pollution-free electricity generating resources, transmission, and energy storage" are inevitable (U.S. NDC, 2021, p. 4). However, these international pledges require national actions. This thesis has revealed that most policy proposals that would foster battery production or battery usage are only introduced in the House or the Senate, but then lose steam and never become law (cf. Figure 2 in subchapter 3.2 Introducing a new Datase). However, precisely such national laws are necessary to avoid technological lock-ins and set a "smart" policy framework for battery storage innovation that allows using the full potential of battery storage technologies.

Moreover, this thesis has shown that policy-makers do not act in a vacuum when making decisions and choosing what policy designs they favour, but they are significantly influenced by interests from industries present in their constituencies. Therefore, the primary addressees of innovative battery storage policies must be the battery producing sector and the battery using sector. These sectors can benefit from technology policies that provide planning security and set incentives to foster innovation. Consequently, these firms can increase their production capacities, hire more people, benefit from economies of scale and ultimately – more brainpower also means more innovation.

However, these firms also take an active role in influencing policy-makers' technology policy design preferences. Consequently, policy-makers need to be aware of the power firms have on their decision-making process. As a result, they must react to these firms' needs and be aware of their own role. They must take an active – and by all means economical – role that goes beyond fixing market failures to provoke state investments that are "not only 'smart' (innovation-led), but also more 'inclusive' and more 'sustainable'" (Mazzucato, 2018, p. 2). Thus, policy-makers *can* influence what technologies and applications are promoted. By designing a "smart" political framework that considers technologies *and* technological application, innovation can be accelerated – and technological change and innovation are facilitated.

5.3 The future of battery storage

After an extensive discussion on the importance of technology policy designs to foster battery storage innovations, critical readers may still wonder whether battery storage is, after all, a relevant case. They may have realised that the U.S. wide employment shares of the battery producing sector were *only* at 0.6 per cent by 2018, and that of the battery using sector *just* at 4.1 per cent. Are these low industry shares relevant with regard to the future? The clear answer is yes. There are several reasons why these industry sectors, although they may seem small at first sight, currently matter and why they are likely to gain even more importance in the upcoming years:

Between 2010 and 2018, there was a 2.5-fold increase in the employment share of the battery producing sector, from 0.27 per cent in 2010 to 0.65 per cent by 2018, accompanied by a remarkable increase in the manufacturing capacity of lithium-ion batteries, one of the core battery storage technologies, in the United States. However, an increase in manufacturing capacity could not only be observed in the United States but worldwide. Lead by China and South Korea, the cell manufacturing capacity in GWh has increased globally, from basically zero to almost 600 GWh between 2001 and 2018. In this context, and despite holding 13 per cent of the worlds' battery manufacturing capacity by 2018, the United States lags behind the other big players in the field (Sewerin et al., 2020). Still, they are likely to expand the manufacturing capacity of storage batteries in the forthcoming years due to rising international competition because of significant structural changes in the electric power markets. Therefore, the substantial increase of the employment share in the battery producing sector since 2010 has only been the start of a new era. The installation of new large-scale battery storage capacity is expected to increase ten times between 2019 and 2023, up to an additional 10'000 megawatts. Additionally, small-scale battery storage facilities continue to grow, especially in California, Vermont, Texas and Hawaii (U.S. Department of Energy, 2021). A catalyst in this regard are Tesla's Gigafactories, the first already running in Nevada and the second one planned in Texas. They are hotspots for innovation in battery storage technology and speed up technological change. As a result, the costs of storage battery production are likely to continue to decrease with an increase in technological learning and experience, making mass production attractive for a wider range of businesses (Schmidt et al., 2017). Consequently, despite its seemingly small employment share, the battery using sector will likely gain importance in the upcoming years.

In contrast, the employment share of 4.1 per cent in the battery using sector is already relatively large. This is not surprising since the battery using sector includes, among others, car manufacturing. Car producers and their suppliers are the largest manufacturing sector in the United States in terms of job creation and are responsible for 3 per cent of the United States GDP (American Automotive Council, 2020). Thus, the decarbonisation of the mobility sector will hit the automotive industry substantively. Furthermore, with the market penetration of electric vehicles, one of the core applications of storage batteries, the mobility sector is changing drastically. Additionally, public awareness for electric transportation increases, misconceptions regarding limited range and safety concerns are reduced, and ultimately, practical experience with electric vehicles increases social acceptance (Franke et al., 2012; Melton et al., 2020; Peters and Dütschke, 2014; Schneidereit et al., 2015). Summing up, with the increasing market shares of electric vehicles, which will fully replace combustion engines in the following years due to the necessity to decarbonise the mobility sector, car manufacturers have to change their production concepts to remain competitive. In consequence, battery storage applications will definitively gain prominence in the future.

Ultimately, the battery using and battery producing sectors are very likely to grow and become more prominent in the upcoming years, particularly due to national and international policy interventions that are inevitable to foster the decarbonisation of the mobility sector, speed up the deployment of renewable energies, and reach the 1.5-degree target stated in the Paris Agreement.

5.4 Limitations of this thesis

Despite all the advantages of the newly introduced dataset that serves as the basis of this master thesis and contributes to advancing the policy design literature, the dataset exhibits some limitations. When creating the dataset, I coded the *most specific* application and technology design levels of each bill. However, given that the lengths of the bills and laws vary from a few pages to over a thousand pages, it is questionable whether this approach is accurate to identify the scope of each bill regarding the technology and application specificity covered.

By accounting for each bill's length in the multinomial logistic regression, I approximated the complexity of each bill, expecting that longer bills are more likely to target multiple design levels. However, other approaches would surely be more precise. Instead of working on the document level, one could choose to work on the paragraph level and code each relevant paragraph according to its technology and application specificity. For example, the SPARK project conducted by the Energy and Technology Policy Group at ETH Zürich chose such an approach[10]. However, also this approach is accompanied by caveats. Coding each paragraph of the 363 battery storage bills would have gone beyond the scope of feasibility of this thesis. As an alternative, it could be interesting to remain on the document level but code each instance of technology and application specificity – not only the most specific levels. Then, the number of instances per design dimension could be summed up and

[10]https://epg.ethz.ch/news-and-events/EPGNews/2019/11/epg-researchers-acquire-snf-spark-grant.html

would, as such, provide a more accurate picture of the extent to which each particular bill covers battery storage.

As the proxy for the industry influence on policy-makers, I used the employment share for the multinomial logistic regression model. Alternatively, I also collected data on the number of firms along the value chain of a lithium-ion battery, including their firm size, distinguishing between firms with more and less than 500 employees. I decided to use the employment share instead of the firm size because it better approximates the economic circumstances of the battery producing sector and the battery using sector in the states policy-makers represent. However, a closer investigation of firm sizes could also provide interesting new insights, especially since large firms can lobby a lot easier. Smaller firms need to first find an association or have competing interests and fight to overcome collective action problems[11]. Another alternative proxy for the economic circumstances could be the manufacturing capacity of lithium-ion batteries, as was done for the year 2010 to 2020 by the Energy and Technology Policy Group at ETH Zürich. However, focusing on manufacturing capacity would not allow the distinction between the battery using and the battery producing sector. Yet other alternatives to the employment share could be the volume of sales or revenues. Due to data availability and concerning the above considerations, I decided that the employment share in the battery using and the battery producing sector serves best to explore the indirect influence of industries on policy-makers' policy design preferences.

Finally, for the exploratory part on the subset of bills that attracted lobbying, data provided by LobbyView was used. Although this data provides valuable insights into what bills attracted lobbying by firms along the lithium-ion battery value chain and who sponsored these bills, it does not directly link industries and policy-makers. Having information on such direct links would be interesting to study further how industry interests directly influence policy-makers policy design preferences. An example of an initiative providing such information is conducted by the Swiss NGO Lobbywatch (Lobbywatch.ch, 2021). Lobbywatch publishes information on each member of the Swiss Parliament and with what interest groups they are associated. Moreover, each parliamentarian can authorise two lobbyists of their Fchoice to access the Bundeshaus. These two people can be considered representing the interests most important to each parliamentarian. Consequently, the lobbying data used in this thesis only allows for a first glimpse into what bills attracted lobbyism by the battery using sector and the battery producing sector. More data would be needed to explore the direct link between firms and policy-makers in order to explore how firms directly influence policy-makers policy design preferences.

5.5 Avenues for further research

I will next outline a number of avenues for further research. This thesis explores how industries, and particularly the battery producing and the battery using sector, influence technology policy designs by

[11] Thank you, Laurenz Derksen, for this valuable input.

using battery storage as a case. The thesis has primarily focused on the indirect influence of industries on policy-makers' technology policy design preferences, arguing that policy-makers are responsive to the industries' needs in their constituencies and translate these interests into policy design preferences. In contrast, due to limited data, the direct link between industry interests and policy designs could only broadly be explored.

To better understand the causal mechanism linking industry interests and policy designs, additional data will have to be collected by, for instance, expanding the number of search terms used to identify relevant battery storage bills and laws. This data could be complemented by interviews with members of Congress and representatives from industries. The list of firms of the battery producing and the battery using sector provided as parts of the results could serve as the basis for these next steps. Moreover, newspaper analyses and other text documents could serve to better understand policy-makers' attitudes towards industries and industry interests. Furthermore, process tracing may help as a method to better understand the link between industries, policy-makers, and their technology policy design preferences.

Apart from increasing the available data, further research should also concentrate on a more in-depth study of the battery using and the battery producing sector. These two categories used in this thesis only very broadly distinguish industries along the value chain of a lithium-ion battery. Moreover, not all industries included by Annegret et al. (2017) are equally important in influencing policy-makers' technology policy design preferences. Therefore, future studies should investigate what industry branches within these sectors are the ones most actively lobbying.

In line with this, the concept of design coalitions should further be explored and empirically tested to determine how they form coalitions, and whether there are competing interests within these sectors regarding policy design preferences. In my thesis, I argued that the battery using and the battery producing sector form "technology coalitions" and "application coalitions" to influence policy-makers technology policy design preferences. In this regard, I could show that policy-makers representing a state with a larger battery producing sector favour more technology-specific policy designs, and those representing a state with a larger battery using sector favour more application-specific policy designs. In a next step, the proposed theoretical mechanism should therefore be applied to other technologies to test for a wider external validity of the results.

Finally, a deeper analysis of bills and laws should be done regarding their policy designs. Are bills that made it through Congress and became law significantly different from bills that lost steam in the policy-making process? The first insights of this thesis lead to the assumption that bills that attract lobbying are designed more specifically regarding the Technology dimension of a policy design. However, more data will have to be collected to validate these findings and explore whether there are similar trends regarding the Application Specificity of the policies.

6 Conclusion

This thesis contributes to the policy design literature by studying a new facet of the politics behind policy-making. It explores how industries influence policy-makers' technology policy design preferences, and eventually, the design of a policy regarding its Technology and its Application Specificity. I propose a new theoretical mechanism hypothesising that the producing sector favours technology-specific policy designs and therefore forms "technology-specific design coalitions" with policy-makers to promote technology-specific policies. In contrast, the using sector favours application-specific policy designs and thus forms "application-specific design coalitions" with decision-makers to promote specific technological applications and ultimately application-specific policies. Industries can thereby influence policy-makers' policy design preferences and ultimately the design of a policy indirectly, through pressure on the constituency level, or directly, through lobbying activities. In the case of *indirect industry pressure*, I scrutinise whether policy-makers representing a constituency with a larger battery producing sector are more likely to support technology-specific policy designs; and whether policy-makers representing a constituency with a larger battery using sector are more likely to support application-specific policy designs.

To explore the *direct industry pressure* of industries on policy designs, I investigated whether bills that attracted lobbying by the battery producing sector were designed more technology-specfic; and bills that attracted lobbying by the battery using sector were designed more application-specfic. The emipircal analyses underlying this thesis centre around battery storage policies in the United States. The analyses are based on a newly collected dataset on battery storage bills and laws in the United States between 1999 and 2020 containing information on battery policy designs regarding their Technology and Application Specificity, on sponsors and co-sponsors of each bill and law, and the economic situation in the states they represent regarding battery manufacturing along the value chain of a lithium-ion battery. Furthermore, the dataset provides information on whether a bill attracted lobbying by the battery producing and the battery using sector.

The results of the first step of the analysis confirm that policy-makers are significantly affected by the economic circumstances of their constituencies. Policy-makers representing a state with a larger battery producing sector are more likely to support technology-specific policies; policy-makers representing a constituency with a larger battery using sector are more likely to favour application-specific policies. However, time matters. Whereas higher economic activities in the battery producing sector were mostly relevant until around 2010, economic circumstances of the battery producing sector only started affecting policy-makers' policy-design preferences in recent years.

The second step of the analysis exploring the direct links between industries and firms through lobbying was only possible in a descriptive way due to the limited availability of data on direct lobbying activities. As a result, the hypotheses that bills that attracted lobbying by the battery producing (using) sector were designed more technology-specfic (application-specific) could not be confirmed. In conclusion, further research will be needed to investigate the causal mechanism linking industry interests and technology policy designs.

In conclusion, the findings of this thesis, including the creation of the new dataset on battery storage policies, contribute to an emerging field of research that adds insights from innovation studies literature to the study of policy designs. This thesis goes one step beyond classical policy design literature by considering how specific industry sectors, namely the battery producing sector and the battery using sector, influence policy makers' technology policy design preferences, and ultimately the design of technology policies with respect to the specific technologies and applications targeted by them. Using battery storage policies as a case is imminent due to the increasing importance of storage technology in the upcoming years. Ultimately, there is a growing awareness of climate change and an urgency to transform the mobility sector and expand the use of renewable energies outlined in the Paris Agreement. Consequently, national technology policy interventions are inevitable to set a "smart" political framework for battery storage innovation to develop its full potential.

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A Appendix

A.1 Codebook for the Battery Storage Dataset, 1999–2020

1. General Information on Battery Storage Bills and Policy-Makers

id: Distinct number for each bill.
leg nr: Distinct legislative number of each bill, i.e. H.R. 1022 for a bill introduced by a representative of the House, or S. 2882 for a bill introduced by a representative of the Senate.
introduction status: The latest working status of the bill is categorised as follows: Introduced, Passed House, Passed Senate, Became Law.
term: The period of Congress is displayed, ranging from 106 to 116.
url: The link to each bill to the www.congress.gov webpage.
congress: The data frame covers the period from the 106th Congress (1999-2000) to the 116th Congress, (2019–2020).
title: The official title of each bill is listed.
s/h: The label "Sen" shows that the Senate deals with the bill, "Rep" show that the House of Representatives deals with the bill.
last name: The last name of the sponsor and co-sponsor is listed.
first name: The first name of the sponsor and co-sponsor is listed.
party: The party membership of the sponsor and co-sponsor is listed, distinguishing between Republicans (0), Democrats (1), and Independent members of Congress (2).
state: The state which is represented by the sponsor and co-sponsors of the bill is listed.
district: The district of each policy-maker is listed. The district abbreviation only appears for the representatives of the House and is NA for the representatives of the Senate.
co-sponsors: The label "S" represents the sponsors of each bill, "C" the co-sponsors.
full info mp: This variable includes the Committee membership, full name, state, district and party membership of each representative as provided by the Congress.gov hompepage (Congress.gov, 2021).
sex: The sex of each policy-maker is distinguished between "female" and "male".
chamber seniority: For members of the House of Representatives the term served in Congress is used. For Senate members the term served in Congress is used. The variable represents the total time of service, not just the continuous one. **lifetime score:** The lifetime score provided by League of Conservation Voters (2020) shows how environmentally friendly a policy-maker's decisions are. The information is only available for a subset of the data.
regions: The United States can be separated in multiple regions. The data distinguishes between the west, midwest, northeast, southeast, and the rust belt.
majority party: This variable displays what party had the majority in Congress in a given term, distinguishing between a majority held by the Republicans (0), the Democrats (1), or when one party had the majority in one chamber and the other party the majority in the other chamber (2).

nr co-sponsors: The number of co-sponsors of each bill is listed.
nr pages: This variable indicates the number of pages of a bill downloaded as PDF document.

2. Policy Instruments

The policy instrument variables cover eight distinct levels (Ingold et al., 2016; IEA, 2019; Schmidt and Sewerin, 2019a). Several instruments can appear in one bill.

regulatory: The state uses regulatory authority to change the behaviour and activities of relevant stakeholders by directing the flow of money. These instruments include order and prohibition, regulation, codes and standards, licences, charges, and obligation schemes.
general economic: These policies aim at changing the behaviour and activities of relevant stakeholders based on market mechanisms by providing financial and fiscal incentives. These instruments include subsidies, loans, emission trading rights and direct investment, as well as fees, grants, provisions and credits.
tax: These policies aim at changing the behaviour and activities of relevant stakeholders based on tax breaks, tax credits and other interventions which include taxes.
tariff: These policies aim at changing the behaviour and activities of relevant stakeholders based on tariffs.
organisation: These instruments are targeted at direct state activities. They include state-owned enterprises (i.e. state investment bank or state-owned utilities), state-investment (i.e. infrastructure) and public enterprises, and the creation of new advisory or government bodies.
rdd: These policy instruments target, finance and incentivise research, development and deployment of new technologies. They include demonstration projects, research programs and research funds.
information: This instrument increases knowledge among the relevant stakeholders. I include information provision and campaigns, advice and performance labels, and supporting information and aid in implementation by existing government bodies.
education: This instrument includes education and job creation related to energy storage, batteries and electric vehicles. **voluntary:** These instruments aim at increasing voluntary activities of relevant stakeholders. They include public, voluntary schemes, unilateral commitments of the private sector, round tables and fora.

3. Technology Specificity Policy Design Dimension

Policies target different technology levels (Schmidt et al., 2016). They can be categorised on five different levels. The lowest level a bill touched upon was coded as 1.

economy: The policy affects no specific sector but various economic sectors which are related to battery technology. If the policy is not more specific, it is considered as neutral.
field: The policy targets particular categories of battery technology within a sector.
technology: One or several single battery specific technologies are targeted. They may include electrochemical, thermal, mechanical, chemical, or electrical/electromagnetic energy storage. Everything related to electric vehicles which is not further specified falls into this category (e.g.plug-in electric vehicles, plug-in hybrid electric vehicles, and hybrid electric vehicles).
subtechnology: The policy targets a specific subset of technology, including advanced batteries. It may include a lithium-ion battery, lead-acid battery, nickel-based batteries, flow batteries, metal-air batteries, molten salt batteries, and supercapacitors; molten salt thermal storage, ice thermal storage, latent heat thermal storage; flywheels, pumped hydro, gravity batteries, compressed air energy storage; power to gas, hydrogen, biofuels; and capacitors, as well as superconducting magnets.
design: Technology design: These policies target the design of batteries. This level includes lithium iron phosphate (LFP), nickel manganese cobalt (NMC), nickel cobalt aluminum (NCA), lithium cobalt oxide (LCO), lithium titanate (LTO), lithium manganese oxide (LMO), solid state LIB, valve regulated lead acid (VRLA) batteries, nickel metal hydride batteries, nickel cadmium batteries, nickel iron batteries, vanadium redox flow batteries, zinc bromine flow batteries, organic flow batteries, lithium-air batteries, aluminium-air batteries, sodium sulphur batteries, sodium-nickel chloride (Zebra) batteries, as well as lithium-polymer batteries, lithium thionyl chloride batteries and zinc-air batteries.
ts ordinal: This variable summarises the technology specificity level from economy (1) to design (5) in one ordinally coded variable.

4. Application Specificity Policy Design Dimension

Policies target different application levels (Schmidt et al., 2016). They can be categorised on four different levels. The lowest level a bill touched upon was coded as 1. For more details, cf Figure 16.

economy: The policy affects all applications of a certain technology and does not distinguish between different applications. This policy is considered to be application neutral.
industry: The policy targets the applications within a distinct sector of the economy or industry. This level can be divided into the categories consumer electronics, automotive, and electric power.
application: On this level of specificity, single or multiple applications within a specific field of industry are targeted.
subapplication: If the policy is targeted at a specific subset of an application.
as ordinal: This variable summarises the application specificity level from economy (1) to subapplication (4) in one ordinally coded variable.

5. Committees

Committees: All the involved committees are listed.
Number Committees: There are often several committees involved in the law-making process. This variable indicates how many committees were involved in the law-making process (Clinton and Lapinski 2006).
List of Committees: There are often several committees involved in the law-making process. The rest of the data frame shows on a 0/1 scale which committee was involved in introducing bills related to energy storage, batteries, and electric vehicles. The following committees were engaged at least once: 1) House: Energy and Commerce 2) House: Commerce 3) House: Education and Labor 4) House: Science, Space and Technology 5) House: Science and Technology 6) House: Science 7) House: Ways and Means 8) House: Armed Service 9) House: Appropriations 10) House: Natural Resources 11) House: Resources 12) House: Transportation and Infrastructure 13) House: Agriculture 14) House: Financial Service 15) House Budget 16) House Veteran's Affairs 17) House: Judiciary 18) House: Foreign Affairs 19) House: International Relations 20) House: Oversight and Reform 21) House: Oversight and Government 22) House: Oversight and Government Reform 23) House: Government Reform 24) House: Government Reform and Oversight 25) House: Education and Workforce 26) House: Small Businesses 27) House: Homeland Security 28) House: Intelligence (Permanent) 29) House: Rules 30) House: Administration 31) Senate: Banking, Housing and Urban Affairs 32) Senate: Finance 33) Senate: Budget 34) Senate: Commerce, Science, and Transportation 35) Senate: Environment and Public Works 36) Senate: Energy and Natural Resources 37) Senate: Armed Services 38) Senate: Homeland Security and Governmental Affairs 39) Senate: Foreign Relations 40) Senate: Judiciary 41) Senate: Health, Education, Labour, and Pension 42) Senate: Agriculture, Nutrition, and Forestry 43) Senate: Appropriations

5. Economic Circumstances in the U.S. states

The value chain of a lithium-ion battery serves as the basis to separate firms into different industry sectors Battke et al. (2016); Stephan et al. (2017). Sector 1 includes the main components of a battery, sector 2 the peripheral components, sector 3 the battery cell system, sector 4 battery integration, and sector 5 the research sector across all industry sectors. Sectors 1 to 3 together for the battery producing sector, whereas sector 4 represents the battery producing sector. The data on the economic circumstances exists for the years 1999 to 2018.

firms vc1: The number of firms of the industry sector manufacturing main battery components for each state.
firms vc2: The number of firms of the industry sector manufacturing peripheral battery components for each state.
firms vc3: The number of firms of the industry sector manufacturing battery cell systems for each

state.
firms vc4: The number of firms of the industry sector integrating batteries into multi-component applications for each state.
firms vc5: The number of firms researching along the value chain of a lithium-ion battery for each state.
empshare vc1: The employment share of the industry sector manufacturing main battery components per state.
empshare vc2: The employment share of the industry sector manufacturing peripheral battery components per state.
empshare vc3: The employment share of the industry sector manufacturing battery cell systems per state.
empshare vc4: The employment share of the industry sector integrating batteries into multi-component applications per state.
empshare vc5: The employment share for the sectors researching along the value chain of a lithium-ion battery per state.

5. Lobbying by industry sector

LobbyView (2021) provides data on the amount in USD spent on bills by lobbying firms. A discussion on the validity of this data can be found in the master thesis.

amount vc1: This variable shows the amount in USD spent on a particular bill by a firm of the industry sector manufacturing main battery components.
amount vc2: This variable shows the amount in USD spent on a particular bill by a firm of the industry sector manufacturing peripheral battery components.
amount vc3: This variable shows the amount in USD spent on a particular bill by a firm of the industry sector manufacturing battery cell systems.
amount vc4: This variable shows the amount in USD spent on a particular bill by a firm of the industry sector integrating batteries into multi-component applications.
amount vc5: This variable shows the amount in USD spent on a particular bill by a firm of the industry sector doing research along the value chain of a lithium-ion battery.
amount vc1: Based on "amount vc1", it is shown whether a bill attracted lobbying (1) or not (0).
amount vc2: Based on "amount vc2",it is shown whether a bill attracted lobbying (1) or not (0).
amount vc3: Based on "amount vc3", it is shown whether a bill attracted lobbying (1) or not (0).
amount vc4: Based on "amount vc4", it is shown whether a bill attracted lobbying (1) or not (0).
amount vc5: Based on "amount vc5", it is shown whether a bill attracted lobbying (1) or not (0).

A.2 Technology Specificity dictionary

Level	**Examples of technologies**
Economy	Neutral
Field	Energy storage
Technology	Electrochemical energy storage, thermal, mechanical, chemical, electrical/electromagnetic, *advanced batteries*
Sub-technology	(Lithium-ion battery, lead-acid battery, nickel-based batteries, flow batteries, metal air batteries, molten salt batteries, supercapacitors); (molten salt thermal storage, ice thermal storage, latent heat thermal storage); (flywheels, pumped hydro, gravity batteries, compressed air energy storage); (power to gas, hydrogen, biofuels); (capacitors, superconducting magnets)
Technological design	(LFP (lithium iron phosphate), NMC (nickel manganese cobalt), NCA (nickel cobalt aluminum), LCO (lithium cobalt oxide), LTO (lithium titanate), LMO (lithium manganese oxide), solid state LIB, VRLA (valve regulated lead acid) battery, nickel metal hydride battery, nickel cadmium battery, nickel iron battery, vanadium redox flow battery, zinc bromine flow battery, organic flow battery, lithium-air battery, aluminum-air battery, sodium sulphur battery, sodium-nickel chloride (Zebra) battery, *lithium-polymer battery, LTC (lithium thionyl chloride), zinc-air batteries*

Figure 15: Original Technology Specificity Dictionary

The dictionary has been developed by the Energy and Technology Policy Groups (EPG) at ETH Zürich (Schmidt et al., 2016). Some additionally identified categories are described in chapter 3.1 Dictionaries of the Seminar paper which I wrote in the seminar on "Topics in Public Policy: Governing the Energy Transition" (857-0103-00L) and for which I developed the first version of the "US Battery Storage Dataset 1999–2019". The paper will be made available in the supplementary material of this thesis.

A.3 Application Specificity dictionary

Economy	Industry	Application	Sub-application
Neutral	Consumer electronics	Health care	Pacemaker
			Mobile dialysis
		Personal devices	Phone
			Laptop
			Tablet
	Automotive	Passenger vehicle	Sedan/saloon
			SUV
		Commercial vehicle	Bus
			Truck
		2- and 3-wheel vehicle	Bicycle
			Scooter
			Motorcycles
		Trailer	Trailers
			Semi-trailers
		Special purpose vehicle	Logistics car
			Postal car
			Sanitation car
	Electric power	Power quality	RET smoothing
			Area and frequency regulation
			Voltage regulation
			End-consumer power quality
		Power reliability	Black start
			Reserve capacity
			End-consumer power reliability
		Increased utilization of existing assets	Load following
			RET firming
			T&D investment referral
			Increase of self-consumption
		Arbitrage	RET arbitrage
			Wholesale arbitrage
			End-consumer arbitrage

Figure 16: Original Application Specificity Dictionary

The dictionary has been developed by the Energy and Technology Policy Groups (EPG) at ETH Zürich (Sewerin et al., 2020). Some additionally identified categories are described in chapter 3.1 Dictionaries of the Seminar paper which I wrote in the seminar on "Topics in Public Policy: Governing the Energy Transition" (857-0103-00L) and for which I developed the first version of the "US Battery Storage Dataset 1999–2019". The paper will be made available in the supplementary material of this thesis.

A.4 Email correspondence with LobbyView on 30.3.2021 and 6.4.2021

Me: "I checked for some of my bills and could not find them. Does this mean that there was no lobbying activity on that particular bill? In other words, how complete is your database?"

Elden Griggs (Research Support Associate at LobbyView): "So in short, the process of linking bills to specific reports is actually really complicated and the team is still working on it. The long version/problem is that the lobbying reports contain the bills lobbied on, but bill numbers are not unique to years and so there can be multiple H.R. 1s across congresses (congress numbers are not included in the reports) and determining which congress is correct based on the lobbying report is a computationally difficult problem. Sadly, this means we are not ready to release the data right now. [. . .] Our data examines the issue text in the lobbying reports so in terms of the reports our data should be as far as I know very comprehensive, but as noted [above] which bills go to which reports is still a work in progress."

A.5 Finding an appropriate quantitative model

Initially, I calculated logistic regression models, once with the technology specificity as the dependent variable, once with the application specificity as the dependent variable. I split the dependent variables, application specificity and technology specificity, into two groups, a technology neutral and a technology specific category on the one hand, and an application neutral and an application specific category on the other hand. In a second step, control variables were added. To account for the longitudinal format of the data, which may lead to a violation of the iid-assumption, state and term fixed-effects were added. The disadvantage of the logistic regression model is that information is lost when categories are collapsed. This changes the research question to a very different one (UCLA, 2021b).

Given the network-like structure of the data, I continued by considering calculating a Temporal Network Autocorrelation Model (TNAM). The idea behind using such a model is that I assume that my observations are not fully independent of each other, which is strictly speaking necessary for regression models. The choice of one policy-maker to sponsor or co-sponsor a policy may depend on other policy-makers choice to support a policy. It is likely that members of Congress who support the same policies co-sit in the same committees or talk to each other in the House or the Senate. Moreover, it may be that policies formulated in one term show similarities to policies formulated in a subsequent year due to experiences and learning effects of policy-makers. TNAM can account for complex network dependencies among observations on the independent variable side resulting from non-random population sampling, and also account for time trends (Glaus et al., 2021). There are a few caveats concerning the application of a TNAM to the given data. TNAM requires cross-sectional or panel data (Leifeld, 2017). However, since policy-makers are elected into and out of office over the time period of 20 years, the data has a longitudinal structure but does not show the classical features of panel data. Furthermore, TNAM allows for binary outcome variables (Varone et al., 2017). Like the logistic regression model, this is associated with a loss of information, given the different outcome levels of the dependent variables.

To get a clearer picture on how industry pressure is associated with the different design levels of energy storage policies, ordinal logistic regression models should be calculated. Ordinal logistic regression is an extension of the binomial logistic regression. It is useful when multiple levels of the dependent variables with ordered categories exist, as it is the case for the technology-specificity and the application-specificity dimension of the energy storage bills (Vidhya, 2016). The models should be calculated once with technology specificity as the dependent variable, and a second time with the application specificity as the dependent variable. This approach was driven by the assumption that the outcome variables are truly ordered (UCLA, 2021b). The main assumption that needs to be met for an ordinal logistic regression model to be valid is the parallel regression, parallel lines or proportional odds assumption (Brant, 1990). It assumes that the relationship between all pairs of outcome groups is identical, i.e. that the relationship between the independent variables and for example the lowest vs all the higher categories of the dependent variable are the same as those between the second lowest category and all the higher categories. If this is not the case, we need different models to characterise the relationship between each pair of the outcome groups, otherwise one model is sufficient (UCLA, 2021c). The parallel regression assumption can be tested using the Brant test in R (Lee, 2019; Schlegel and Steenbergen, 2020). The assumption holds if all p-values are above 0.05. In that case, the the null hypothesis that the coefficients do not change across multiple cut points of the dependent variable, and thus that the parallel lines assumption holds, cannot be rejected (Liang et al., 2020). When testing my regression models, without and with control variables, the value for the overall model (Omnibus) and for the individual coefficients is below 0.05. In conclusion, either the tested models are misspecified (Williams, 2016), however, the chances that this is the case could be reduced by testing different combinations of control variables, or, an ordinal logistic regression model is not appropriate for the given data. Since the ordinal logistic regression models did not meet parallel regression assumption, the less strict alternative is to use multinomial logistic regression model (Liang et al., 2020).

A.6 Multinomial logisitc regression robustness checks

Regression tables underlying the predicted probability plots on p. 36 and 39 in the thesis

The remaining regression tables for the predicted probability plots in Figure 13 and Figure 12 are shown in Table 12 and 13.

Robustness checks using different time splits

To test the robustness of the thesis's multinomial regression models, I will test whether the results are comparable when splitting the data one term before and one term after the original data split.

First, the predicted probability plots for the robustness test are shown for the data splits 1999-2006 vs. 2007-2018, cf. 17 and 18. The results for the mechanisms of interest (producing sector/technology specificity and (using sector/application specificity) are not in line with the original results for this data split. This is likely because of the category sizes that partly do not include any observations, e.g. there is no policy designed on the economy level of the Technology Specificity dimension in the first period and only five policies designed on the Design level. The two regression tables are shown in Table 14 and 15. Note: some odds are really large, this is likely to be due to the very small number of data in these categories.

Second, the predicted probability plots for the robustness test are shown for the data splits 1999-2010 vs 2011-2018, cf. Figures 19 and 20. The results for the mechanisms of interest (producing sector/technology specificity and (using sector/application specificity) are in line with the original results for this data split! The two regression tables are shown in Tables 16 and 17.

Finally, I also tested whether using the control variable House vs Senate membership would be a good alternative to committee co-sitting to test for the collaboration among Congress members. However, for all the models calculated, the Akaike information criterion (AIC) was larger for the models with the House/Senate than for the models including committee membership. Moreover, including both variables was no option because of high multicollinearity. Therefore, I decided to use the committee variables to approximate collaboration among Congress members.

Table 12: Multinomial logistic regression with employment share in the Battery Producing Sector regressed on Application Specificity

	Dependent Variable: Application Specificity					
	Economy	Industry	Application	Economy	Industry	Application
	1999 - 2008	1999 - 2008	1999 - 2008	2009 - 2018	2009 - 2018	2009 - 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Employment Share in the Producing Sector	4.131^{***}	1.379^{***}	1.451^{***}	0.500	-1.372^{**}	0.868^{***}
	(0.383)	(0.314)	(0.247)	(0.316)	(0.619)	(0.325)
Democrats (Ref = Republicans)	0.295	1.667^{***}	1.153^{***}	0.636^{***}	1.994^{***}	1.091^{***}
	(0.411)	(0.300)	(0.162)	(0.226)	(0.452)	(0.229)
Chamber Seniority	0.085^{***}	0.043^{**}	0.017	0.015	0.015	0.031^{**}
	(0.021)	(0.019)	(0.013)	(0.015)	(0.021)	(0.014)
House Committee: Energy and Commerce	−0.311	1.272^{***}	-0.968^{***}	0.918^{***}	−0.804	0.456^{*}
	(0.475)	(0.400)	(0.242)	(0.245)	(0.519)	(0.251)
Senate Committee: Energy and Natural Resources	0.743	-7.328^{***}	1.740^{***}	-0.561^{*}	−0.474	-1.176^{***}
	(0.566)	(0.001)	(0.448)	(0.294)	(0.388)	(0.286)
House Committee: Ways and Means	-4.444^{***}	-1.053^{***}	2.178^{***}	-1.659^{***}	-2.821^{***}	-0.972^{***}
	(1.021)	(0.358)	(0.252)	(0.232)	(0.582)	(0.245)
Senate Committee: Finances	-2.031^{***}	2.208^{***}	−0.178	-0.656^{**}	-2.110^{***}	-0.543^{*}
	(0.787)	(0.455)	(0.297)	(0.308)	(0.533)	(0.302)
Number of Pages	-0.022^{***}	-0.017^{***}	-0.002^{***}	0.002^{***}	0.0003	-0.004^{***}
	(0.004)	(0.002)	(0.0003)	(0.001)	(0.001)	(0.001)
Constant	-8.205^{***}	-13.799^{***}	1.555^{***}	-0.687^{*}	-5.333^{***}	−0.290
	(0.443)	(0.425)	(0.281)	(0.359)	(0.680)	(0.354)
State Fixed Effects	yes	yes	yes	yes	yes	yes
Term Fixed Effects	yes	yes	yes	yes	yes	yes
Akaike Inf. Crit.	2,787.711	2,787.711	2,787.711	2,697.974	2,697.974	2,697.974

Note: *p<0.1; **p<0.05; ***p<0.01
The reference category of the dependent variable is Subapplication
The number or observations is n = 2576 for models 1-3 and n = 1228 for models 4-6.

Table 13: Multinomial logistic regression with employment share in the Battery Using Sector regressed on Technology Specificity

	Dependent Variable: Technology Specificity							
	Economy	Field	Technology	Design	Economy	Field	Technology	Design
	1999 - 2008	1999 - 2008	1999 - 2008	1999 - 2008	2009 - 2018	2009 - 2018	2009 - 2018	2009 - 2018
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment Share in the Battery Using Sector	-1.874^{***}	-0.779^{***}	-0.359^{***}	-2.126^{***}	-0.260	-0.717^{**}	0.095	0.941^{***}
	(0.256)	(0.063)	(0.059)	(0.170)	(0.197)	(0.298)	(0.256)	(0.171)
Democrats (Ref = Republicans)	12.787^{***}	1.546^{***}	-0.670^{***}	0.361	-0.976^{*}	2.321^{***}	1.878^{***}	-0.704^{*}
	(0.143)	(0.248)	(0.127)	(0.777)	(0.570)	(0.411)	(0.352)	(0.373)
Chamber Seniority	-0.006	-0.065^{***}	-0.049^{***}	-0.120	-0.035	-0.017	0.031^{**}	-0.033
	(0.186)	(0.015)	(0.010)	(0.147)	(0.033)	(0.025)	(0.016)	(0.025)
House Committee: Energy and Commerce	-6.537^{***}	-0.681^{***}	-0.105	-4.137^{***}	-7.467^{***}	3.442^{***}	-0.357	2.425^{***}
	(0.602)	(0.192)	(0.140)	(0.007)	(0.002)	(0.656)	(0.293)	(0.440)
Senate Committee: Energy and Natural Resources	-8.171^{***}	-1.730^{***}	-1.394^{***}	1.530^{**}	3.486^{***}	5.015^{***}	-0.988^{***}	4.457^{***}
	(0.005)	(0.448)	(0.367)	(0.683)	(0.673)	(0.766)	(0.325)	(0.576)
House Committee: Ways and Means	-11.602^{***}	-3.141^{***}	-1.372^{***}	-10.878^{***}	-7.384^{***}	0.067	-2.015^{***}	1.445^{***}
	(0.032)	(0.240)	(0.194)	(0.015)	(0.002)	(0.349)	(0.293)	(0.353)
Senate Committee: Finances	-9.747^{***}	-0.859^{***}	-0.235	0.440	0.333	2.811^{***}	-0.748^{**}	4.065^{***}
	(0.003)	(0.323)	(0.242)	(0.601)	(1.138)	(0.788)	(0.314)	(0.529)
Number of Pages	-0.018	-0.009^{***}	-0.002^{***}	-0.003	-0.002	-0.003^{***}	-0.009^{***}	0.004^{***}
	(0.019)	(0.001)	(0.0003)	(0.011)	(0.003)	(0.001)	(0.002)	(0.001)
Constant	-0.143	-18.531^{***}	20.303^{***}	20.283^{***}	-2.610^{**}	-6.262^{***}	-1.865	-16.536^{***}
	(0.140)	(0.393)	(0.461)	(0.328)	(1.126)	(1.920)	(1.661)	(1.120)
State Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Term Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Akaike Inf. Crit.	3,807.683	3,807.683	3,807.683	3,807.683	2,121.842	2,121.842	2,121.842	2,121.842

Note: *p<0.1; **p<0.05; ***p<0.01
The reference category of the dependent variable is Subtechnology
The number or observations is n = 2576 for models 1-4 and n = 1228 for models 5-8.

Table 14: Multinomial logistic regression with employment share in the battery producing sector regressed on Technology Specificity (robustness check, 1999–2006 [models 1-4] vs. 2007–2018 [models 5-8])

	Dependent Variable: Technology Specificity						
	Economy	Field	Technology	Design	Economy	Field	Technology
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment Share in the Battery Producing Sector	202.216***	0.083	23.490***	−0.571	−2.351***	−0.334	−0.338
	(1.319)	(0.473)	(0.00000)	(0.862)	(0.420)	(0.344)	(0.474)
Democrats (Ref = Republicans)	−26.990***	−1.684***	−8.561***	−0.555	2.137***	0.348***	−0.775**
	(0.629)	(0.408)	(0.000)	(0.487)	(0.225)	(0.124)	(0.337)
Chamber Seniority	0.056	−0.054*	1.118***	−0.031	−0.018	−0.011	−0.042*
	(0.351)	(0.030)	(0.00000)	(0.028)	(0.012)	(0.009)	(0.023)
House Committee: Energy and Commerce	22.518***	1.323	51.549***	−1.179	0.460**	0.512***	2.298***
	(1.975)	(1.064)	(0.000)	(1.062)	(0.179)	(0.142)	(0.427)
Senate Committee: Energy and Natural Resources	18.322***	0.265	−58.642***	3.013***	0.476	−0.823***	4.133***
	(1.238)	(1.213)	(0.000)	(0.580)	(0.296)	(0.252)	(0.540)
House Committee: Ways and Means	−103.240	−3.597***	−104.851***	−6.023***	−1.514***	−0.649***	1.324***
		(1.132)	(0.000)	(0.306)	(0.198)	(0.160)	(0.341)
Senate Committee: Finances	−215.464	1.846*	−56.980***	−0.174	−0.139	−0.450**	4.062***
		(0.949)	(0.000)	(0.999)	(0.273)	(0.218)	(0.511)
Number of Pages	0.018***	0.003***	−0.068***	−0.003	−0.015***	−0.014***	0.003***
	(0.006)	(0.001)	(0.00003)	(0.003)	(0.001)	(0.001)	(0.001)
Constant	−75.879***	263.807***	174.073***	−4.661***	−1.810***	−1.330***	−9.262***
	(1.204)	(0.713)	(0.00000)	(0.973)	(0.381)	(0.272)	(0.924)
State Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Term Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Akaike Inf. Crit.	820.874	820.874	820.874	4,859.454	4,859.454	4,859.454	4,859.454

Note: *p<0.1; **p<0.05; ***p<0.01

The reference category of the dependent variable is Application

Table 15: Multinomial logistic regression with employment share in the battery using sector regressed on Application Specific (robustness check, 1999–2006 [models 1-3] vs. 2007–2018 [models 4-6])

	Dependent Variable: Application Specificity					
	Economy	Industry	Application	Economy	Industry	Application
	(1)	(2)	(3)	(4)	(5)	(6)
Employment Share in the Battery Using Sector	-3.891^{***}	-1.782^{***}	-0.479^{***}	0.032	-0.519^{***}	0.006
	(0.254)	(0.140)	(0.144)	(0.102)	(0.070)	(0.076)
Democrats (Ref = Republicans)	-10.791^{***}	-0.034	-1.518^{***}	0.689^{***}	1.777^{***}	1.496^{***}
	(0.087)	(0.715)	(0.548)	(0.186)	(0.277)	(0.138)
Chamber Seniority	0.230	0.057	-0.029	0.036^{***}	0.011	0.015
	(0.245)	(0.048)	(0.034)	(0.012)	(0.014)	(0.011)
House Committee: Energy and Commerce	-13.309^{***}	4.822^{***}	0.941	0.347	-0.059	-0.604^{***}
	(0.020)	(0.845)	(0.906)	(0.212)	(0.277)	(0.168)
Senate Committee: Energy and Natural Resources	-0.231	-26.104^{***}	0.731	-0.889^{***}	-0.728^{**}	-0.617^{***}
	(1.284)	(0.000)	(0.841)	(0.259)	(0.328)	(0.237)
House Committee: Ways and Means	5.337^{**}	2.710^{***}	5.114^{***}	-2.594^{***}	-4.229^{***}	-0.110
	(2.718)	(0.787)	(1.012)	(0.212)	(0.339)	(0.181)
Senate Committee: Finances	-20.500^{***}	6.175^{***}	0.955	-1.251^{***}	-0.859^{***}	-0.637^{***}
	(0.016)	(1.069)	(0.636)	(0.282)	(0.323)	(0.238)
Number of Pages	-0.009^{**}	-0.038^{***}	-0.009^{***}	0.003^{***}	0.003^{***}	0.003^{***}
	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-9.078^{***}	-24.931^{***}	2.327^{*}	1.242	1.681^{***}	2.485^{***}
	(0.595)	(0.790)	(1.231)	(0.776)	(0.513)	(0.573)
State Fixed Effects	yes	yes	yes	yes	yes	yes
Term Fixed Effects	yes	yes	yes	yes	yes	yes
Akaike Inf. Crit.	813.075	813.075	813.075	4,695.317	4,695.317	4,695.317

Note: *p<0.1; **p<0.05; ***p<0.01
The reference category of the dependent variable is Subapplication

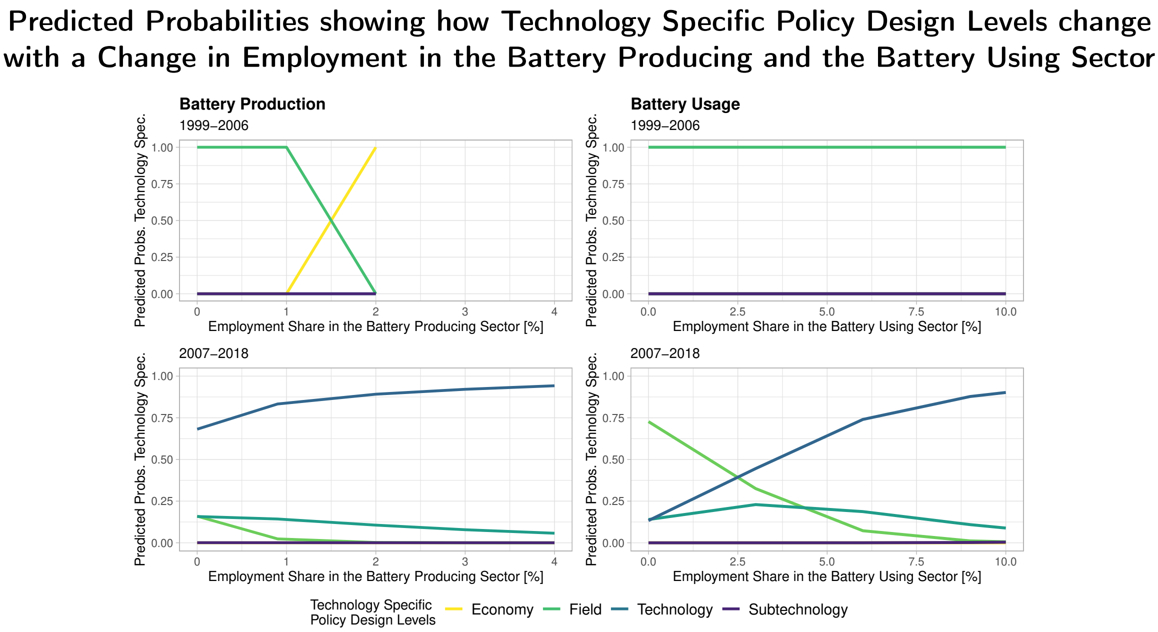

Figure 17: Predicted Probability Plots for Technology Specific Policy Design Levels (robustness check 1)

Robustness check splitting the data for 1999–2006 and 2007–2018. *Souce:* Own figure.

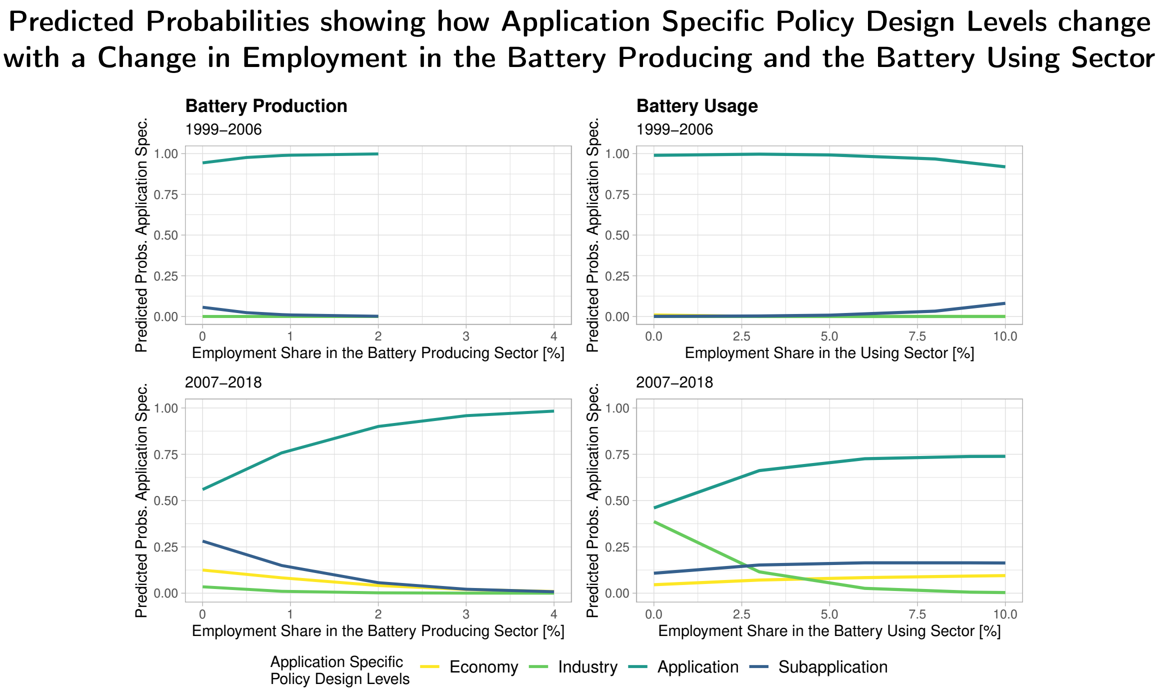

Figure 18: Predicted Probability Plots for Application Specific Policy Design Levels (robustness check 1)

Robustness check splitting the data for 1999–2006 and 2007–2018. *Souce:* Own figure.

Table 16: Multinomial logistic regression with employment share in the battery producing sector regressed on Technology Specificity (robustness check, 1999–2010 [models 1-4] vs. 2011–2018 [models 5-8])

	Dependent Variable: Technology Specificity							
	Economy	Field	Technology	Design	Economy	Field	Technology	Design
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment Share in the Battery Producing Sector	−1.155*	2.137***	−1.104***	16.637***	−1.535***	−2.932**	0.073	−0.269
	(0.613)	(0.255)	(0.198)	(0.640)	(0.533)	(1.328)	(0.664)	(0.692)
Democrats (Ref = Republicans)	2.201***	1.563***	−0.219*	1.671*	−2.209**	2.092***	1.613***	−1.033**
	(0.840)	(0.224)	(0.114)	(0.985)	(0.866)	(0.747)	(0.511)	(0.446)
Chamber Seniority	0.116*	−0.065***	−0.043***	−0.223**	−0.047	−0.100**	−0.003	−0.048
	(0.064)	(0.013)	(0.009)	(0.091)	(0.041)	(0.047)	(0.025)	(0.029)
House Committee: Energy and Commerce	−0.939	−0.522***	−0.077	−5.083***	−11.091***	24.701***	−0.322	3.331***
	(0.973)	(0.185)	(0.133)	(0.010)	(0.0004)	(0.495)	(0.381)	(0.541)
Senate Committee: Energy and Natural Resources	−5.050***	−0.342	−1.366***	1.684*	4.184***	−13.459***	−0.472	5.284***
	(0.030)	(0.302)	(0.260)	(0.901)	(0.882)	(0.000)	(0.569)	(0.690)
House Committee: Ways and Means	−11.599***	−3.261***	−2.128***	−9.053***	−10.547***	1.205**	−0.588	2.107***
	(0.226)	(0.230)	(0.169)	(0.053)	(0.0003)	(0.497)	(0.367)	(0.397)
Senate Committee: Finances	−0.613	−0.843***	−0.639***	−1.470**	−20.245***	23.807***	−0.261	4.771***
	(1.033)	(0.293)	(0.211)	(0.726)	(0.00000)	(0.483)	(0.457)	(0.633)
Number of Pages	0.008***	−0.010***	−0.003***	0.006**	−0.018**	−0.002*	−0.008***	0.007***
	(0.003)	(0.001)	(0.0003)	(0.003)	(0.007)	(0.001)	(0.002)	(0.002)
Constant	−18.722***	−25.524***	19.935***	5.044***	1.365	−28.331***	−6.745***	−2.419***
	(0.573)	(0.326)	(0.307)	(0.762)	(1.297)	(0.744)	(0.710)	(0.931)
Akaike Inf. Crit.	4,475.375	4,475.375	4,475.375	4,475.375	1,456.480	1,456.480	1,456.480	1,456.480

Note: *p<0.1; **p<0.05; ***p<0.01
The reference category of the dependent variable is Application

Table 17: Multinomial logistic regression with employment share in the battery using sector regressed on Application Specific (robustness check, 1999–2010 [models 1-3] vs. 2011–2018 [models 4-6])

	Dependent Variable: Application Specificity					
	Economy	Industry	Application	Economy	Industry	Application
	(1)	(2)	(3)	(4)	(5)	(6)
Employment Share in the Battery Using Sector	0.283^{***}	0.318^{***}	0.098^{*}	-0.253^{*}	-2.290^{***}	-0.572^{***}
	(0.078)	(0.070)	(0.054)	(0.147)	(0.092)	(0.124)
Democrats (Ref = Republicans)	0.741^{***}	2.176^{***}	1.374^{***}	-0.435	1.437^{**}	0.044
	(0.271)	(0.266)	(0.133)	(0.299)	(0.559)	(0.356)
Chamber Seniority	0.060^{***}	0.049^{***}	0.036^{***}	0.004	0.037	0.001
	(0.016)	(0.016)	(0.011)	(0.020)	(0.029)	(0.022)
House Committee: Energy and Commerce	-0.862^{***}	1.009^{***}	-0.628^{***}	1.791^{***}	-0.647	0.323
	(0.311)	(0.339)	(0.195)	(0.302)	(0.615)	(0.324)
Senate Committee: Energy and Natural Resources	-1.133^{***}	0.917^{**}	0.346	-0.283	-2.561^{***}	-1.025^{**}
	(0.380)	(0.404)	(0.256)	(0.358)	(0.669)	(0.434)
House Committee: Ways and Means	-2.390^{***}	-1.398^{***}	1.282^{***}	-1.494^{***}	-3.020^{***}	0.047
	(0.352)	(0.306)	(0.200)	(0.281)	(0.714)	(0.330)
Senate Committee: Finances	-1.042^{***}	1.635^{***}	-0.166	-1.006^{***}	-2.442^{***}	-0.584
	(0.375)	(0.385)	(0.254)	(0.377)	(0.604)	(0.417)
Number of Pages	-0.003^{***}	-0.013^{***}	-0.002^{***}	0.001^{*}	0.001	-0.006^{***}
	(0.001)	(0.002)	(0.0003)	(0.001)	(0.001)	(0.001)
Constant	-7.830^{***}	-14.050^{***}	2.117^{***}	3.254^{***}	7.258^{***}	5.505^{***}
	(0.473)	(0.412)	(0.380)	(0.908)	(0.658)	(0.773)
Akaike Inf. Crit.	3,990.101	3,990.101	3,990.101	1,765.052	1,765.052	1,765.052

Note: *p<0.1; **p<0.05; ***p<0.01
The reference category of the dependent variable is Subapplication

Predicted Probabilities showing how Technology Specific Policy Design Levels change with a Change in Employment in the Battery Producing and the Battery Using Sector

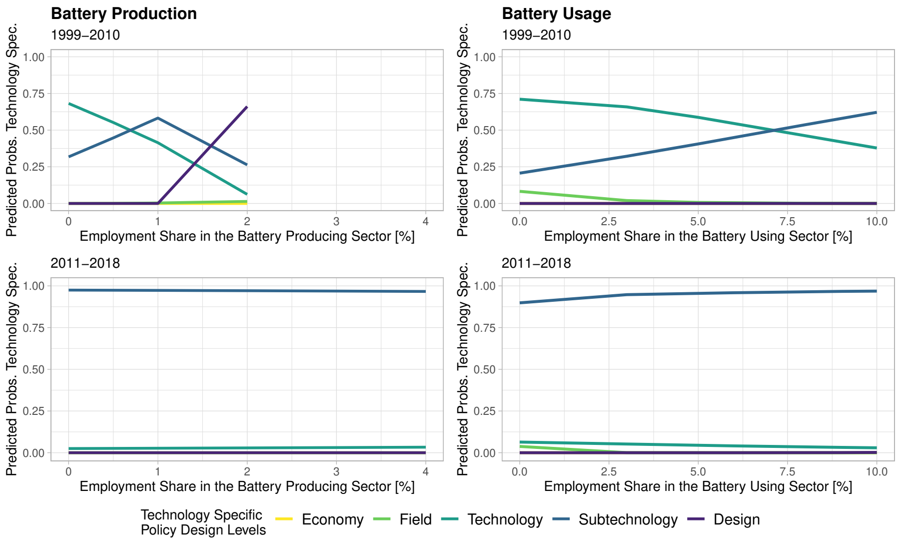

Figure 19: Predicted Probability Plots for Technology Specific Policy Design Levels (robustness check 2)

Robustness check splitting the data for 1999–2010 and 2011–2018. *Souce:* Own figure.

Predicted Probabilities showing how Application Specific Policy Design Levels change with a Change in Employment in the Battery Producing and the Battery Using Sector

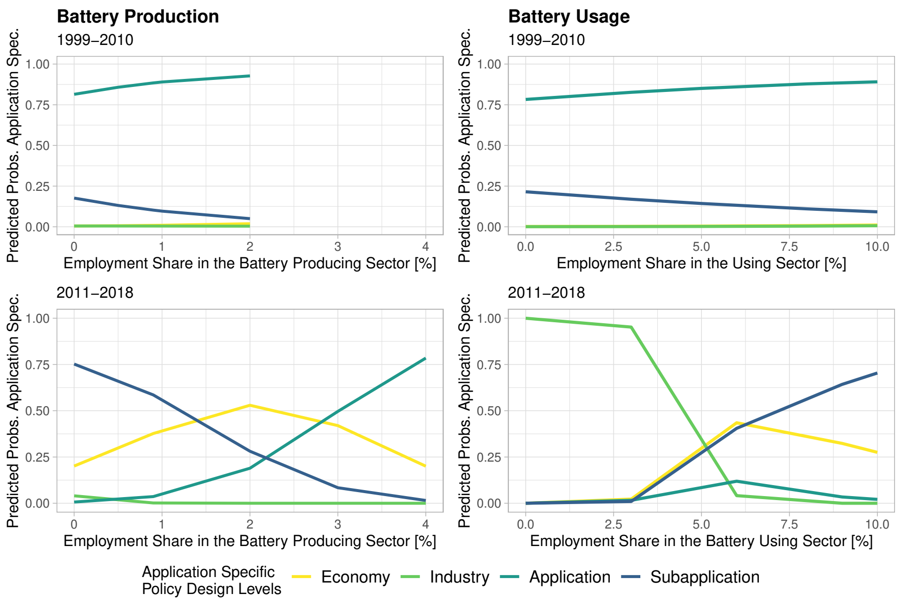

Figure 20: Predicted Probability Plots for Technology Specific Policy Design Levels (robustness check 2)

Robustness check splitting the data for 1999–2010 and 2011–2018. *Souce:* Own figure.

A.7 The most active firms of the battery producing sector lobbying for battery storage policies

Battery Producing Sector	Frequency
AMERICAN PACIFIC	18
Air Products and Chemicals, Inc.	12
DOW AGROSCIENCES	9
CHEMTURA CORPORATION	3
CLIFFS NATURAL RESOURCES INC.	3
DCP Midstream, LLC	3
Eaton Corporation	3
Jupiter Aluminum Corporation	3
NUCOR CORPORATION	3

Table 18: Most active firms of the battery producing sector that lobbied for battery storage policies.

Battery Using Sector	Frequency
EDISON ELECTRIC INSTITUTE	30
ICE ENERGY, INC.	24
DELPHI	18
Lennox International	12
Securing America's Future Energy Alliance	9
Beacon Power Corporation	6
CENTEX CORP	6
Gary Williams Energy Corporation	6
General Dynamics	6
Hovwest/K. Hovnanian Enterprises	6
Joy Global Inc.	6
KB Home	6
Lennar Corporation	6
M & M ENERGY LLC	6
M.D.C. Holdings, Inc.	6
M/I Homes, Inc.	6
Meritage Homes Corporation	6
Orleans Home Builders	6
Pulte Homes Inc.	6
Shea Homes Inc.	6
Standard Pacific Corporation	6
Toll Brothers, Inc.	6
TOUSA, Inc.	6
Volkswagen Group of America, Inc.	6

Table 19: Most active firms of the battery using sector that lobbied for battery storage policies

A.8 Exploration of lobby firms' policy interests

	Lobbyed by Producing Sector	Lobbyed by Using Sector	Extract from Summary	Topics
1	1	0	Title II: Energy Tax Provisions - (Sec. 201) Extends through 2008: (1) the tax credit for electricity produced from certain renewable resources; (2) the tax credit for holders of clean renewable energy bonds; (3) the tax deduction for energy efficient commercial buildings; (4) the tax credit for new energy efficient homes; (5) the tax credit for residential energy efficient property; (6) the energy tax credit; and (7) special excise tax rates for qualified methanol and ethanol fuel.	Renewable energies
2	1	0	Amends federal transportation law to direct the Secretary of Transportation to develop a national tire fuel efficiency program for passenger cars and light trucks." Terminates the limitation on the number of qualified hybrid and advanced lean burn technology vehicles eligible for the alternative motor vehicle credit.	Electric vehicles
3	0	1	Allows the Secretary to authorize any military installation to accept any financial incentives, financial assistance, or services generally available from a gas or electric utility or state or local government to use or construct an energy system using solar or another renewable form of energy, if consistent with DOD energy performance goals and plans.	Renewable energies
4	0	1	Comprehensive American Energy Security and Consumer Protection Act - Title I: Federal Oil and Gas Leasing - Subtitle A: Outer Continental Shelf Oil and Gas Leasing	Energy security
5	1	1	Title I: Energy Production Incentives - Subtitle A: Renewable Energy Incentives - (Sec. 101) Extends the tax credit for the production of electricity from renewable resources: (1) through 2009 for wind and refined coal facilities; and (2) through 2010 for closed and open-loop biomass, geothermal or solar energy, small irrigation power, landfill gas, trash combustion, and hydropower facilities. Modifies tax credit rules for refined coal, trash, and biomass facilities and for hydropower production.	Renewable energies
6	0	1	Division B: Energy Improvement and Extension Act of 2008 - Energy Improvement and Extension Act of 2008 - Title I: Energy Production Incentives - Subtitle A: Renewable Energy Incentives	Renewable energies
7	1	1	Establishes the Energy Security Fund to implement the Alternative Fuels Grant Program, which the Secretary of Energy, acting through the Department of Energy (DOE) Clean Cities Program, shall establish to expand the availability of alternative fuels to consumers. Sets forth conditions of supply shortages under which the President is authorized to declare that a federal energy emergency exists	Energy security
8	1	1	Title I: Energy Security Through Improved Vehicle Fuel Economy - Subtitle A: Increased Corporate Average Fuel Economy Standards - Ten-in-Ten Fuel Economy Act - (Sec. 102) Amends federal transportation law to instruct the Secretary of Transportation (Secretary in this title) to prescribe separate average fuel economy standards for passenger and for non-passenger automobiles for model years 2011-2030. Subtitle B: Improved Vehicle Technology - (Sec. 131) Instructs the Secretary of Energy to establish a competitive grants program to: (1) encourage the use of plug-in electric drive vehicles or other emerging electric vehicle technologies by governmental and quasi-governmental entities and private or nonprofit entities; and (2) conduct qualified electric transportation projects.	Energy security Electric vehicles
9	0	1	Subtitle C: Energy Security - (Sec. 2821) Revises generally requirements under a comprehensive master plan for achieving the energy performance goals of DOD. Requires the Secretary to submit	Energy Security

			a current version of such plan at or about the time each budget of the President is submitted to Congress. Requires the consideration of renewable forms of energy for repairs and renovations. (Under current law, such consideration is required only for new construction.) Expands the list of products that will be considered energy-efficient products for such purposes.	
10	1	1	American Clean Energy Leadership Act of 2009 - Title I: Clean Energy Technology Deployment - Subtitle A: Clean Energy Financing - (Sec. 103) Establishes in the Treasury the Clean Energy Investment Fund, consisting of: (1) amounts appropriated for administrative expenses to implement a loan guarantee program that provides incentives for innovative technologies; and (2) amounts deposited in or appropriated for the Fund. Subtitle C: Federal Renewable Electricity Standard - (Sec. 131) Urges the government to continue to support of the use and expansion of renewable energy and energy efficiency in the production and use of energy, the reduction of GHG emissions, and the dependence on foreign oil. Requires the Secretary to establish: (1) a program to support the deployment and integration of plug-in electric drive vehicles in multiple regions of the United States through the provision of financial support to state and local governments and other entities to assist in the installation of recharging facilities for electric drive vehicles; and (2) a grant program to assist states and local governments in the installation of recharging infrastructure for plug-in electric drive vehicles. Authorizes the Secretary to provide grants to state and local governments for demonstration and commercial application of rechargeable infrastructure.	Renewable energies Electric vehicles
11	1	1	Subtitle B: Energy Security - (Sec. 2821) Directs the Secretary to report to the defense and appropriations committees describing and assessing current DOD efforts toward the installation of solar panels and other renewable energy projects on military installations and facilities.	Energy security Renewable energies
12	0	1	Energy Security - (Sec. 331) Earmarks specified DOD O&M funds for the Director of Operational Energy Plans and Programs. Subtitle D: Energy Security - (Sec. 2841) Directs the Secretary to adopt an open protocol energy monitoring and utility control system specification for use throughout DOD in connection with a military construction project, military family housing activity, or other building activity. Allows the Secretary concerned, upon notification to the defense and appropriations committees, to waive such requirement if such Secretary determines that its inclusion in a construction project is not cost effective over the project's life cycle. Directs the Secretary to report to the defense and appropriations committees on items associated with the adoption of an energy monitoring and utility control system specification.	Energy security
13	1	1	American Clean Energy and Security Act of 2009 - Sets forth provisions concerning clean energy, energy efficiency, reducing global warming pollution, transitioning to a clean energy economy, and providing for agriculture and forestry related offsets. Includes provisions: (1) creating a combined energy efficiency and renewable electricity standard and requiring retail electricity suppliers to meet 20% of their demand through renewable electricity and electricity savings by 2020; (2) setting a goal of, and requiring a strategic plan for, improving overall U.S. energy productivity by at least 2.5% per year by 2012 and maintaining that improvement rate through 2030; and (3) establishing a cap-and-trade system for greenhouse gas (GHG) emissions and setting goals for reducing such emissions from covered sources by 83% of 2005 levels by 2050.	Renewable energies
14	1	1	National Energy Security Act of 2009 or the NESA of 2009 - Amends the Federal Power Act to revise requirements concerning the siting of interstate electric transmission facilities, including requiring the	Energy security

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			Federal Energy Regulatory Commission (FERC) to oversee planning for the development of a Clean Energy Superhighway.	
15	1	0	Authorizes the FAA Administrator to implement practices for the incorporation of energy-efficient measures in the construction and renovation of FAA air traffic control facilities.	-
16	0	1	) Charging America Forward Act - Amends the Internal Revenue Code to: (1) extend through 2014 the tax credit for purchasing a new qualified hybrid motor vehicle, increase the the amount of such credit for certain hybrid and heavy vehicles, and provide for the transferability of such credit; (2) increase and extend through 2014 the tax credit for alternative fuel vehicle refueling property; (3) increase the limitation on the number of new qualified plug-in electric drive motor vehicles manufactured in a taxable year that are eligible for a tax credit; (4) make refundable and provide for the transferability of the tax credit for new qualified plug-in electric drive motor vehicles; (5) allow accelerated depreciation of smart meters and smart grid systems; (6) allow a 50% tax credit for investment in qualified used energy storage property (30% for energy storage property used for onsite storage); and (7) allow a nonbusiness energy tax credit for qualified used energy storage property.	Electric vehicles
17	0	1	The bill authorizes appropriations and sets forth policies for Department of Energy national security programs, including the National Nuclear Security Administration.	Energy security
18	0	1	This bill addresses several provisions related to highway transportation infrastructure, including provisions to improve road safety, accelerate project completions, improve resiliency to disasters, and reduce highway emissions.	-
19	0	1	The bill also authorizes appropriations and sets forth policies for Department of Energy national security programs, including the National Nuclear Security Administration and the Defense Nuclear Facilities Safety Board	Energy security
20	1	1	Transportation, Housing and Urban Development, and Related Agencies Appropriations Act, 2020.	-

Figure 21: Extracts on energy and electricity the 20 bills that attracted lobbying by the battery producing and the battery using sector

ETH

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