PROPOSAL MASTER THESIS

Open Innovation in Battery Research

How firms' willingness to participate in consortia depends on governing rules for data sharing

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Introduction

This study examines a timely topic: advancing the state of battery technology from an organisational point of view. The examination of collaborative drivers in R&D productivity is motivated by three main phenomena.

First, there is a strong need to improve energy storage and thus battery performance from a societal point of view. Advanced batteries, such as those utilizing lithium-ion were worth $27 billion in 2014 and expected to gross $55 in 2020 (Taiyou Research 2015). It is anticipated that this need keeps accelerating due to climate goals, bold moves of the private sector in electric mobility and a growing demand in personal, medical and military devices that are powered by portable power.

Second, improving battery performance shares challenges with other fields that require convergence of basic research by academia, the public sector and applied research by industry. It is understood, that a joint effort trumps isolation to bring grand discoveries to commercial fruition in terms of time and efficiency. Likewise, there is robust evidence how the right amount and type of industrial partners improves academic innovation (Lin 2016). But to concert different stakeholders in order to maximize social as well as private gains remains a practical and scholarly challenge (Morandi 2013). Theoretical models explain competing and fragile equilibria if both academic and market based incentives exist (Mukherjee & Stern 2009): open and cumulative progress on the one hand, secret and divergent progress with lower social welfare on the other hand. In terms of for-profit firms, industrial partners intensify measures to appropriate knowledge the higher the degree of openness measured in number of sources and partners used across many sectors (Laursen & Salter 2014). However, nuanced strategies that utilize combinations of appropriation mechanisms and therefore harmonize with varying types of openness remain unexplored (ibid).

Third, the general trend of data-intensive scientific discovery (Hey et al. 2011) finds its way into battery research and development. An increased usage of digital technologies became practical on the level of materials up to how software increases efficiency in operating battery packs. Thereby, lower-cost discovery processes and lower-granularity learning processes from real-world experiments emerge (Kelly-Detwiler 2016). The importance of knowledge creation and dissemination with digital means can be assumed to rise, which motivates to explore collaboration from this perspective.

By exploring the link between appropriation mechanisms for digitally enabled forms of openness and firm participation, this study contributes to the practice of battery research and theory of Open Innovation (OI). The next section will explain why improving organizational arrangements is desirable in battery research and concludes with the research question. By reviewing literature, preliminary hypotheses are formulated about how choices of appropriation mechanisms influence the willingness to participate in a data-sharing consortia. The proposal will conclude with the methodology, its limitations and a preliminary table of contents.

Problem Definition

First, basic barriers to cumulative progress towards better batteries are explained by the interplay of a technical and knowledge sharing perspective. Afterwards, the most important inefficiencies in joint research consortia are highlighted. And lastly, assessing the role of digital knowledge sharing allows to frame a research question.

Lack of knowledge integration across sectors and firms

The quest for novel batteries is characterized by a costly trial-and-error process with a vast space of possible solutions (Crabtree 2015). Therefore, a sequential approach of transferring knowledge from academia to the private sector is ineffective. First, publishing a peer reviewed paper adds around two years until broad accessibility. Moreover, much needed “failures” are less rigorously communicated due to a publication bias in experimental material science (Raccuglia et. al 2016). Thus, experiments are duplicated and dead alleys not abandoned fast enough. Lastly, claims from the lab often don’t translate well to mass production because of narrow conditions required to reproduce them and unforeseen problems when scaling up (Bullis 2015).

In addition to problems stemming from researchers who are unaware of other’s up- and downstream results, accessing prior work that is known is another barrier. For example, Walsh et al. (2007) determined that negotiating for biomedical research materials takes academics more than a month for horizontal relationships (university-to-university) in 21% of the cases and 35% for vertical relationships (university-to-industry). Interestingly, patenting did not clearly increase refusals to share materials. Also, in the long-term, academic reuse is only moderately impeded by formal knowledge protection (Murray & Stern 2007). Therefore, the study is less concerned whether IPRs have been granted or not, but if there are frictions before such knowledge is created and the possible pathways to overcome them.

The inability to access knowledge from peers before or irrespective of patents is not only a problem in basic, but also in applied research. As an academic turned industrial researcher who was tasked to scale-up a beyond lithium-ion technology without sharing ideas outside the building, speaking in public or writing papers suspected, *“the problems with the science of solid-state batteries could be solved faster by conferring, even if cautiously, with other experts”* (LeVine 2015).

Consortia for joint research

Public-private partnerships (PPPs) are meant to address costs of accessing knowledge fully within and to varying degree outside their bounds. As case in point, experts agree that a consortium led by the Vehicle Technology Office advanced the state of vehicular batteries by about 6 years from 1998 to 2010 (Link et al 2015, p. 54). PPPs perform because of well-known mechanisms such as central pooling of IP, umbrella NDAs and overcoming differences in culture and incentive systems between academia and industry. Consortia like the JCESR further intensify knowledge exchange within their bounds (DOE Industrial Consortia Initiative Case Study). One novel mechanism includes frequent adaptations to a joint roadmap with the ability quickly react on failed experiments. In essence, PPPs reduce costs of integrating complementarity knowledge from multiple stakeholders in return for efforts to onboard them.

However, the model of a PPP is not without challenges. In the field of drug discovery, forging partnerships is reportedly taking up to several years or flatline all together due to concerns of IP ownership (Edwards 2008). In these cases, upfront costs and the ongoing costs of resolving conflicts outweighs perceived synergies and grant money (cf. Busom & Fernández-Ribasb 2008). Such complications prompted advocates to take IP stipulations entirely off McGill’s charter, a PPP for Neuroscience. Through that, a new equilibrium between increased R&D productivity vs. increased uncertainty in appropriating knowledge is embraced (Owens 2016). In McGill’s PPP, it is not mandated to release all findings into public domain, but left at the discretion of the individual researcher. However, it can be speculated that without rules to limit disproportional commercial gains or differences of the knowledge codified between patents and papers and/or a lack investment into scientific norms, a welfare maximizing equilibrium becomes unstable (Mukherjee & Stern 2009). Therefore, transaction costs to access knowledge are likely to accrue between individuals instead of in between IP departments. Also, technology which is closer to the market needs to be appropriable for much coveted industry partners, as a company representative commented on the McGill charter: *“If there's too little protection, there's no way to capture the value”* (Owens 2016).

In battery research specifically, there have been efforts to reduce time and uncertainty to onboard industrial partners through standardized contracts (Chao 2015a). At the same time, those standards imply that *“each project is completely airtight and isolated from [...] other projects”* per default (FAQ, Energy Storage Lab Berkeley). Thus, this setup excludes exploiting synergies from horizontal partnerships ex ante. With the high costs to establish consortia that integrate academia and multiple industrial partners in mind, the specifics of digitally enabled knowledge sharing and creation should be explored.

Digital collaboration

The purpose of this section is to establish where knowledge is created, transferred and recombined through digital means in battery research. The existence of such phenomena should provide a first clue where new forms of collaborative models are applicable. Examples include innovation from end-users (Baldwin & Hippel 2011), trading knowledge on online platforms (Dushnitsky & Klueter 2011) or broadcasting problems to a crowd of solvers (Felin & Zenger 2014). The core value chain for batteries can be segmented into three steps: (1) materials for cell components (electrodes, electrolytes, separators and other), (2) single cells and (3) battery systems or packs (Golembiewski et al. 2015).

An important approach to cut down costs of experimenting for new designs is *ab initio* calculation, or simulation by first principles. On the level of materials, it has become common practice to screen large arrays of candidate materials, select only the most promising for further real-world experiments and make them publicly available to others (Jain et al. 2016). Grounded within the larger field of material science, such databases found adoption by industry and academics. For example, the Materials Project registered around 8 million remotely downloaded records and 12,000 users with 71% from academia and 12,6% from industry (Persson, LBL Industry Day 2015). The resounding enthusiasm from battery and automotive industry evidences the value proposition of such large-scale repositories (e.g. being *"incredibly happy"* about the effort, appreciating the project's *"free and easy access"* and reducing weeks of work to 15min, ibid). The MaterialsProject also offers workflows to accept user contributions, thereby laying grounds for new collaborative models on the material level (Qu et al. 2016). Moreover, so-called “Apps” like the battery explorer as part of the Electrolyte Genome section of the MaterialsProject help researchers to reduce costs of discovering new designs (Chao 2016).

The need to reap cost and time savings across the entire value chain with predictive models, has been summarized by Pesaran et al. (2011, see Fig. 1). The CAEBAT project matured over the last years and produced several submodules. It was co-created between three industrial partners and academia, is of recently used by over 60 licensees (Smith et al. 2015) and has an open source variant (batterysim.org).

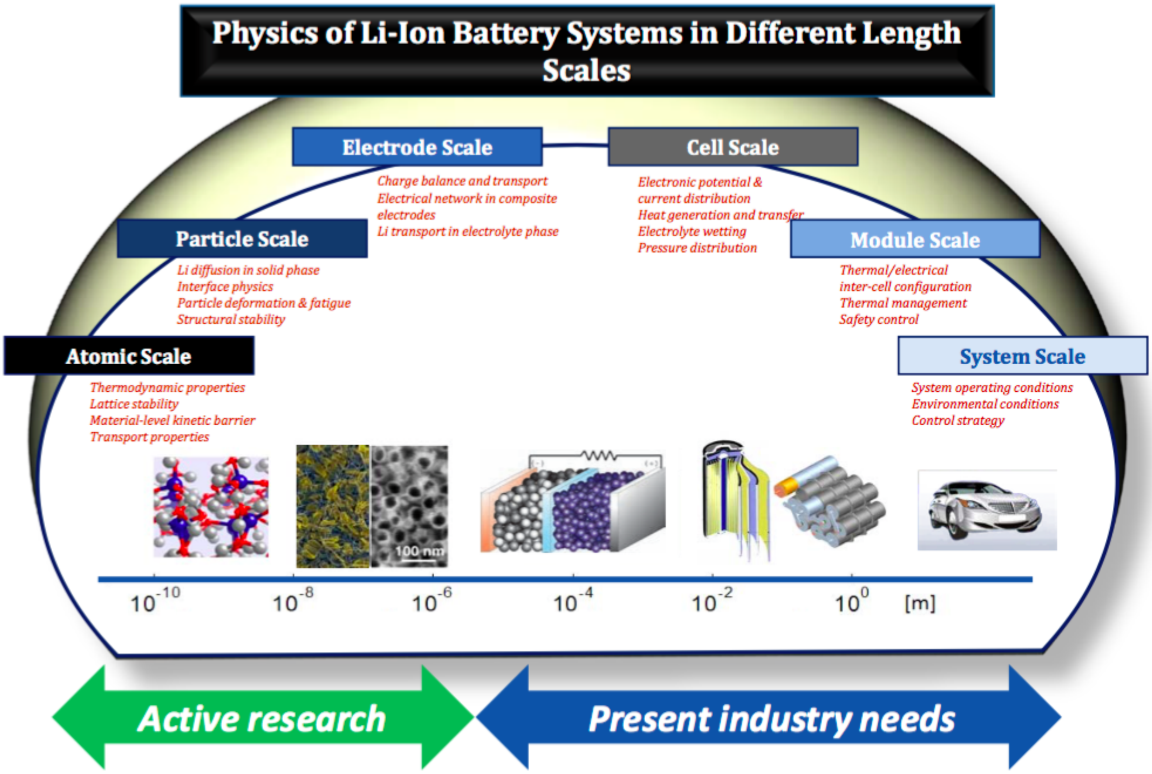

Fig. 1. Pesaran et al. (2011) on Computer-Aided Engineering for Electric Drive Vehicle Batteries (CAEBAT).

Simulation tools are present from various sources and for various scopes and purposes: material discovery, ageing prediction, cost, thermal and abuse modeling (see Fig 2. for preliminary overview). They are also coveted because of the aggregated knowledge they embody. For example, around 1998 a techno-economic battery model has been developed at a national lab and now *"GM uses it, everyone is using"* but *"they don't tell you what they've done"* (Crabtree 2015b). What is important and also seemingly uniform across predictive models, is the need to augment them with real-word data and thus, often source them from other organizations. For example, the National Renewable Energy Laboratory (NREL) tackles lifetime predictive modeling from two sides: first, an *ab initio* model (suitable to avoid cell designs with hampered lifetime due to mechanical stress) and second, an empirical model (suitable to develop advanced charging and system-control software that maximizes lifetime). One automotive partner Ford supplied end-of-life packs and requested a validated prediction model in return while other long-term data is produced with pack manufacturers. Yet, more the long-term data is needed (Smith et al. 2015). On the material level, systematic errors due to approximate computation methods or incomplete theories must be resolved with knowledge from the real world (Nosengo 2016).

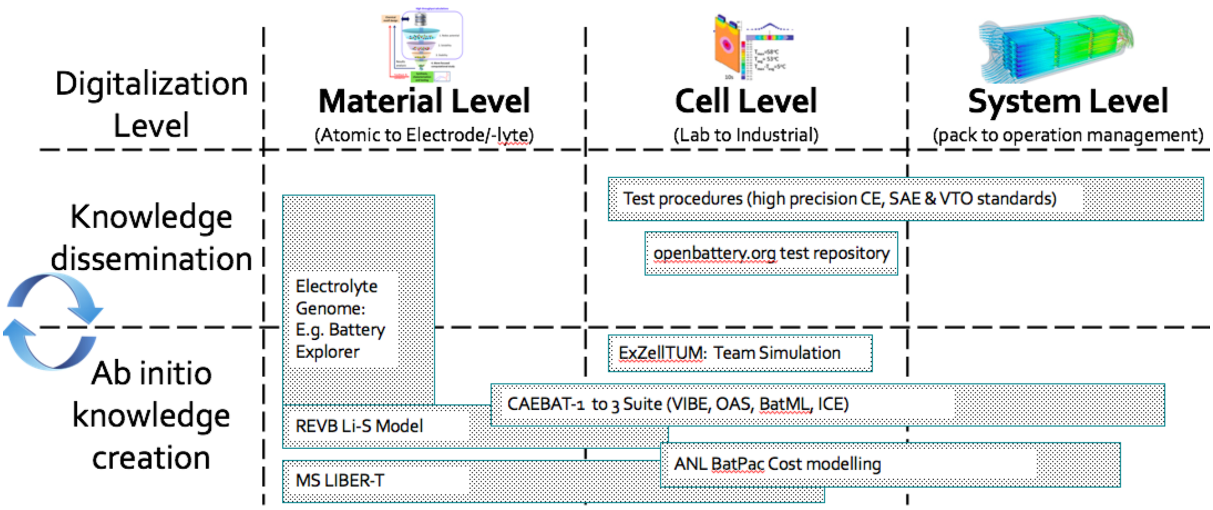

Fig. 2 Own illustration: Digitalization across the battery value chain (preliminary version).

Even without a corresponding design software, data in standardized form constitute trade secrets on the cell level: Jeff Dahn pioneered testing methods that allow to conclude long-term cycle-life in a short period of time. Industry has embraced this innovation and sent cells to be tested with novel additive formulations, without disclosing what they are (Dahn 2013). Both additive formulas and test results (time series data) are compact data which increase in value if recombined because of a generally synergistic effect when multiple additives are present (Wang et al. 2014). Lastly, there exist other data initiatives to make simulation and tests on the cell and system level more comparable and thus insightful. For example, the initiative between universities and a provider of Open Source battery management software host a platform where load cycles from electric vehicles and abuse discharge cycles are hosted (openbattery.org).

To summarize, digitization in battery research occurs on two important trajectories: knowledge dissemination and *ab initio* knowledge creation. The former method builds upon the ability to codify properties of materials, processes to synthesize such materials, and performance figures of real-life systems with existing or emerging standards. The latter is dependent on this codification in order to validate and enhance predictive models which can then be used to prototype new designs or operate systems more effectively. In both instances, data embodies value for owners and becomes more powerful if aggregated. As a preliminary conclusion, collaborating through the exchange of (rather standardized) data is a viable asset with which to compete and collaborate for certain constellations along the value chain.

Summary

The main organisational problems of jointly inventing better batteries are three-fold:

1. There are few incentives for academics to publish failed experiments
2. Knowledge from the basic science is insufficient to cross the “valley of death”
3. Integrating industrial partner’s know-how is a cumbersome process and aggravated if multiple rivals are involved

This study focuses on the third problem. Shared data repositories in general and predictive models augmented by data are one way to tackle a subset of this problem. Given the profit motive of industrial partners, the question becomes: which appropriation mechanisms (i.e. confidentiality guarantees, rights of first refusal, etc.) are ideal for firms to share data within consortia?
What is more, conditions differ both technologically and commercially along the value chain. This leads to the follow-up question, of how choices vary in that regard. In the next section literature review allows to formulate preliminary hypotheses.

Literature Review

From a firm’s point of view, consortia can be seen as multiple dyadic links to academia, suppliers, customers and competitors. Thus, several literature streams provide avenues for hypotheses. Rich case studies about data-sharing consortia are found in analogue industries, especially in the life sciences. Conceptual richness with regards to firm behavior on the other hand, is sourced from the Open Innovation (OI) and strategic alliance literature. The intersection of both streams also indicates the research gap that this study addresses. For example, Perkmann & Schildt (2015) examined a consortium between public sector organizations and competitors that resolved protein structures of future drug candidates.

Successful discoveries were mandated to become public domain. Thus, IPR mechanisms to appropriate knowledge were unavailable. The three reasons why partners still opted-in were their ability to (1) influence the academic research agenda, (2) hide their own agenda from rivals by voting which proteins to research only to a trusted committee and (3) appropriate discoveries by complementary assets. However, because the knowledge produced was from basic science, future studies should examine the willingness to participate in open data collaborations that are more applied. Thus, the exact preconditions that enable multiple firm participation in increasingly competitive research context are yet unknown. Perkmann & Schildt (2015) hypothesize, that stewardship about sensitive information and privileges, such as commercially protected or advance access then become more important. In other words, privileges are substitutes to openness. Nevertheless, protecting firms' research agenda is likely to have a positive effect on their willingness to share data, regardless of the degree of openness to outsiders. This is substantiated by a consortium for stem cell research that did not mandate to relinquish IPRs (Morrison et al. 2015). Initially, for-profit partners rejected a draft that required their detailed intent why to access materials for proprietary research. By weakening requirements to specify only a limited set of predefined cases and optionally, discuss ethically sensitive cases with the data custodian in private was hence accepted unanimously. In both situations, the role of a trusted middleman while focusing on the transactional value for horizontal partnerships is highlighted. This coincides with Rindfleisch's (2000) observation: trust is only relevant for enhancing vertical partnerships and plays no role for horizontal partnerships. In summary, it can be argued that:

> **H1:** Irrespective of the degree of openness to the outside, firms willingness to participate increases when their research agenda is protected from rivals by a trusted middleman.

Revisiting Perkman & Schildt (2015) yields another possible effect regarding experimental failures. Whereas all successful discoveries have been released to the public, the identity of proteins failed to be resolved were never disclosed. In light of the importance of sharing failures for battery research, this raises the question about the original intent to keep failed attempts secret. One possible explanation is that the consortium didn't want to signal the common but unsatisfied desire for a certain protein to outsiders, who could then be motivated to seek a patent instead. At this point, it is only clear that hiding failures was a deliberate choice, leading to speculate that:

H2: Firms willingness to participate is influenced (in either direction) whether experimental data is considered a failure or not.

Exploring isolated effects of data specific governance rules is an insufficient simplification though. Managers take into account the combinatorial effects of different appropriation mechanism (Fischer & Henkel 2013). For example, owning strong patent protection and a strong position in standard setting is seen detrimental. On the contrary, lower power through patents but equally strong position in standard setting is seen *"as a license to print money"* (ibid). Therefore, the task to hypothesize complex interactions between appropriation mechanisms in data-sharing partnerships will be completed through further literature review. For example, Rai et al. (2008) suggested a two-step process to lower cost and perceived risks of opportunism for participants: before joining, the synergy of potential industry partners is ascertained by a trusted custodian and after pooling know-how (again kept in custody), a protocol to share future revenues (and knowledge sharing) is devised based on predefined performance metrics of experiments to come.

Methodology

Fischer & Henkel's (2013) studied combinatorial effects perceived by managers of one firm and therefore ask to replicate findings in different settings, different industries and extend the limited set of appropriability mechanisms. To also satisfy the last condition, two steps are undertaken. First hypotheses are derived from analogue industries and theory to inform a guideline. Second, a mix of semi-structured and structured interviews is chosen as a means to explore fresh concepts (Bryman 2006). Structured elements will draw from the conjoint method of Fischer & Henkel (2013): participants are asked to rank constellations according to their preference and managerial judgement. The exploratory element will be achieved by asking for similar situations the interviewee experienced, explanations of their choice, further suggestions and possible improvements to a status quo. For a preliminary constellation, see Fig. 3.

As a pack manufacturer, you are working in a consortium to improve cell geometry standards and pack assembly. The programme tests 10 different cells (manufacturers, chemistries, geometries) by gathering detailed log data from the battery management system into a central repository over one year. It is expected that by trying different welding processes and fixation systems, pack efficiency can be increased by 15% over the whole life-time. The collective insight will be used by a university lab to design candidates for improved cell designs.

In addition, the consortium struck a deal with cell manufacturers that the final candidates will be exclusively available to participants for 3 years. Because of the high number of variations to test, 20 firms (more or less similar to yours) participate in this initiative.			
Constellation	**A**	**B**	**C**
Casting votes for new cell standard	Anonymous	Anonymous	Open
Identity protected by the lab	Yes	Yes	No
Unsuccessful variations will be published	Yes	No	No
Overlap with other participants, market wise (eg. car, truck, boat, home storage)	Diverse	Single	Diverse
Choose: (B)est and (W)orst			

Fig. 3. Example choices for interviewees for the last step in the value chain. Loosely based on technical claims of Kreisel, NREL life-time validation needs and intentions to move towards improved geometries (Kreisel, Tesla). First three items are from own hypotheses.

In the section about digital collaboration it was assumed and partly described how data has unique properties compared to knowledge referred to in literature, but also inherits most if not all properties. Therefore, it is expected that most well-known appropriation mechanisms and risks still apply, such as lead-time, asset complementarity (Teece 1992), influencing industry-wide movement (Alexy et al. 2013), complementarity of rivals' knowledge (e.g. Kehrel et. al 2016), the firm's capability to handle the paradox of sharing (Yang et al. 2014) and competitiveness on the market (Rindfleisch 2000). Those factors are either controlled for by incorporating them in the base constellation or discussed by asking counterfactual questions (e.g. *"what if you had much more time of exclusivity than presented in the beginning?"*).

The generalizability of this study is determined in two ways. First, battery research shares many structural similarities to other fields such as biotech, pharmaceutical and high-tech manufacturing (Satell 2016). Thus novel findings from a data-centric perspective will be applicable to a significant extent. On the flipside, sample size and representativeness is limited by the limited scale and ability to gain access to interview partners. Ideally, theoretical sampling from academic-turned industrial researchers allows to reach saturation with little ambiguity. This risk to fall short on suitable interview partners is mitigated by the following fallback tactics:

- Shift or limit focus along the value-chain towards more accessible and potentially less competitive stages
- Ask academic researchers as a proxy
- Substitute or augment data by reviewing contracts of realized projects

Proposed Table of Content

(Phrases in brackets are sub chapters)

<u>1) Introduction</u>
1a) Macro view (investment, technological drivers, industry convergence (e.g. by patent analysis))
1b) The three phenomena (societal change, change in scientific research, digitalization)
1c) Structure of the Thesis

<u>2) Literature Review</u>
2a) Battery research and structural similarities to other industries (biotech, pharma, [others])
2b) Sharing-data: what is specific and what is generic?
-- concepts (open source: reciprocity, strategic alliances: trust, open innovation: selective revealing)
-- best practices (consortia, vertical R&D partnerships, horizontal R&D partnerships)
2c) The industry structure of battery research
-- value chain and technologies
-- which sector knows what?
-- which sector protects which knowledge?
-- rivalry and collaboration
2d) Research question

<u>3) Research Design</u>
3a) Objective
3b) Methodology (method, external experts consulted)
3c) Sampling and Data collection

<u>4) Results (sample description, quantitative, qualitative)</u>

<u>5) Discussion (conclusion, limitation, further research)</u>

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