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Essays on Technological Progress toward Clean Energy and Manufacturing

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Abstract

In the face of global climate change and other environmental pollution, sustainable, green, carbon-free, and low-pollution development is necessary and urgent. To this end, society requires large-scale and multi-faceted innovation and technological change, in the energy sector and beyond. This thesis examines magnitudes and drivers of green technological change for key energy technologies and manufacturing. Its findings indicate the benefits of more differentiated system modeling for better policy recommendations and provide further energy and innovation policy guidance toward a sustainable and green economy.

The first part estimates robust learning rates for onshore wind energy in Europe using a multi-factor learning curve model. Learning rates strongly depend on the measure of technological change as onshore wind has seen quality improvements in terms of capacity factor that are reflected in significant learning in levelized cost of electricity but not in upfront investment costs. Moreover, patents and public research and development expenses as measures of knowledge yield similar results but the latter are much more sensitive to small changes in the specification. The second part leverages on project-level total system price data for distributed battery storage to estimate the effect of learning and further technical change determinants. The results show that end-user prices benefit from much lower learning effects than previously reported for battery stacks. Instead, scale effects and limited competition strongly influence prices. The third part investigates the role of labor unions toward more sustainable manufacturing. It finds that facilities increase toxic waste releases but reduce toxic waste handling after unionization. The findings highlight the conflicts between different stakeholders groups that local pollution affecting multiple stakeholders cannot remedy alone.

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Nomenclature

Abbreviations

2SLS	Two-stage least squares
BLS	Bureau of Labor Statistics
BOS	Balance-of-system
CAS	Chemical Abstracts Service Registry Number
Cata	Catastrophic releases
CF	Capacity factor
CI	Commodity (price) index
CMA	China Meteorological Administration
CO_2	Carbon dioxide
CPUC	California Public Utility Commission
CSP	Concentrated solar power
DUR	Duration
EC	European Commission
EIA	(US) Energy Information Administration
EOP	End-of-pipe
EOS	Economies of scale
EPA	(US) Environmental Protection Agency
EPCRA	Emergency Planning and Community Right to Know Act
ETC	Endogenous technological change
e.g.	exempli gratia (for example)
EXP	Experience
FE	Fixed effects
GDP	Gross domestic product
GW	Gigawatt
GWEC	Global Wind Energy Council
HHI	Herfindahl-Hirschman index
i.a.	inter alia (among other things)
IAM(s)	Integrated assessment model(s)
IC	Installment (or investment) cost
i.e.	id est (this means)

IEA	International Energy Agency
IGB	Leibniz-Institut für Gewässerökologie und Binnenfischerei
Inno	Innovative pollution prevention
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
KS	Knowledge stock
kW	Kilowatt
kWh	Kilowatt-hours
LA	Labor costs
LBD	Learning by doing
LBS	Learning by searching
LCOE	Levelized cost of electricity
Ln/ln	Natural logarithm
LNS	Labor Network for Sustainability
Max	Maximum
Min	Minimum
MSE	Mean squared error
MW	Megawatt
N	Number of observations
NETS	National Establishment Time Series
NLRB	National Labor Relations Board
OLS	Ordinary Least Squares
OSHA	Occupational Safety and Health Administration
P25	25th percentile
P75	75th percentile
PAT	Patent(s)
PCT	Patent Cooperation Treaty
PV	Photovoltaics
RBB	Rundfunk Berlin-Brandenburg (Berlin-Brandenburg Broadcasting)
R&D	Research and development
RD&D	Research, development, and demonstration
RDD	Regression discontinuity design
RQ	Reportable quantity
RTW	Right-to-work
SCTE	SolarCity and Tesla Energy
SD	Standard deviation
SDG(s)	Sustainable Development Goal(s)
SGIP	Self-Generation Incentive Program
SPILL	Industry spillover
TC	Technological change
TRI	Toxic Release Inventory
TWh	Terawatt-hours
UN	United Nations

USD	United States dollar
WACC	Weighted average cost of capital
WHO	World Health Organization

Symbols

#	Number of projects or units
%	Percent
$	United States dollar

1 | Introduction

1.1 Introduction: Sustainability and Technological Progress

Our planet and its ecosystems are struggling with anthropogenic effects like global warming due to carbon emissions or environmental pollution from manufacturing waste (IPCC, 2021). These adverse consequences might cause even greater havoc when combined, as tragically illustrated by the massive fish mortality in the Polish-German part of the river Oder. As a consequence of toxic substances produced by an algae bloom in August 2022, approximately 200 to 400 tons of fish died, representing up to 50% of total fish or up to four times as much as caught annually. The occurrence of these algae has likely resulted from an unfortunate combination of high temperatures, extremely low water levels, and (illegally) discharged industrial waste (IGB, 2022a,b, RBB, 2022).

Despite calls for more "sustainability" from all kinds of actors[1] over the last couple of decades, problematic global greenhouse gas concentrations in 2021 are higher than ever before (Blunden and Boyer, 2022). Moreover, all kinds of manufacturing emissions and other sources of pollution are still sizeable across nations (Keiser and Shapiro, 2019, EC, 2022, WHO, 2022, EPA, 2022d).

"[Sustainable] development [...] meets the needs of the present without compromising the ability of future generations to meet their own needs."

— Brundtland Report Our Common Future, 1987

The United Nations propose 17 Sustainable Development Goals (SDGs) to achieve significant progress on various sustainability dimensions, e.g. peoples' health, education, the economy, and the environment (UN, 2015b). The focus of this thesis are components and interactions

[1] Examples include the United Nations, the Business Roundtable with its 2019 statement on the new purpose of corporations, signed by 181 CEOs (Business Roundtable, 2019), asset management giant Blackrock (Fink, 2020), and the labor for sustainability network (LNS, 2016).

of the SDGs related to the decarbonization of energy and industrial sustainability, one of six SDG transformations proposed by Sachs et al. (2019). Central to operationalizing this SDG transformation are carbon-free electricity as well as reducing air, land, and water pollution (Sachs et al., 2019).[2]

Another important international policy step toward more sustainability is the Paris Agreement in which the Parties of the United Nations consent on limiting global warming to well below 2 °C and ideally 1.5 °C (UN, 2015a). As such, there are partial synergies with environment-related SDGs but the Paris Agreement is legally binding. Specifically, nations are required to submit Nationally Determined Contributions, i.e. actions and direct strategies for reducing their greenhouse gas emissions. While the original national targets under the Paris Agreement imply an improvement to previous efforts, they are not on track to keep even the 2 °C threshold (Rogelj et al., 2016, Armstrong McKay et al., 2022). Scientists warn that surpassing the temperature targets (potentially already the 1.5 °C target) increases the risks of reaching climate tipping points that trigger self-reinforcing and likely catastrophic climate change effects (Rockström et al., 2009, Steffen et al., 2018, Armstrong McKay et al., 2022).

"[Climate change] is the number one issue facing humanity. And it is the number one issue for me."

— Joe Biden, President, United States of America

To avoid a climate disaster and achieve the political targets of the Paris Agreement and the SDGs, innovation and technological progress are essential (Geels et al., 2017, Stern, 2022). However, market failures restrain technological progress in general and "clean", i.e. environmentally sustainable technological progress in particular (Jaffe et al., 2005) Consequently, policymakers have adopted support policies like supply-side research grants and demand-side renewable energy feed-in tariffs. Moreover, regulating hazardous substances and pricing negative externalities from economic activity are further means to level the playing field between clean and incumbent "dirty" technologies. "Making the price right" potentially represents economics' greatest contribution to environmental protection (Stavins, 2011) but there is an ongoing broad need for economists (and social scientists in general) to address the urgent climate change challenge because of its radical socio-economic consequences (Grundmann, 2016, Hong et al., 2020). Accurate

[2]Within these transformations and across the 17 SDGs, goals not necessarily reinforce each other but can even have negative interactions with other goals. For instance, achieving universal electricity access by means of burning fossil fuels counteracts decarbonization and health goals (Nilsson et al., 2016).

economic modeling of climate change and technological progress that considers its multi-faceted, interdependent nature, market imperfections, and uncertainty is still in its infancy (Stern, 2022).

In this thesis, we[3] aim to improve our understanding of drivers of low carbon and low pollution technological progress. We also investigate the dynamics of technological progress for key energy technologies to inform policymakers as well as researchers that model future optimal technology mix in our energy or power system (and thus advise on current investment priorities). Moreover, we shed light on the roles of different actors toward more sustainability and how interests of selected actors shape technological progress. Throughout the thesis, we employ statistical and econometric techniques in order to present quantitative results. While some of our data and estimation results are specific to onshore wind and distributed battery storage, technological progress for other technologies is arguably subject to similar driving forces and underlying mechanisms.

The introduction to this thesis proceeds as follows. In the next section, we provide a brief characterization of climate change and climate change mitigation, highlighting its relation to clean manufacturing and the importance of technological progress. Next, we explore different approaches to modeling and measuring technological change. Then, we discuss drivers of innovation and technological change. To showcase progress for key technologies, we continue with data from the electricity sector. Lastly, we introduce the specific research questions, research designs and results of the subsequent chapters. These chapters are based on papers published in or submitted to peer-reviewed academic journals. Thus, each chapter also represents a stand-alone essay with an individual contribution.

1.2 Background: Climate Change and Pollution

1.2.1 Facets and Effects

Climate change is real. Global average surface temperatures in 2020 have increased by 1.09 °C relative to pre-industrial levels (IPCC, 2021). The temperature increase and related changes in climatic conditions result from increasing concentrations of greenhouse gases like carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) (Blunden and Boyer, 2022, IPCC, 2021). Related climatic changes encompass, i.a., ocean acidification due to anthropogenic CO_2 emissions,

[3]For the sake of consistency and inclusion, the author uses the first person plural throughout this thesis.

a retreat of arctic sea ice, and melting glaciers. Moreover, although it is important to differentiate weather and climate (e.g. Kew et al., 2021), extreme weather events such as heat waves, droughts, and heavy precipitation become more likely and more severe (IPCC, 2021).

"The alarm bells are deafening, and the evidence is irrefutable: greenhouse gas emissions from fossil fuel burning and deforestation are choking our planet and putting billions of people at immediate risk."

— Antonio Guterres, Secretary-General, United Nations

The likelihood for compound extreme events, e.g. simultaneous heatwaves and droughts or wildfires also increases (Goss et al., 2020). These extreme weather events are already happening in 2022 (and before), at extreme dimensions and on a global level (IPCC, 2021). For instance, Southern China has experienced one of the most extreme heatwaves ever recorded, combined with an extreme drought (CMA, 2022). Similarly, heatwaves and droughts have extraordinarily affected many parts of Europe in August 2022, with 64% of the area being on a warning or alert scale according to the Combined Drought Indicator (Toreti et al., 2022). Dry soils and vegetation also relate to increasingly severe wildfires, e.g. in Spain in 2022, and the risk of flooding when dry and compacted soils cannot absorb heavy rainfall. Moreover, such feedback effects cause additional greenhouse gases, e.g. from wildfires and thawing of permafrost soils, that aggravate climate change (IPCC, 2021).

Furthermore, climate change threatens biodiversity of species and ecosystems, from bumble bees to coral reefs (Donner et al., 2005, Soroye et al., 2020). The negative effect of climate change can significantly add to further human-induced pressures such as land use changes (Halsch et al., 2021).

Finally, scientists increasingly reveal multi-faceted socio-economic consequences of climate change. Excess mortality (Vicedo-Cabrera et al., 2021), agricultural and human productivity losses (Dell et al., 2012, Graff Zivin and Neidell, 2014, Ortiz-Bobea et al., 2021), increasing energy demand (van Ruijven et al., 2019), financial instability (Lamperti et al., 2019), and crime imply significant costs for economies (Hsiang et al., 2017). In addition, climate change widens global inequality (Dell et al., 2012, Diffenbaugh and Burke, 2019).

As mentioned in the SDGs, sustainability not only refers to combating climate change, but also to maintaining or restoring a low-pollution environment. Yet, despite improvements in some industrial nations, pollution of land, rivers and air, e.g. due to manufacturing activities, agriculture, or burning of fossil fuels, continues to be problematic and costly (Schwarzenbach et al., 2010, Keiser and Shapiro, 2019, WHO, 2022). Key air pollutants are particulate matter, sulfur dioxide, nitrogen dioxide, ground-level ozone, lead, and carbon monoxide (EPA, 2022b). The underlying list of more or less toxic chemicals, metals, and other elements is substantially longer, as 86,000 US Toxic Substances Control Act chemicals alone exemplify (EPA, 2022a).

Scholars find that environmental pollution also causes some similar detrimental effects as climate change, i.a. worse health levels (Currie et al., 2015, Schlenker and Walker, 2016, Deryugina et al., 2019), declining productivity (Graff Zivin and Neidell, 2012, Chang et al., 2016, He et al., 2019), and departures of skilled employees from firms (Levine et al., 2020, Xue et al., 2021). Moreover, recent research increasingly identifies interregional and trans-boundary negative pollution effects, both directly through atmospheric particle transport and indirectly through trade (Zhang et al., 2017, Dedoussi et al., 2020). In the future, climate change might aggravate some of these effects through its impact on air pollution (Silva et al., 2017).

"We must treat climate change as an immediate threat, just as we must treat the connected crises of nature and biodiversity loss, and pollution and waste, as immediate threats."

— Inger Andersen, Executive Director, United Nations Environment Program

In sum, climate change and pollution pose major challenges for sustainability on the local, regional, and global level. The underlying sources and atmospheric properties of corresponding emissions greatly overlap (von Schneidemesser et al., 2015). This linkage also offers potential for mitigating both challenges at the same time.

1.2.2 Mitigation of Climate Change and Pollution

Fortunately, the list of climate change mitigation measures is long and diverse. The subsequent paragraph describes selected opportunities for reducing greenhouse gas (and potentially other) emissions but is by no means exhaustive. First behavioral changes of society at a large scale have huge potential. For instance, such behavioral changes entail dietary habits – e.g. consuming less animal protein, and beef in particular (Poore and Nemecek, 2018, Humpenöder et al., 2022, Sun et al., 2022) – as well as mobility – e.g. increasing bicycle use worldwide to the levels of current frontrunner countries like Denmark (Chen et al., 2022). Second, leveraging nature-based solutions like afforestation, protection of wetlands, restoration of coastal ecosystems, and other sustainable (agricultural) land use practices do not only address mitigation of carbon emissions but offer substantial co-benefits of reducing air pollution, filtering water, or increasing resilience to climate change (Griscom et al., 2017, Cook-Patton et al., 2020, Seddon et al., 2020, Behrer and Lobell, 2022). [4]

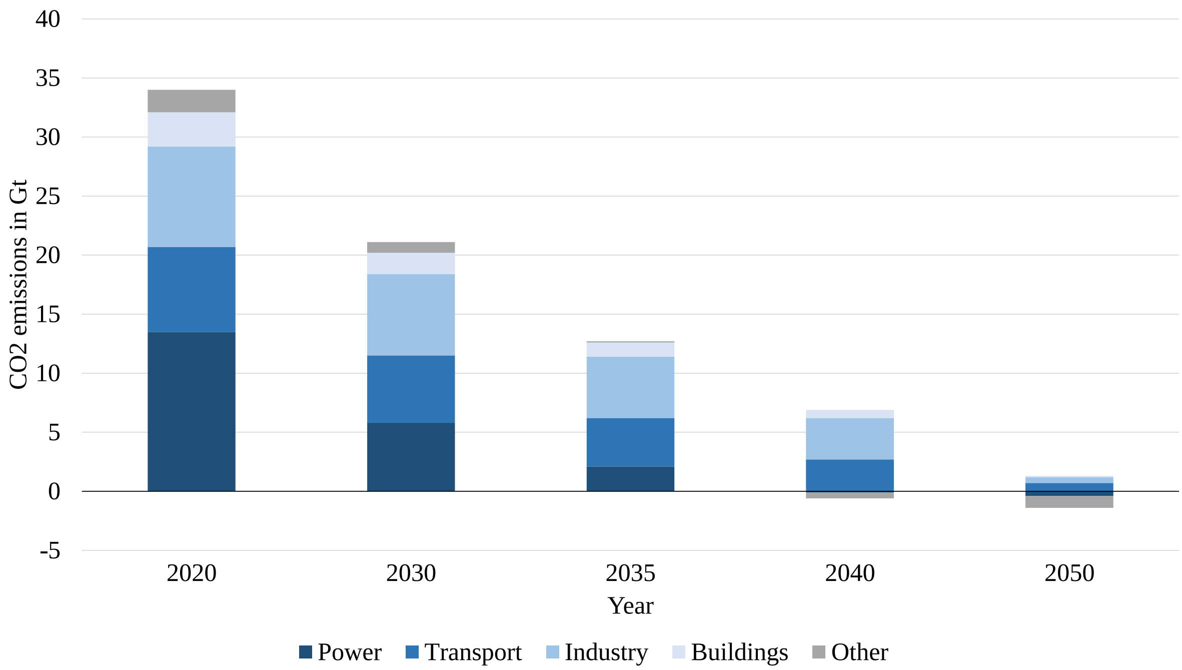


FIGURE 1.1: Sector Emissions in IEA Net Zero Energy System Scenario.
Notes: Data and projections are from the net zero energy system scenario by the International Energy Agency (IEA, 2021).

Third, climate change mitigation requires a global reduction and ultimate phase-out of fossil fuels as energy source combined with energy-efficiency efforts, rather sooner than later. In recent years, the use of energy has accounted for approximately three quarters of greenhouse gas emissions and up to 90% of CO_2 emissions annually (Gütschow et al., 2021, IEA, 2021). As shown in Figure 1.1, energy-related CO_2 emissions amount to 33.9 Gt, with 40 % attributable to the power sector, 25% to industry, 21 % to transport, and 9% to buildings. In a net-zero scenario compatible with the 1.5 °C target, this composition changes dramatically in the years and decades to come. By massively increasing renewable energy generation capacity, primarily wind and solar photovoltaics (PV), the power sector has to reduce emissions by 57% until 2030 and another 64% until 2035. Transport and industry decarbonize at a lower pace because not all necessary technologies are already commercially available. Consequently, the industrial sector will overtake the power sector as largest CO_2 emitter in this net-zero scenario (IEA, 2021).

[4] The contribution to climate change mitigation of these nature-based solutions is potentially large: Roe et al. (2019) project a mitigation potential of up to 15 Gt CO_2 equivalents per year, corresponding to 30% of the required mitigation.

It is important to note that the sectors and their mitigation potential are highly linked. Specifically, decarbonizing power generation soon and rapidly has spillover effects into transport and buildings where electrification is a critical component to decarbonization. Some necessary technologies like electric vehicles and heat pumps are increasingly adopted but there is an ongoing need for technological progress, market scale-up, grid flexibility incentives, and complementary infrastructure to further improve economics (Barnes and Bhagavathy, 2020, Ruhnau et al., 2020, Mauler et al., 2021, Renaldi et al., 2021, Thomaßen et al., 2021, Ziegler et al., 2021).

In addition, electrification represents one piece of the puzzle toward more sustainable industries and industrial decarbonization. However, new technologies and manufacturing processes are necessary (Miller et al., 2021, Vogl et al., 2021). Even if technology and processes advance as predicted, some industries like metal production continue to remain hard to abate. When produced more climate-friendly and environment-friendly, corresponding manufactured goods will become considerably more expensive while arguably still threatening compliance even with the 2 °C target. Consequently, downstream mitigation measures like lowering consumption and improving recycling rates need to complement previously mentioned technology and fuel choices (Fan and Friedmann, 2021, Vogl et al., 2021, Yokoi et al., 2022). Many mitigation measures related to energy decarbonization imply significant environmental co-benefits, e.g. in terms of air quality improvements through less toxic pollution (Nemet et al., 2010, Driscoll et al., 2015). Additional measures for specifically mitigating manufacturing pollution include good operational practices, e.g. better inventory management or substitution of chemicals, and redesigning products to either make toxic materials obsolete or to improve recyclability (e.g. Ranson et al., 2015).

Taken together, these measures illustrate that climate change mitigation is a global task across sectors and actors. Importantly, projections of mitigation potentials partially rely on substantial technological product and process improvements. In the next section, we characterize green[5] technological progress from an economic perspective.

[5]We use green and clean interchangeably.

1.3 Green Technological Progress

1.3.1 Background, Modeling, and Measurement

Technological progress and innovation are and will be crucial in slowing and halting climate change. However, sustainable, clean innovations replacing incumbent dirty technologies face two market failures related to the public good natures of environmental protection and knowledge (Jaffe et al., 2005, Stavins, 2011). Pollution from dirty technologies is a negative externality, imposing significant costs on society as illustrated by the consequences of climate change and environmental pollution in section 1.2.1. Knowledge creation generates positive externalities because other parties than the knowledge creator can typically capture returns to knowledge, i.e. there is limited appropriability even in the presence of intellectual property rights (e.g. Romer, 1986).

Consequently, free markets fail to provide the social optimum of environmental protection and innovation which calls on regulators to step in. The first-best policy to address the negative externality of any kind of pollution is a Pigouvian tax that puts a price tag on pollution, thereby internalizing the externality (Pigou, 1920, Stiglitz, 2019). In the context of climate change, several countries started to introduce carbon taxes as a means for converging to market outcomes based on "true", i.e. societal costs. As an alternative, although arguably less effective strategy, cap-and-trade mechanisms have evolved that regulate the quantity rather than the price of emissions (Nordhaus, 2007, Green, 2021). Examples include the EU Emissions Trading System, and, recently launched in 2021, China's national carbon market.[6] Regardless of the exact instrument to correct for negative carbon externalities, prices have mostly been below scientific calculations. Hence carbon prices only have had a limited steering effect in the past (e.g. Ellerman et al., 2016, Green, 2021), although there is positive evidence from China's regional carbon markets (Cui et al., 2021).[7]

[6] The described dual externality and policy measures to address them extend to other greenhouse gases and pollutants as well. For instance, a US cap-and-trade program regulates sulfur dioxide and nitrogen oxides, now as part of the Cross-State Air Pollution Rule (EPA, 2022c).

[7] Scholars typically derive the price of carbon in integrated assessment models (IAM) as the "social cost of carbon". Calculated social costs of carbon span a wide range of USD 43 to USD 279 per ton of CO_2 for 2020, e.g. due to diverging discount rates, factor productivity assumptions, and target temperatures (Gillingham et al., 2018, Nordhaus, 2019). The value of IAMs is discussed controversially (e.g. Pindyck, 2013, 2017, Weyant, 2017). An alternative approach based on expert elicitation provides a best estimate of USD 80 to USD 100 per ton of CO_2 (Pindyck, 2019).

While carbon pricing can incentivize innovation (Aghion et al., 2016, Calel and Dechezlepretre, 2016), governments can also directly address underinvestment in knowledge resulting from its positive externalities by means of research and development (R&D) subsidies or other support policies. Combining carbon pricing with R&D support significantly amplifies its innovation and climate change mitigation impact (Acemoglu et al., 2012, 2016, Aghion et al., 2016).[8]

How could such policies look like in practice and how do they impact climate, the economy or specific sectors such as the energy sector in the future? These are among the questions for which integrated assessment models (IAM) and other climate or energy policy models can provide guidance. Technological change in these models, as mentioned before, is one key parameter. The first wave of general economic growth models implements technological change as an exogeneous parameter, typically influenced by time (e.g Solow, 1956). Since policies can not influence technological change within these models, more recently developed growth models include technological change as an endogeneous parameter (Arrow, 1962, Romer, 1986, 1990). Thus, feedback processes are included such that technological progress calculates as a function of knowledge or experience accumulation.

"[E]ndogeni[z]ing innovation in large-scale models is important for deriving policy-relevant conclusions."

— Grubb et al. (2021)

Very different model types, including IAMs, can endogeneously represent technological change but the associated levels of detail and modeling choices depend on model scope and complexity (Gillingham et al., 2008, Louwen et al., 2020). Hence, the type of the model partially determines how technological progress can be implemented. An approach commonly used in holistic, high-level models like IAMs draws on common measures for innovation or knowledge. These entail, most importantly, R&D expenses (or investment) as input-oriented measures of innovation or patents as an output-oriented measure of innovation.

A different approach that lends itself especially to implementation of endogeneous technological change in more detailed energy or electricity sector models with a detailed set of technologies,

[8] Similarly, endorsing further policies – e.g. renewable energy generation quotas and subsidies in the context of electricity markets – might further optimize the policy portfolio that is superior to single policies (Fischer and Newell, 2008).

follows the famous learning curve concept (Wright, 1936, Arrow, 1962). The next section introduces learning curves in detail. [9]

1.3.2 The Learning Curve, Extensions, and Drawbacks

In the learning curve approach, technological progress results from previous experience with the technology through learning by doing (LBD). Originally, Wright (1936) measured technological progress as labor cost and experience as the quantity of manufactured airplanes (specifically airframes). He formulates the basic one-factor learning curve as a power law

$$TC = TC_0 * Q^b, \tag{1.1}$$

that is typically log-transformed, to

$$Ln(TC) = TC_0 + \beta * ln(Q) + \epsilon, \tag{1.2}$$

assuming a multiplicative error term ϵ. The learning elasticity β then translates into the learning rate as $1 - 2^{\beta}$ which indicates the percentage change in the technological change measure TC associated with a doubling in the quantity Q. Wright (1936) calculates a learning rate of 20% for airplanes.

The basic learning curve theory has seen many extensions and modifications over time. For instance, modifications of the functional form entail S-shaped or plateau learning curves but the original log-log learning curve dominates the literature to date (e.g. Yelle, 1979, Yeh and Rubin, 2012). [10] Moreover, researchers extend its scope from a single manufacturing process to firms to entire industries while using cost, price, or performance as proxy for technological change, amongst others. A popular example is the experience curve by the Boston Consulting Group, which relates *industry* experience to technology cost for competition analysis and firm strategy

[9] The price-induced representation constitutes another approach to model endogeneous technological change. In this approach, an increase in price of one production factor, e.g. energy, induces innovation away from this factor, e.g. via energy-efficiency (Popp, 2002, Gillingham et al., 2008).

[10] Several similar models for projecting future technology costs exist that are, however, not learning curves. The arguably most famous one is Moore's law which implies that technology costs fall exponentially over time (Moore, 1965). Nagy et al. (2013) test the power of these models and finds Wright's law, i.e. the learning curve, to be most accurate, closely followed by Moore's law.

development (Boston Consulting Group, 1968). [11] Another well-known example is the two-factor learning curve where technological progress occurs through LBD, proxied by experience, and learning by searching (LBS), proxied by knowledge accumulation (Kouvaritakis et al., 2000, Isoard and Soria, 2001, Jamasb, 2007). Such extensions of the learning curve aim at disentangling learning by doing effects from other drivers of technological change.

Despite its widespread use, basic learning curves have several drawbacks. First, learning curves generally lack causality and correlations might be spurious (Gillingham et al., 2008, Witajewski-Baltvilks et al., 2015, Odam and de Vries, 2020), even though lagged experience can at least mitigate reverse causality concerns. Second, basic learning curves typically suffer from omitted variable bias, i.e. inconsistent regression coefficients, as learning is not the only driver of technological change (Nemet, 2006, Söderholm and Sundqvist, 2007). Multi-factor models accounting for multiple learning challenges and other controls can mitigate omitted variable concerns. For system modeling, both drawbacks are less important as long as the underlying relationships continue into the future.

This implicit assumption of learning curves – i.e. the past being informative for future development – also implies that modeling of breakthrough innovations or discontinuities in general is difficult (Nemet, 2006, Farmer and Lafond, 2016). Expert elicitation as an alternative approach could potentially inform on such discontinuities. Yet, the performance of learning curves is superior to these approaches (Meng et al., 2021). Nevertheless, a combination of the different methods, be it expert elicitation or bottom-up cost modeling with or without related technology data, likely improves understanding of technological change and surrounding uncertainties (Kavlak et al., 2018, Beiter et al., 2021, Trancik, 2021). An additional benefit of such comparisons is to address the high sensitivities of learning rates to data and assumptions (Nemet, 2006, Söderholm and Sundqvist, 2007, Lindman and Söderholm, 2012, Williams et al., 2017). Testing for sensitivity of learning rates can also be performed within a learning curve analysis, e.g. by reporting errors, checking for robustness, or otherwise estimating a distribution of future technology costs (van Sark, 2008, Farmer and Lafond, 2016, Lafond et al., 2018, Bavafa and Jónasson, 2021). Such testing should also include an investigation of potential changes in "quality"

[11] The terms learning curve and experience curve are not used consistently in the literature (e.g. Junginger et al., 2005, Rubin et al., 2015, Schmidt et al., 2017). From section 2 on, we refer to learning curves when modeling technological change with a cost or performance measure and to experience curves when using a price measure, following Schmidt et al. (2017). Subsequently described extensions and shortcomings generally apply to learning and experience curves.

that learning curve models based on costs often do not account for (Clarke et al., 2006, Coulomb and Neuhoff, 2006, Nemet, 2006, Ziegler and Trancik, 2021).

Finally, learning curves, and experience curves in particular, are agnostic about the actors behind cost reductions. For instance, industry experience curves assume homogeneous spillovers where experience from one firm factors into a joint experience stock of the entire industry. However, spillovers might be heterogeneous, e.g. depending on a firm's absorptive capacity or geographic proximity (Nemet, 2006, Anderson et al., 2019).

Despite these drawbacks, learning curves are a flexible method for estimation of technological change and its endogeneous implementation in complex system models. Moreover, disentangling learning by doing effects from other drivers of technological change, and thereby also mitigating omitted variable bias, is possible by extending the basic learning curve model.

1.3.3 Drivers of Green Technological Progress

Learning by doing, i.e. learning from prior experience, is the core driver of technological change in the learning curve model. Clearly, other factors also drive technological change and understanding these underlying factors is highly relevant for risk assessments, budgeting, and many other aspects of policy making and research (Trancik, 2021). The subsequent list of drivers intends to grasp general drivers while presenting specific examples from renewable energy technologies.

First, next to learning by doing, there are other *learning* channels that can drive technological change. These entail learning by searching through knowledge accumulation, as mentioned previously, and learning by using a technology (Junginger et al., 2006). Further learning channels are learning by interacting, a form of social learning where two parties only learn together (Kellogg, 2011, Tang and Popp, 2016, Tang, 2018), as well as learning from spillovers. Learning from spillover occurs when one party – e.g. a firm, industry, university, region, country, or technology – benefits from the experience, knowledge, policies, or other characteristics from another party. Empirical evidence reports mixed results on the existence and magnitude of spillover effects that appears to depend on focal technology and geographic scope (for intra-technology spillovers (Nemet, 2012b, Grafström, 2018, Hoppmann, 2018, Anderson et al., 2019, Bollinger and Gillingham, 2019, Nemet et al., 2020); for inter-technology spillovers (Nemet, 2012a, Dechezleprêtre et al., 2014, Duch-Brown and Costa-Campi, 2015). Moreover, there is general technological progress, e.g. because of advances in basic research (Malerba, 1992). [12]

"It is good business and good economics to lead a technological revolution and define market trends."

— Barack Obama (2017), former US President

Second, production, scale, location, market structure, regulation, and macroeconomic factors can drive sustainable innovation and technological change. Production factors include prices and compositions of raw material (Nemet, 2006, Hettinga et al., 2009, Yu et al., 2011, Bolinger and Wiser, 2012, Gan and Li, 2015, Pillai, 2015, Voormolen et al., 2016, Green, 2019, Hsieh et al., 2019), labor costs (Bolinger and Wiser, 2012, Gillingham et al., 2016, Elia et al., 2020), and firm, process, or plant characteristics (Nemet, 2006, Swanson, 2006, Horbach, 2008, Powell et al., 2012, 2015, Amore and Bennedsen, 2016, Gillingham et al., 2016). Scale effects can drive technological change on three levels: the unit, e.g. the size of a PV module or the hub height of a wind turbine (Bolinger and Wiser, 2012, Wilson, 2012, Duffy et al., 2020, Odam and de Vries, 2020, Sweerts et al., 2020), the manufacturing facility (Nemet, 2006, Yu et al., 2011, Goodrich et al., 2013, Green, 2019), and the power plant (Qiu and Anadon, 2012, Benini et al., 2019, Beiter et al., 2021). Location entails resource potential, e.g. solar radiation or wind speed (Vartiainen et al., 2020, Beiter et al., 2021), accessibility, e.g. distance to shore or water depth in the case of offshore wind (Voormolen et al., 2016), and other regional or national characteristics (Pillai, 2015).

Different factors characterizing markets for green technologies also impact technological progress. Strategic considerations for gaining a competitive edge, also known as the Porter Hypothesis, can induce firms to drive environmental innovation (Porter, 1991, Porter and van der Linde, 1995, Kesidou and Demirel, 2012, Ambec et al., 2013). The extent of competition is also associated with technological progress and specifically costs (Bolinger and Wiser, 2012, Gillingham et al., 2016, Voormolen et al., 2016, Dong et al., 2018, Hayashi et al., 2018, O'Shaughnessy, 2019, Macher et al., 2021), as are supply-demand imbalances (Zheng and Kammen, 2014, Reichelstein and Sahoo, 2018), search or customer acquisition costs (Seel et al., 2014, Gillingham et al., 2016, Gillingham and Bollinger, 2021), and characteristics of complementary markets (Tang, 2018).

[12] An ample literature investigates organizational factors behind the learning curve, e.g. training and forgetting (e.g. Argote and Epple, 1990, Argote et al., 1990, Adler and Clark, 1991, Benkard, 2000, Argote et al., 2021). While highly relevant, this literature is generally beyond scope. However, the existence of forgetting experience and knowledge – and, equivalently, old knowledge becoming less relevant – has implications for modeling technological change (Klaassen et al., 2005, Anderson et al., 2019, Bollinger and Gillingham, 2019).

Furthermore, a booming body of theoretical and empirical literature examines the effect of regulation and policies on sustainable innovation, technology costs, or other measures for technological progress (see reviews Popp et al., 2010, Popp, 2019, Stern and Valero, 2021). Environmental regulations such as carbon pricing (Brunnermeier and Cohen, 2003, Acemoglu et al., 2016, Aghion et al., 2016, Calel and Dechezlepretre, 2016), government funding for R&D as technology push, green certificates or quotas (Fischer and Newell, 2008, Johnstone et al., 2010, Peters et al., 2012, Feldman et al., 2020), and other demand-pull policies directly subsidizing technology adoption (Peters et al., 2012, Hoppmann et al., 2013, Gillingham et al., 2016, Lindman and Söderholm, 2016, Dong et al., 2018, Gao and Rai, 2019, Lin and Chen, 2019) appear to influence technological change and costs. Permitting processes (Dong and Wiser, 2013, Seel et al., 2014, Burkhardt et al., 2015), local content requirements (Qiu and Anadon, 2012, Probst et al., 2020), and green public procurement (Krieger and Zipperer, 2022), and regulatory (or other stakeholder) pressure (Kesidou and Demirel, 2012, Berrone et al., 2013) represent additional regulatory drivers – or hurdles – of technological progress.

Lastly, scholars identify macroeconomic factors like energy or electricity prices (Popp, 2002, Bolinger and Wiser, 2012, Macher et al., 2021), financing/interest rates (Egli et al., 2018, Vartiainen et al., 2020, Duffy et al., 2020), foreign exchange rates (Bolinger and Wiser, 2012, Lilliestam et al., 2020), and government debt (Ek and Söderholm, 2010) as drivers of green innovation and technology costs.

Improvements in some of the non-learning factors may realize in part due to learning effects. Thus, if the improvements can be attributed to LBD, they can even be captured by basic learning curves. Nevertheless, disentangling these effects improves our understanding of key drivers and allows for more precise and flexible future projections.

1.3.4 Technological Progress in Action: Renewable Energy Technologies

The previous sections motivate why phasing out electricity generation from fossil fuels – especially coal, lignite, gas, and oil[13] – is essential for sustainable development and net zero while emphasizing the paramount importance of technological progress.

[13] We will not discuss nuclear energy in detail because of its particularities: a potentially low carbon and dispatchable technology but running on a finite "fuel" (uranium) with questionable resiliency against climate change, a need for permanent radioactive waste storage, the risk of a maximum conceivable accident, and challenging economics. The interested reader is referred to the literature (e.g. Grubler, 2010, Davis, 2012, Markard et al., 2020, Ahmad, 2021).

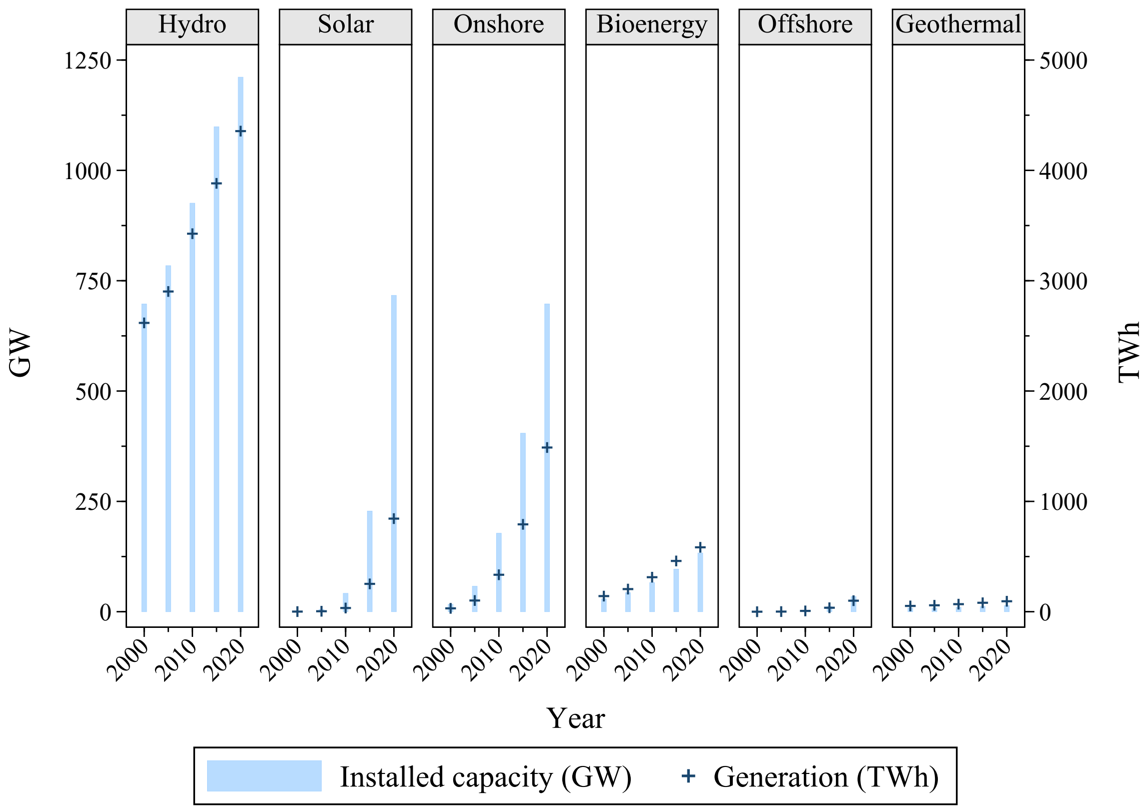


Figure 1.2: Renewable Energy Capacity and Generation.
Notes: Data is from the International Renewable Energy Agency (IRENA, 2022a).

As shown in Figure 1.2, the first steps toward a cleaner electricity sector have been made over the last few decades, even though 4,748 GW of fossil fuel power plants have still generated 19,402 TWh of electricity in 2020, i.e. almost three times as much as all renewables. Hydropower constitutes the largest renewable energy source to date, both in terms of installed capacity and electricity generation. Thanks to strong growth rates, solar PV and onshore wind energy are catching up, with ca. 710 GW and 697 GW of installed capacity in 2020. Since onshore wind farms typically achieve more full load hours, i.e. higher capacity factors, they generate almost 1,500 TWh of electricity compared to 844 TWh from solar. Other important renewable energy sources are bioenergy such as biofuels or biogas with 133 GW installed capacity in 2020, offshore wind (34 GW) and geothermal energy (14 GW). [14] For several technologies, these statistics are changing rapidly, sometimes also in the form of a (regional) "boom-and-bust". A recent example for a booming technology is the offshore energy, where 2021 represents a record year

[14]Note that solar in Figure 1.2 also contains a small share of capacity and energy generation attributable to concentrated solar power (CSP). While CSP capacity in 2000 was almost 1/3 of total solar capacity, it accounts for less than 1/100 in 2020. Wave or tidal energy is another renewable source with few installations.

with capacity additions of about 21 GW (i.e. a plus of 62%), driven by China in particular (GWEC, 2022, IRENA, 2022a).

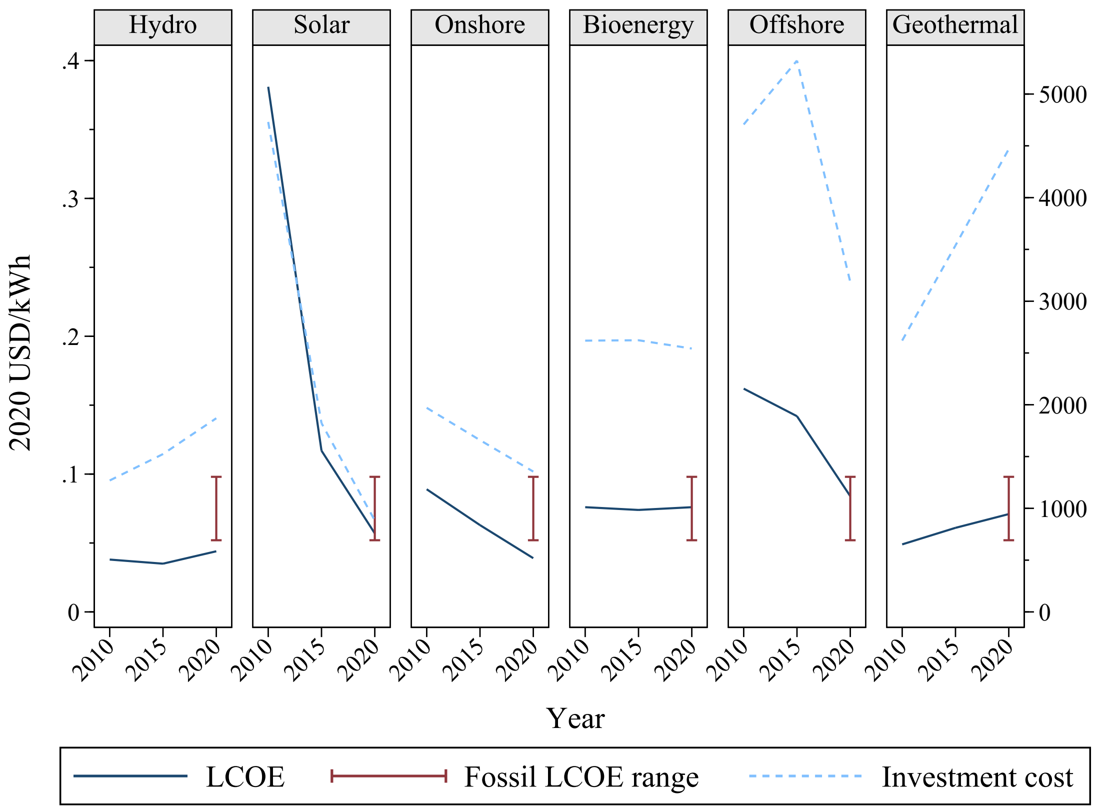


FIGURE 1.3: Cost Development of Renewable Energy Technologies.
Notes: Data on renewables' cost is from IRENA (2021). The fossil fuel interval depicts the lowest cost at the 25% quartile and the highest cost at the 75% quartile from IEA (2020b).

The growth in renewable energy capacity is associated with declining costs for several key technologies, as illustrated in Figure 1.3. In favorable conditions (e.g. as in the Persian Gulf region), it is possible to generate electricity from solar PV at a levelized cost of electricity (LCOE) of below 0.02 USD/kWh (Apostoleris et al., 2021). While its global average LCOE is higher at about 0.057 USD/kWh, solar PV has still seen a remarkable decline from 0.4 USD/kWh in 2010. Onshore and offshore wind have experienced similar, though less extreme cost declines both in terms of LCOE and investment cost. The rapid technological change of PV and wind have consistently been underestimated by (learning curve) models and experts (Creutzig et al., 2017, Meng et al., 2021, Victoria et al., 2021, Wiser et al., 2021, Xiao et al., 2021).

Other renewable energy technologies (hydro, biomass, geothermal) have always been highly competitive with fossil fuels in suitable locations between 2010 and 2020, although we do not observe cost reductions. Overall, electricity generated from all these technologies, *on average*, is now at parity with or cheaper than electricity generated from fossil fuels and far below household electricity prices. [15] Recent extraordinary developments at commodity markets, increasing carbon prices, and lower full load hours due to the merit order effect tend to strongly affect the LCOE of fossil generation (IEA, 2020b). Thus, the marron interval in Figure 1.3 tends to significantly shift upwards, approaching 0.20-0.30 USD/kWh or more in some regions (Kost et al., 2021, IRENA, 2022b).

The described dynamics and current costs might suggest that there are few further hurdles to fully decarbonize the power sector in an efficient and affordable way, as designated e.g. by SDG7. However, solar and wind, i.e. the technologies with the fastest growth and largest potential as of today, are not dispatchable. Their intermittency incurs additional cost for the power system, e.g. because additional measures and infrastructure for balancing supply and demand are necessary. With increasing shares of intermittent electricity generators, these costs tend to rise, and consequently, wind's LCOE and PV's LCOE from Figure 1.3 cannot be fairly compared to a dispatchable technology (Joskow, 2011, Borenstein, 2012).

While some of this intermittency can be addressed with demand-side flexibility (e.g. Ruhnau et al., 2020), energy storage technologies are increasingly required at grid-scale to balance electricity supply and demand at all times. Since many energy storage technologies are still at a relatively early stage in their technology life-cycle, their future technological progress will likewise be of major importance for a decarbonized electricity system. Battery storage represents one of the more developed technologies that shows promising potential across different applications and high learning curves of up to 30% (Schmidt et al., 2017, Ziegler and Trancik, 2021).

Taken together, this section shows rapid sustainable technological progress in the electricity sector. Thanks to this change, renewable energy technologies are now competitive with fossil generation in terms of average LCOE. Quantifying these dynamics and relating them to previously presented models and innovation drivers implies many uncertainties and unanswered research gaps. Subsequently, we explain how the main body of this thesis contributes to reducing these gaps.

[15] The global averages naturally disguise notable heterogeneity within time, across regions, and power-generating units. This heterogeneity facilitates the analyses in chapters 2 and 3.

1.4 Methodology, Research Results, and Contribution

1.4.1 Estimating Learning Curves for Onshore Wind Energy

Having established the general relevance of understanding technological progress for more sustainability, we now present research questions, contributions, research designs, and core findings of the three essays constituting the main part of this thesis. We begin with a European country-level analysis of technological progress in onshore wind energy. As shown in section 1.3.4, onshore wind has seen increasing installed capacities globally. Nevertheless, for a low-carbon energy system, huge capacity additions in every world region are required (IRENA, 2019). Yet, the extent of capacity additions will depend on the future attractiveness of onshore wind, particularly in terms of costs. To estimate future technology costs, various energy and power system models endogenize technological progress (i.e. costs) to enable within-model feedback effects responding to the extent of capacity and knowledge additions (see section 1.3.1). Given the material impact of the learning rate on model recommendations (e.g. Nemet, 2006), the huge, 43 percentage points range of learning rates reported in prior literature causes unsatisfying uncertainty for system modellers and potentially biased results. Hence, we aim to answer the following research question:

Research Question 1:
What are robust learning rates for onshore wind and how do they depend on the measurement of technological change or knowledge?

We approach this question with a multi-factor learning curve model where learning by doing (LBD) occurs through experience, i.e. installed capacity, accumulation and learning by searching (LBS) occurs through knowledge accumulation. We proxy for knowledge using patents and country-level public R&D expenses. Additionally, we control for manufacturing economies of scale, commodity prices, and country fixed effects. Seven major European onshore wind markets between 1998 and 2018 constitute our sample, determined by cost data availability from the International Renewable Energy Agency.

Our main findings are as follows. First, the magnitude of the learning rate depends on the measure of technological progress. While we estimate significant LBD (LBS) rates for the LCOE of 2-3% (7-9%), there is hardly any learning in (upfront) investment cost. As we show, learning in the LCOE is rather driven by learning effects that have led to higher capacity factors. These estimates are robust to several robustness checks, including an instrumental variable specification that addresses endogeneity and reverse causality concerns of costs and cumulative capacity.

Second, we find remarkable differences of LBS rates depending on the knowledge measure and further specifications. Whereas R&D-based LBS rates are absolutely higher in the base scenario with common lag and depreciation assumptions from prior literature, they are much more sensitive to changes in the depreciation rate. Within a reasonable range in depreciation rates of 0% to 10% percent, corresponding LBS rates vary by 12 percentage points, illustrating an often cited drawback of the learning curve approach.

Overall, these results support the inclusion of a knowledge stock in system models with endogeneous technological change in light of the significant LBS rates. Moreover, our findings suggest that modelers should account for improvements in onshore wind capacity factors. Modeling technological progress by means of investment costs only disregards the observed learning in quality that improves the performance of the technology.

1.4.2 System Price Dynamics for Battery Storage

Significant technological learning in some key renewable energy generation technologies like solar PV and onshore wind is well-documented. However, ongoing cost improvements of these intermittent technologies alone won't suffice for an affordable and carbon-free power system with security of supply. Instead, many regions' power system requires energy storage technologies for shifting excessive generation from renewables to periods with insufficient generation. Battery storage has gained policy attention, significant spending in R&D, and a surge in patenting (Kittner et al., 2017, IEA, 2020a, 2022). It is a flexible and modular technology, resembling solar PV modules in this regard. Yet, whereas solar PV can now be installed at highly competitive costs in many regions across the world, governments still widely provide strong financial support for the adoption of battery storage technologies like electric vehicles or distributed storage systems (e.g. Comello and Reichelstein, 2019). Against this backdrop, we investigate pricing and price drivers of distributed storage systems, aiming to answer the following research question.

Research Question 2:

Which role do experience, system scale, and market characteristics play for total system prices of distributed battery storage systems?

To answer this question, we first set up a basic experience curve model that relates prices at each installation date t to industry experience, measured as the cumulative number of projects up to this specific date. We also separate our project-level data into a small, residential segment and a larger, commercial segment. Next, we extend our model to account for a system's size in kWh, its duration in hours, and the Herfindahl-Hirschman index (HHI) at time t in the corresponding county. Moreover, we include county and installer firm fixed effects. The underlying data on project location, size, date, and costs comes from California's Self-Generation Incentive Program (SGIP).

With the basic one-factor experience curve, we estimate experience rates of only 1.3% that are in stark contrast to previously reported learning and experience rates for battery storage components like cells and packs (Kittner et al., 2017, Schmidt et al., 2017, Hsieh et al., 2019, Kittner et al., 2020, Ziegler and Trancik, 2021). To further investigate the role of experience, we separate our observations into a small, residential segment (below/equal to 10 kW) and a larger, commercial segment (above 10 kW) (CPUC, 2016). We find that large systems show significant experience rates of up to 11 % whereas there is slight negative learning by doing in the small segment.

Next, we examine the effect of within-segment size heterogeneity – proxied by duration in hours and capacity in kWh – and competition – proxied by the HHI – while adding county and installer firm fixed effects. As expected, scale effects are significant, both in terms of energy storage capacity in kWh and duration in hours. Furthermore, the HHI is positively associated with system prices. This effect is particularly large and highly significant for small systems. Two additional analyses support and illustrate the role of such balance-of-system (BOS), i.e. non-battery, price components as hurdles to system price declines. First, we estimate lower learning rates for BOS prices in both segments. Second, we find a negative "learning" effect across segments for firms with more installation experience. Put differently, installers seem to be able to charge price premiums the more systems they have previously installed. On the contrary, growing industry experience is associated with lower prices in both segments, indicating small experience spillover effects within the industry.

Taken together, our findings provide some explanations for still challenging end-user economics of battery storage systems. To reduce private and commercial adopters' need for government support in the future, scaling up markets and systems while stimulating competition and price transparency to reduce BOS prices represent high-level policy mechanisms. Facilitating electricity market participation of distributed storage systems and compensating end-users for flexibility provided to the grid could justify larger systems while potentially improving end-user economics. Finally, our finding of significant differences in learning rates between large and small segments calls for more granular models enabling targeted policy recommendations.

1.4.3 Toxic Waste Management after Unionization

So far, countries as an aggregate as well as end-users and firms constitute the actors behind sustainable technological change. In Chapter 4, we investigate the role of another group of actors in progress toward more sustainability: labor unions. We also extent the scope from specific energy technologies to the (manufacturing) industry in general. As discussed in section 1.2, negative environmental externalities do not exclusively occur in the energy sector. Rather, efforts by the industrial sector will play a crucial role for sustainable development, including climate change mitigation but also circular economy efforts and toxic waste reduction. Hence, environmental sustainability subsequently refers to clean, i.e. low-emission manufacturing. Specifically, we raise the following research question.

Research Question 3:
How does unionization affect facilities' toxic waste management practices?

Toxic waste management essentially implies a trade-off for unions: Releasing toxic waste pollutes the environment, thus affecting the workplace and neighboring communities but avoiding toxic releases by handling the waste is costly and relatively dangerous. By means of a local regression discontinuity design, we estimate the causal impact of unionization elections in the US held between 1990 and 2017 on toxic releases and "cure", i.e. waste recycling, use for energy recovery, or other treatment (also referred to as waste handling). We find that on-site, i.e. at the facility where the union election takes place, facilities increase toxic releases but decrease toxic waste cure after unionization. These effects are large: compared to facilities where the union could not reach a majority, facilities increase (reduce) on-site release ratios (cure) by 15 (59) percentage points, on average over the three years after the election. We argue that unions care for workplace safety and thus protect their members from waste cure tasks.

In additional analyses, we rule out changes in production output and financial constraints as alternative explanations, supporting our reasoning that concerns for workplace safety rather than cost saving motives are the main driver behind our main effect. Furthermore, we find that unions might help in achieving multi-win outcomes: catastrophic releases happen less often after unionization – potentially indicating better training – and facilities adopt more innovative pollution prevention measures like eco-designing products.

Our contribution to the literature is twofold. First, we show that unions matter for facilities' environmental performance by affecting toxic waste management. Specifically, we find that unions aggravate low-emission manufacturing. Second, our findings highlight the conflicts of interests between different stakeholder groups on the path toward more industrial sustainability. Previous literature reports such stakeholder conflicts by using environmental, social, and governance scores as well as product recalls (Ertugrul and Marciukaityte, 2021, Heitz et al., 2021, Kini et al., 2021). We show that even locally harmful pollution that affects facilities' neighborhoods, environment, *and* the workforce can only partially align goals as typified by lower catastrophic releases and more innovation. Our findings suggest that unions prioritize safety over environmental sustainability and call upon governments and management to focus on outcomes sufficiently satisfying both objectives for truly sustainable outcomes.

1.5 Structure of the Thesis

The remainder of the thesis is organized as follows. Chapter 2 introduces a taxonomy of cost drivers in the context of energy technologies and estimates robust multi-factor learning curves for onshore wind. Chapter 3 proceeds with the empirical analysis of system price dynamics for distributed battery storage. In this essay, the description of model, variables, and data in the methods section comes at the end, consistent with the style requirements of several *Nature* journals. Chapter 4 presents causal evidence on the role of labor unions in toxic manufacturing emissions and adoption of pollution prevention measures. Chapter 5 concludes the thesis with a discussion of results, and implications for research and policy. Lastly, the Appendix contains additional visualizations, further details on the different samples or variables, and regression results of robustness tests for the three essays.

2 | Mills of Progress Grind Slowly? Estimating Learning Curves for Onshore Wind Energy

by Magnus Schauf and Sebastian Schwenen[16]

Estimated learning rates for onshore wind span a large range of about 40 percentage points. We propose a multi-factor experience curve model with a new economies of scale measure and estimate learning rates for onshore wind using country-level data from seven European countries. We find learning by doing rates of 2%-3% and learning by searching rates of 7%-9% in terms of LCOE. When decomposing LCOE, we find no significant learning in installed costs but significant learning in capacity factors. Accounting for improvements in capacity factors and modeling learning by searching can hence be promising for energy models that endogenize technological change. We confirm our results in several robustness checks, and show that depreciation rates of the knowledge stock have large effects on estimated learning rates.

[16]This essay has been published in Energy Economics. It is reproduced by permission of the publisher. My contributions are as follows: development of the research idea, literature review, formulation of the statistical model, data curation, performing the analysis, creating the visualizations, and writing the original draft.

2.1 Introduction

Onshore wind energy is a key technology to decarbonize the power system. Globally, onshore wind is projected to provide about one third of total electricity by 2050, accounting for more than one quarter of the emissions reductions targeted in the Paris agreement (IRENA, 2019). Whether wind power meets its projected future market shares, however, will ultimately depend on the evolution of technology costs.

To account for advances in technology costs, power system models increasingly endogenize technological change when projecting future market outcomes. In particular, system models approximate technological change with learning rates, that indicate the percentage change in costs associated with an increase in experience, often measured as cumulative installed capacity (Gillingham et al., 2008, Rubin et al., 2015). The extant literature has found learning rates for onshore wind that span about 43 percentage points (Lindman and Söderholm, 2012, Rubin et al., 2015, Williams et al., 2017). As a result, the differences in estimated learning rates can lead to potentially large bias in modeled equilibrium outcomes and market projections of power system models.

In this paper, we address the uncertainty in estimated learning rates by implementing sufficiently robust estimation approaches. Specifically, we identify and select the most crucial determinants of learning rates and exploit novel covariates to improve the estimation of learning rates. We also show how empirical specifications can be tailored to fit the computational needs of power market models.

The existing literature has proposed a variety of research designs to measure learning rates. While learning has often been confined to changes in total installed costs (e.g Jamasb, 2007, Lindman and Söderholm, 2012), scholars started exploring advances in levelized cost of electricity (LCOE) as a more comprehensive cost measure (Williams et al., 2017, Glenk et al., 2021). Recent works found that progress in technology costs also relates to certain cost components, such as operation and maintenance (Steffen et al., 2020), financing costs (Egli et al., 2018) and economic life extensions (Duffy et al., 2020).

In addition, differences in estimated learning rates can result from underlying samples that, e.g., differ in geographical scope or aggregation level (Lindman and Söderholm, 2012, Williams et al., 2017). Furthermore, empirical models typically differ in the number and measurement of controls and assumptions on time lags and depreciation rates.[17]

To capture the existing range of approaches, we propose a model that (i) encompasses different cost measures as outcome variable of interest, (ii) includes a set of common as well as novel covariates that can be tailored to different assumptions on time lags and depreciation rates, (iii) fits recent and rich data from seven European countries, and (iv) can be re-run using instrumental variables. More broadly, our approach is to identify the relevant cost drivers and learning channels for different cost measures, using the same set of data throughout all regressions, and covering twenty years of cost developments. Our goal is to show what cost drivers and learning channels are robust across different specifications and *where* learning takes place, i.e., what parts of technology costs experience technological progress. Finally, we use our results to discuss promising ways to integrate learning curves into power system models.

Our data includes information on installment cost, LCOE, and capacity factors of wind turbines in Denmark, France, Germany, Great Britain, Italy, Spain, and Sweden from 1998 to 2018. To explain changes in these costs measures, we merge in data on capacities of wind energy in each country, as well as on public research, development, and demonstration (RD&D) expenditures, patent data, information on total assets of wind turbine manufacturers, labor costs, and further control variables such as a commodity price index.

First, our results confirm earlier studies in that we find significant cost reductions in the LCOE of wind turbines. We identify both significant learning by doing, i.e., learning as capacity accumulates, and learning by searching, i.e., learning as a result of increases in RD&D expenditures or the number of patents. Specifically, we find learning rates of 2.8% for learning by doing and of 7.1% for learning by searching. These estimates are at the lower end of previously estimated learning rates. We confirm the magnitude of our point estimates using a battery of conceptual and econometric robustness checks. Our results are also robust to controlling for a wide range of control variables. Last, we again confirm the magnitude of our estimates using an IV approach to rule out concerns relating to reverse causality.

Next to our robustness checks, we also probe into the sensitivities of our estimates and find that important drivers of sensitivity are depreciation rates and, somewhat related, the measurement of the knowledge stock in terms of patents versus RD&D. As such, we show that changing

[17] Scholars have also highlighted the difficulty in interpreting estimated learning rates causally (Gillingham et al., 2008).

depreciation rates and measures of the learning stock can, at least in parts, explain some of the observed heterogeneity in previous learning rates.

When breaking down LCOE into installment costs and capacity factor, our findings show that no significant learning takes place in installment costs. Both learning by doing and learning by searching are not significant. Yet, when using capacity factor as outcome variable, we find strong evidence for learning by searching. As such, our results suggest that—from a learning perspective—onshore wind technology is not getting significantly cheaper, but better, and that increases in quality, i.e., the capacity factor, can be largely attributed to innovation as measured in RD&D and patent data.[18] Hence, our results also show that power system models can account for technological change by letting capacity factors for wind depend on input parameters for RD&D expenditures.

Our findings relate to several strands of research on the estimation of learning curves. First, we add to the literature on wind power learning rates (Ek and Söderholm, 2010, Qiu and Anadon, 2012, Tang and Popp, 2016, Hayashi et al., 2018, Tang, 2018, Anderson et al., 2019, Odam and de Vries, 2020). While the extant literature has typically been confined to studying one cost measure, each with distinct data, we add by formulating a multi-factor experience curve model to estimate a variety of cost components, all based on one recent dataset. Our findings hence "control" for differences in sample composition. In addition, we propose a novel measure to capture economies of scale (EOS). Specifically, we propose wind turbine manufacturer size, measured by their average total assets, as an alternative EOS measure borrowed from the innovation economics and finance literature (Whited and Wu, 2006, Kogan et al., 2017). Prior studies use average wind turbine and wind farm size as EOS proxy, i.e., scale effects in operating capacity, but find it hard to econometrically disentangle these effects from learning (Ek and Söderholm, 2010, Odam and de Vries, 2020). Our EOS measure, firm size, explicitly focuses on economies of scale in the manufacturing process, and shows across multiple specifications that higher EOS are significantly associated with lower technology costs.

By studying different cost measures and decomposing LCOE into installment cost and capacity factor we also contribute to recent works that likewise have modeled disaggregate technology costs and their main components (Nemet, 2012b, Neij et al., 2017, Steffen et al., 2020). In particular, Steffen et al. (2020) report strong learning effects in operations and maintenance

[18] These results are robust to controlling for input costs and EOS measures as well as for country-level fixed effects, that absorb differences in capacity factors across countries that stem from weather or different sites of wind farms.

costs. In this context, our results show significant technological progress via learning in quality, i.e., the capacity factor, rather than in installment costs.

More broadly, we also relate to the general literature on learning rates (e.g., Benkard, 2000, Yeh and Rubin, 2012) by identifying the impact of assumptions on depreciation rates and measurements of knowledge on estimated learning rates. Here, we find that different assumptions can lead to differences in estimated learning rates of up to 12%.

The paper is organized as follows. Section 2.2 provides a short review on the estimation of learning curves and presents a taxonomy of cost drivers as identified in the extant literature. Section 2.3 introduces our baseline econometric model, our approaches to robustness and sensitivity checks, and our data. Section 2.4 shows our results. Section 2.5 discusses our findings in view of prior results and outlines implications for the use of learning rates in energy system models. Section 2.6 concludes.

2.2 Estimating Learning Rates for Power Generating Technologies

In this section, we first review learning curve models and their use in energy system models. Subsequently, we provide a taxonomy of cost drivers, i.e., factors that drive learning, as identified from the existing literature. We also discuss the wide range of previous estimates for learning rates.

2.2.1 Technological Change, Learning Curves, and Energy System Models

In its basic form, learning curves relate a measure of experience, EXP, usually cumulative installed capacity, to a cost measure, $COST$, such as upfront total installed costs. Formally,

$$COST = COST_0 * EXP^b, \tag{2.1}$$

where the index 0 denotes any chosen start date and b captures the cost elasticity of learning. Of particular interest is the learning by doing (LBD) rate $1 - 2^b$, which indicates the percentage change in costs associated with a doubling in experience.[19]

Besides applications in policy evaluation and technology studies, learning curves are commonly used to proxy endogenous technological change (ETC) in energy system models (Gillingham et al., 2008, Pizer and Popp, 2008). Learning-based ETC models assume that past decisions on the accumulation of experience determine technology costs, i.e., technological change, at current and future points in time.[20]

Typically, learning curves of energy technologies are estimated using total installed costs as outcome variable. This is, firms/the industry learn as they are installing additional capacity and as a result can reduce overall installment costs (e.g., in $/kW). Instead of using installment costs on the left hand side of equation (2.1), other models use levelized costs of electricity as outcome variable (e.g., in $/kWh). Finally, some models decompose technology costs and estimate learning rates for individual cost components such as operation and maintenance or balance of system costs (Nemet, 2012b, Neij et al., 2017, Steffen et al., 2020).

2.2.2 Factors that Drive Learning

Next to differences in the definition and measurement of technology costs, the heterogeneity in estimated learning rates also results from different measures of experience, or more broadly, variables on the right hand side of equation (2.1) that drive learning. Many studies employ so-called one-factor learning curve models to study learning by doing (LBD). This is, they analyze the relationship between *one* measure of experience, typically cumulative installed capacity, and technology cost.

Yet, the literature has employed a variety of additional factors that drive technology costs. Figure 2.1 presents a brief taxonomy of approaches. As shown, a well established extension within a so-called two-factor learning curve is the inclusion of a knowledge stock through which learning by searching (LBS) takes place (Kouvaritakis et al., 2000, Miketa and Schrattenholzer,

[19] Based on seminal learning curves in airframe manufacturing (Wright, 1936), Arrow (1962) coins the term "learning by doing" as the mechanism through which an increase in experience with the relevant manufacturing processes results in lower costs, e.g., labor or unit costs.

[20] In contrast to learning-based ETC models, models with exogenous technological change include assumptions on future costs that do not depend on prior market outcomes or firm decisions (Gillingham et al., 2008). The more fundamental discussion on empirically separating endogenous from exogenous technological change (e.g., Nordhaus, 2014) is beyond the scope of this study.

2004, Klaassen et al., 2005, Kobos et al., 2006, Jamasb, 2007, Söderholm and Klaassen, 2007). Two-factor learning curves thus combine two originally separate approaches of implementing ETC into energy system models (Gillingham et al., 2008). Other recent works have also focused on mechanisms such as learning by using, learning by interacting or relationship-specific LBD (Kellogg, 2011, Tang, 2018) and learning from spillovers (Irwin and Klenow, 1994, Anderson et al., 2019, Bollinger and Gillingham, 2019, Nemet et al., 2020).

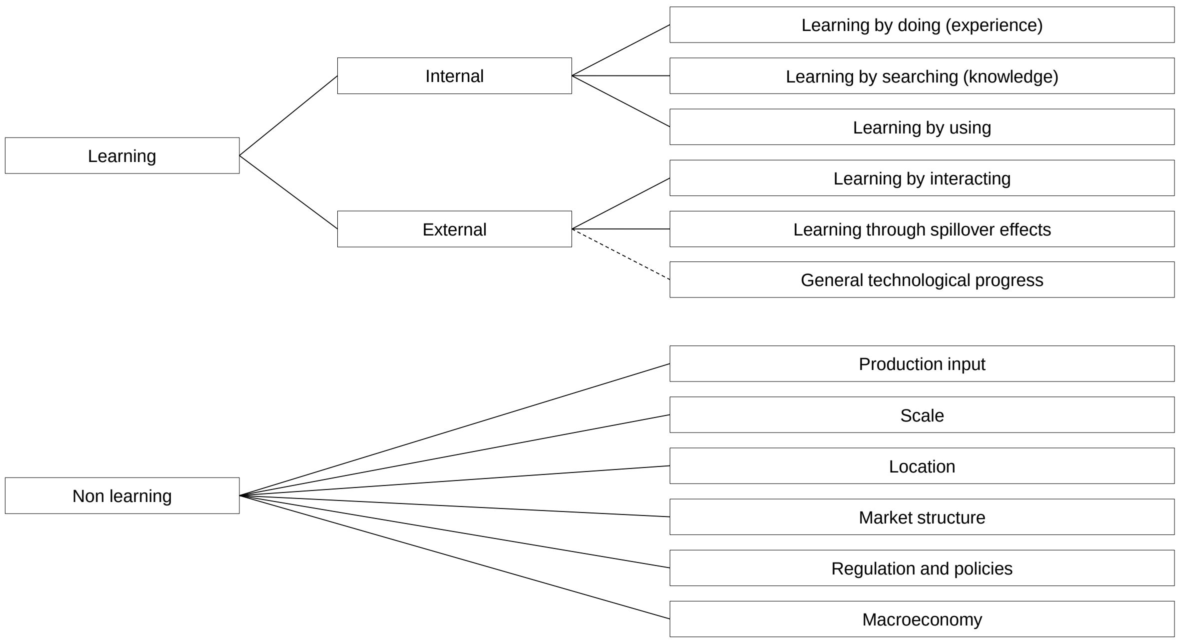


Figure 2.1: Taxonomy of Energy Technology Cost Drivers.

As indicated in Figure 2.1, learning by interacting and learning from spillovers differ from previously mentioned mechanisms because they represent externalities, i.e., firms learn from actions taken by other market actors (Malerba, 1992, Clarke et al., 2006). Finally, technological change is also attributed to external learning in the form of general technological or scientific progress (Malerba, 1992).

Next to learning mechanisms, the literature employs a wide range of covariates not directly related to learning. Mostly, these controls relate to input, scale economies, location-specific, market structure, regulatory, and macroeconomic factors. Examples from onshore wind include materials price indices, wind resource quality, competition, requirements on local value creation, and interest rates.

Importantly, economies of scale have so far been incorporated into learning studies on two different levels: wind farm size and wind turbine unit size (Berry, 2009). Hence, EOS has mostly been measured as the average capacity of a wind farm or average capacity of a wind turbine (Berry, 2009, Qiu and Anadon, 2012, Wilson, 2012).[21] Yet, studies that use these EOS proxies find it hard to disentangle scale effects in operation from learning effects (Ek and Söderholm, 2010, Odam and de Vries, 2020). In our empirical analysis, we introduce firm size as an alternative EOS measure that more explicitly captures scale effects in the manufacturing process. In particular, firm size captures economies of sale in the manufacturing process that relate to, e.g., larger production lines, the distribution of headquarter overhead costs on more units, or procurement volume discounts.

2.2.3 Estimated Learning Rates for Onshore Wind

Figure 2.2 illustrates the range of onshore wind LBD and LBS rates reported in previous studies, each with different cost measures and cost drivers. LBD rates range from -11.4% to 20% and LBS rates from 0% to 27%.[22]

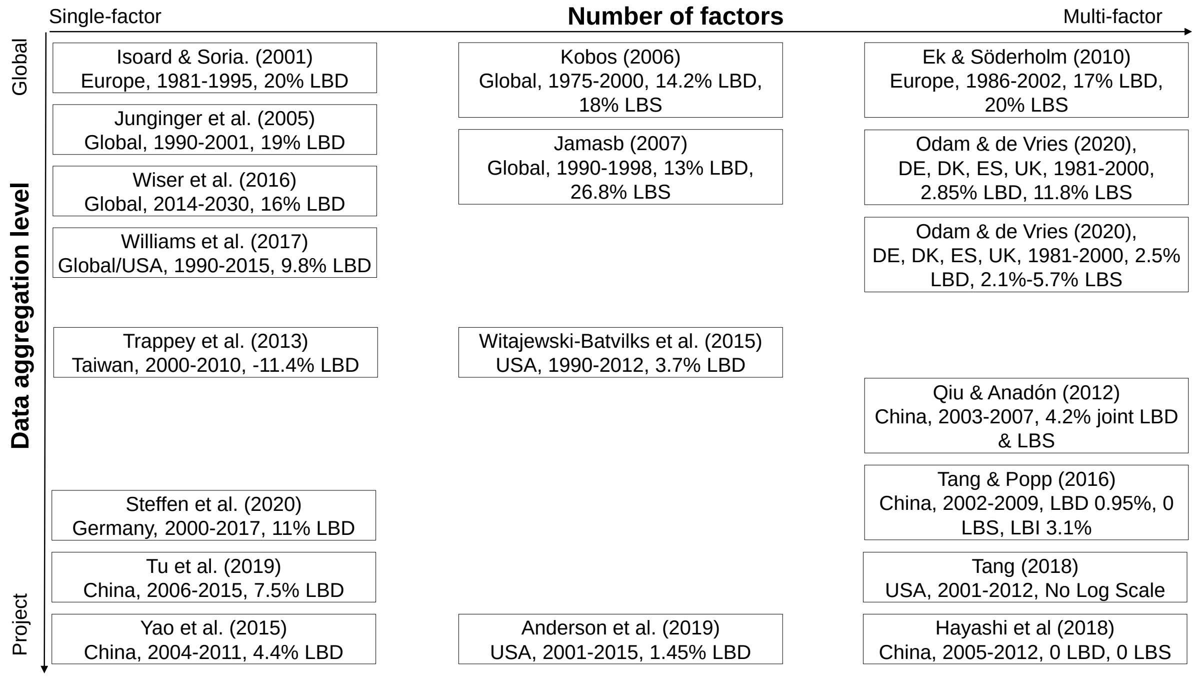


Figure 2.2: Classification of Previous Onshore Wind Learning Rate Studies.

[21] Multi-factor learning curves or cost assessments for other technologies, such as for solar photovoltaics, also include plant size to measure economies of scale in manufacturing (Nemet, 2006, Pillai, 2015).

[22] Including earlier studies amplifies this range.

In particular, Figure 2.2 indicates three findings when reviewing the extant literature. First, more recent studies tend to show lower learning rates. Second, studies using project-level data find lower learning rates than studies based on more aggregated data. Third, the range in learning rates and the sensitivity to model assumptions appears to be smaller when the period of observation is long enough and several factors are examined that can drive technology costs. Taken together, when moving from top left to bottom right corner of Figure 2.2, previous works have found relatively lower learning rates.[23]

Another source of variation in learning rates in Figure 2.2 is the cost measure used to proxy technological progress. While the majority, particularly earlier studies, focuses on installment costs, more recent studies analyze learning in terms of LCOE (Wiser et al., 2016, Williams et al., 2017), capacity factor (Tang and Popp, 2016, Tang, 2018) or component-level cost, such as operations and maintenance (Steffen et al., 2020).

2.3 Methodology and Data

Next, we introduce our empirical approach and present the data used to estimate learning rates for onshore wind energy. To capture the broad channels of learning as reviewed above, we opt for an econometric model that covers all relevant cost drivers and allows for different cost measures as outcome of interest. We also probe into the sensitivities of estimated learning rates by employing a range of differently specified cost drivers as well as control variables.

2.3.1 Econometric Model

We allow onshore wind technology costs to depend on two key learning mechanisms, LBD and LBS, as well as on non-learning cost drivers. Specifically, we estimate the following multi-factor experience curve model for onshore wind:

$$\begin{aligned} log\ LCOE_{i,t} =& \beta_0 + \beta_1\ log\ EXP_{i,t} + \beta_2\ log\ KS_{i,t} + \beta_3\ log\ EOS_t \\ &+ \beta_4\ log\ CI_{i,t} + \beta_5\ log\ LA_{i,t} + FE_i + \epsilon_{i,t}, \end{aligned} \tag{2.2}$$

[23] For learning mechanisms beyond LBD and LBS as well as for some non-learning mechanisms, most notably EOS, the empirical evidence is likewise mixed. While Anderson et al. (2019) do not find experience spillovers, Qiu and Anadon (2012) and Tang (2018), for the operational phase, do. Some studies report a statistically significant relationship between technological change and economies of scale (Qiu and Anadon, 2012, Odam and de Vries, 2020) whereas others find insignificant diseconomies of scale (Ek and Söderholm, 2010, Anderson et al., 2019).

where $LCOE$ is our benchmark measure for technology costs, and subscripts i and t indicate country and year, respectively. We first estimate equation (2.2) using LCOE as outcome of interest. As argued, LCOE is a comprehensible cost measure that captures total installed costs as well as other relevant cost components (e.g., operating and maintenance costs). Further below, we decompose learning into other cost components to shed light what parts of LCOE are subject to learning.

The terms EXP and KS are the two seminal learning channels, experience and knowledge stock. First, EXP captures learning by doing and is measured as depreciated, cumulative installed capacity in MW. More specifically, the experience for country i in year t is computed as

$$EXP_{i,t} = (1 - \delta) * EXP_{i,t-1} + CAP_{i,t}, \tag{2.3}$$

where CAP is new capacity and δ captures depreciating experience, i.e., the forgetting rate (Argote and Epple, 1990). We set δ to 3% in our benchmark specification, following earlier assumptions in the literature (Klaassen et al., 2005, Kobos et al., 2006).

KS is the knowledge stock and captures learning by searching. Depending on the specification, KS is measured as cumulative, depreciated patents granted by the European Patent Office (EPO) in $t - 3$ or as cumulative, depreciated public wind energy RD&D expenses in $t - 5$. Formally, when using patents

$$KS^{PAT}_{i,t} = (1 - \delta) * KS^{PAT}_{i,t-1} + PAT_{t-3}, \tag{2.4}$$

where PAT are patents of the class F03D (wind rotors) that are granted by the EPO. As indicated, we use a three-year time lag for learning. As for experience, we use a depreciation rate δ of 3%. This approach again follows previous assumptions on magnitudes of depreciation rates for knowledge (Griliches, 1979, Klaassen et al., 2005, Popp et al., 2011, Odam and de Vries, 2020).

When re-running our model using public RD&D spending as a commonly employed alternative measure (Klaassen et al., 2005, Söderholm and Klaassen, 2007), we compute the knowledge stock as

$$KS^{RDD}_{i,t} = (1 - \delta) * KS^{RDD}_{i,t-1} + RDD_{t-5}. \tag{2.5}$$

Because RD&D expenditures occur upfront to knowledge creation and the applications of patents, we use a longer time lag of five years and a higher depreciation rate of 6%. Further below, we introduce several sensitivity checks to the computation of experience and knowledge stock.

EOS in equation (2.2) captures economies of scale in manufacturing, approximated by the average firm size of the three largest listed European wind turbine producers Vestas, Siemens Gamesa, and Nordex. These three firms had a joint global market share of 37.6% in 2018 (REN21, 2019) and are the largest players on the European market.[24] Following common approaches in the innovation economics and finance literature (e.g., Whited and Wu, 2006, Kogan et al., 2017), we measure firm size as total assets reported in the annual financial statements. For robustness, we also construct EOS by proxying firm size with average deflated revenues as in Kogan et al. (2017).

Last, CI is commodity index, LA is relative unit labor cost, and FE_i captures country fixed effects.[25] Finally, we calculate the LBD rate as $LBD = 1 - 2^{\beta_1}$ and the LBS rate as $LBS = 1 - 2^{\beta_2}$.

2.3.2 Robustness

Learning curve estimation is subject to simultaneity bias (Jamasb, 2007, Söderholm and Klaassen, 2007, Witajewski-Baltvilks et al., 2015). Arguably, increases in capacity can reduce costs via LBD while, vice versa, increases in capacity can stem from an increase in demand due to lower technology costs. We therefore perform a robustness check using two-stage least squares (2SLS) estimation. Following Jamasb (2007), we instrument experience with time fixed effects. In addition, we use GDP per capita as well as the financing conditions by country, because we expect countries with higher GDP to have deeper pockets for investing into new capacity, and high interest rates to make deployment more costly and less attractive, given the large investments required upfront. Hence, we instrument experience with time fixed effects, the log of GDP per capita, and long-term interest rates in the first stage. The second-stage equation is equivalent to equation (2.2) with experience now being instrumented. Another concern could be that public RD&D expenditures are allocated to "promising industries" where cost declines

[24] See Bloomberg New Energy Finance at https://about.bnef.com/blog/vestas-still-rules-turbine-market-but-challengers-are-closing-in/.

[25] The Hausman and Breusch-Pagan tests reject random effects.

are expected. Following Jamasb (2007), we hence run our 2SLS robustness checks only using patents as measure for knowledge stock.

2.3.3 Sensitivities

To probe into the sensitivities of estimated learning rates, we re-run our model using a range of different assumptions on the main measures of learning, i.e., experience and knowledge stock. The existing literature has often measured experience and knowledge using different assumptions, in particular on time lags and depreciation rates. Many studies integrate depreciation into knowledge stocks. Conversely, depreciating experience has received minor attention, although empirical evidence suggests the presence of forgetting in multiple contexts (Argote et al., 1990, Benkard, 2000, Thompson, 2007). Prior studies for wind or solar PV that implement forgetting assume a rate of around 10% per year (Hayashi et al., 2018, Bollinger and Gillingham, 2019). Our benchmark specification assumes a lower forgetting rate of 3%, which we have set equal to typical assumptions on the depreciation of the knowledge stock. These depreciation rate assumptions are subject to significant uncertainty (Yeh and Rubin, 2012). To gauge into the effects of these assumptions, we assess the sensitivity of our results with respect to different time lags and depreciation rates for both the experience and knowledge stock measures. Specifically, we re-run our specification in (2.2) and vary depreciation rates using values between 0% and 20% in steps of 2.5%.

2.3.4 Decomposing Technology Costs

Finally, we investigate learning in different cost components. In addition to LCOE as cost measure, we estimate equation (2.2) using two further measures for technological progress. We do so to explore what parts of technology costs are ultimately affected by learning, and what part of technology costs are particularly relevant for projecting technological change.

Importantly, note that LCOE typically is an outcome variable of power market models. When endogenizing technological change of renewable generation in power market models, typical input parameters are installment costs and capacity factor. Below, we therefore focus on installment costs (IC) and capacity factor (CF) to make our result implementable in power system models.[26] While changes in installment costs can be understood as direct cost-reducing technological change, we use the capacity factor to measure improvements in quality of wind turbines.[27] We perform these tests by exchanging the dependent variable in equation (2.2) and leaving all variables on the right hand side unchanged.

2.3.5 Data

Our main data comprise a set of country-level variables. We make use of cost data for onshore wind from seven European countries which is available from the International Renewable Energy Agency (IRENA, 2020).[28] For the experience and knowledge measures we use data on country-specific onshore wind capacities and RD&D data from IRENA and the International Energy Agency (IEA). Further, we add patent data from OECD iLibrary and PATSTAT. In particular, we employ patent data from the OECD iLibrary using the class F03D "wind rotors". For robustness checks, we use PATSTAT data and the Y-scheme patent classification, specifically class Y02E 10/70 and subclasses.[29]

We also merge in yearly data on average total assets of the three largest listed European wind turbine manufacturers, Vestas, Siemens Gamesa, and Nordex, that we obtain from Thomson Reuters. These data constitute our EOS variable. Finally, we source data on commodity prices and firm indicators, likewise from Thomson Reuters.[30] Data on economic variables, primarily labor cost, is also from the OECD iLibrary.

[26] As well known, the LCOE is the ratio of total lifetime costs over total electrical output. The installment costs constitute the bulk of total lifetime costs, while the capacity factor can be seen as a proxy for total electrical output.

[27] We assume that, for wind energy, capacity factors are independent of power market characteristics and not endogenous due to the position of wind power in the merit order and flexible demand from storage and power-to-X facilities (e.g., Ruhnau et al., 2020, Glenk and Reichelstein, 2019) that can reduce curtailment.

[28] The countries included are Denmark (DNK), Germany (DEU), Spain (ESP), France (FRA), the United Kingdom (GBR), Italy (ITA) and Sweden (SWE). The use of IRENA's cost data, particularly LCOE, comes with the assumption of a homogeneous WACC of 7.5%.

[29] The Y-scheme classification allows to find patents related to wind energy from multiple different patent classes and subclasses. For our dependent variable, experience and knowledge stock measures, we interpolate occasional missing data. Especially, we interpolate two implausible outliers in Spanish and British cost data.

[30] The data codes are WC02999, HWWISR$, LAHCASH, LCPCASH for firms total assets, steel, aluminum, and copper, respectively. Iron ore prices are publicly available at the FRED at https://fred.stlouisfed.org/series/PIORECRUSDM. We calculate the commodity price index following Moné et al. (2017) as $CI_t = 0.74 * Steel\ Price_t + 0.11 * Iron\ Ore\ Price_t + 0.02 * Aluminum\ Price_t + 0.01 * Copper\ Price_t$. Cross-sectional variation stems from deflating the commodity index with country-specific deflation rates. We deflate the commodity index with deflators from the IEA but do not find our results to be sensitive to non-deflation.

Table 2.1: Descriptive Statistics

Variable	Mean	SD	Min.	P25	Median	P75	Max.
Panel A: Raw data							
LCOE	0.11	0.03	0.05	0.09	0.11	0.12	0.16
IC	2127.07	281.67	1276.00	1923.00	2135.00	2318.00	3134.00
CF	0.26	0.04	0.18	0.23	0.25	0.28	0.40
New capacity	620.92	882.35	−33.00	41.00	233.38	846.02	4871.00
EPO patents	10.60	21.78	0.00	0.00	1.31	8.06	116.57
RD&D	11.88	13.20	0.14	2.66	7.12	15.83	86.03
CI	294.08	114.47	117.28	165.34	310.80	384.23	511.02
EOS	4276.30	3131.95	159.53	1571.63	4785.79	5598.60	11721.44
LA	103.17	6.90	85.84	100.00	102.16	106.28	123.58
Panel B: Experience and knowledge stocks							
EXP	6933.15	8311.92	14.32	1296.21	3237.15	9122.91	40643.99
KS^{PAT}	97.20	177.09	0.97	7.22	22.25	75.30	777.23
KS^{RDD}	118.64	95.31	5.81	45.52	101.14	157.93	453.83

Notes: This table shows descriptive statistics. The number of observations is 147, except for EOS, where we have 21 yearly observations. Panel A displays raw data. We measure LCOE in \$/kWh, IC in \$/kW, CF in %, new capacity in Megawatt (MW), RD&D and EOS in \$ millions, and LA as a relative unit cost index. All monetary data except EOS are in 2019 \$, EOS are nominal. New capacity contains data from 1990 to 2018 and patents (RD&D) from 1984 to 2015 (2013). Panel B presents experience and knowledge stocks that we compute from the data.

The availability of our EOS measure determines the sample starting year, 1998, and the use of patent data our end year, 2018, resulting in 147 observations. Due to the time lag until new patents or RD&D enter the knowledge stock and to account for its character as a stock, we include patents and RD&D from 1984 on. For similar reasons, we start constructing the experience stock in 1990. Commercial uptake of onshore wind farms and data availability determine these starting dates for the computation of the stock variables. Table 2.1 provides the summary statistics.

2.4 Results

This section presents our empirical results. We discuss our baseline estimates and a battery of robustness checks, including the instrumental variable approach and our sensitivity analysis.

2.4.1 Main Results

Table 2.2 depicts the results of estimating equation (2.2) when LCOE is the dependent variable. Column 1 shows the results when using patents to construct the knowledge stock. We estimate an LBD rate of 2.8% and an almost three-times larger LBS rate of 7.1%, both statistically different from zero at the 1% level. Hence, a doubling of the depreciated cumulative capacity (patents) is associated with an LCOE decrease of 2.8% (7.1%). All non-learning covariates have the expected impact: The commodity index and labor costs are strongly positively associated with LCOE whereas EOS are negatively associated with LCOE, all significant at the 1% level. In terms of magnitude, we find that an increase in EOS as measured by total assets of one percent is associated with a decline of 0.08% in technology costs.

Table 2.2: Regression Results for LCOE

Dependent variable: LCOE	(1) OLS	(2) OLS	(3) 2SLS
EXP	-0.041^{***}	-0.028	-0.085^{***}
	(0.014)	(0.017)	(0.019)
KS^{PAT}	-0.106^{***}		-0.104^{***}
	(0.015)		(0.015)
KS^{RDD}		-0.136^{***}	
		(0.041)	
CI	0.180^{***}	0.169^{***}	0.191^{***}
	(0.040)	(0.045)	(0.042)
EOS	-0.080^{***}	-0.158^{***}	-0.045^{*}
	(0.024)	(0.023)	(0.026)
LA	0.450^{***}	0.612^{***}	0.386^{**}
	(0.171)	(0.191)	(0.177)
Constant	-3.701^{***}	-3.683^{***}	-3.753^{***}
	(0.799)	(0.948)	(0.819)
Country FE	Yes	Yes	Yes
LBD (in %)	2.77	1.89	5.73
LBS (in %)	7.06	9.00	6.98
Adjusted R^2	0.77	0.71	0.74
N	147	147	147

This table presents our main regression results on log-log scale. We estimate the model twice, first with patents (column 1), then with RD&D as the knowledge variable (column 2). Column 3 contains the results of our instrumental variable approach using the two-stage least squares (2SLS) estimator. We use time dummies, per capita GDP and interest rates as instruments for EXP but also include all other covariates in the reduced form. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Column 2 re-estimates the model using the RD&D-based knowledge stock that targets input to innovation. As can be seen, switching the knowledge stock definition to RD&D reduces LBD to

1.9% (significant at 10.4%) but increases LBS to 9%. Whereas estimates slightly change, they hence remain comparable to using patents as knowledge measure. In addition, both specifications clearly show that LBS rates are several orders of magnitude higher than LBD rates. Lastly, the impact of all covariates remains robust and as conjectured throughout both specifications.

Our core results of Table 2.2 remain virtually unchanged when (1) counting patents in several different ways with respect to patent class, quality indicator, e.g., family size, or weights for quality (Popp et al., 2011, Nemet, 2012a), (2) approximating experience with cumulative generation instead of capacity, (3) using lagged experience, (4) using average revenue of the three turbine manufacturers as EOS measure, (5) varying start year and end year, separately and together, by one year, and (6) deflating commodity prices and firm total assets in different ways. Appendix Table A.1 contains estimation results of robustness check (1), Appendix Table A.2 of robustness checks (2) to (4), and Appendix Table A.3 of robustness check (5).

2.4.2 Instrumental Variable Estimation Results

Our results above rely on ordinary least squares regression with regular standard errors.[31] Next, we address potential concerns of simultaneity bias by using the instrumental variable approach. Column 3 of Table 2.2 presents the 2SLS regression results. As can be seen, the LBS rate remains robust in terms of significance and magnitude. However, the LBD rate increases to 5.7%, thereby converging to the estimated LBS rate of 7%. The coefficients of EOS and labor costs both decline in absolute terms. Overall, our IV regression corroborates our prior results that significant learning takes place both for LBD and LBS. In particular, our IV results shows that LBS still outweighs LBD.

2.4.3 Sensitivity in Time Lags and Depreciation Rates

In order to understand the influence of different assumptions on depreciation rates of experience and knowledge, we vary both using values between 0% and 20% in steps of 2.5%, following Kobos et al. (2006).

[31] Using robust standard errors or panel-corrected standard errors (Beck and Katz, 1995) produces largely identical results.

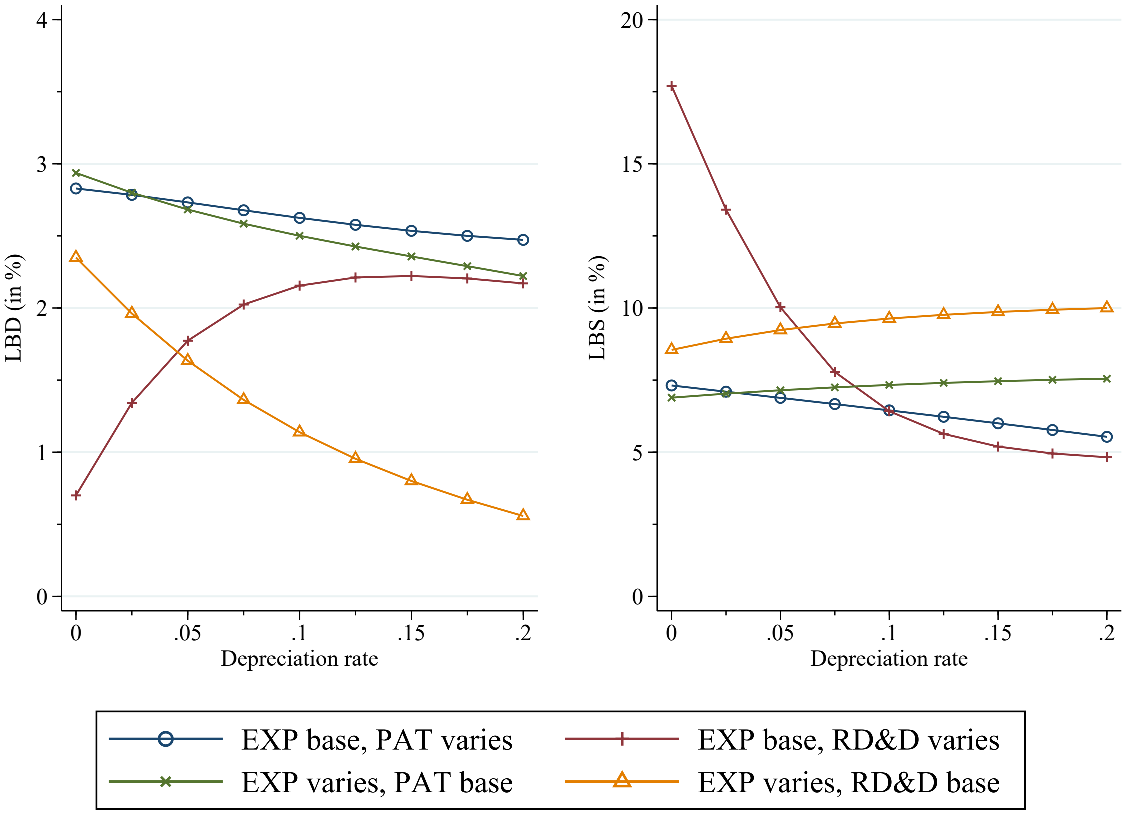


FIGURE 2.3: Sensitivity Analyses with Various Depreciation Rates.

Notes: The left graph shows *LBD* rates in four different scenarios. We vary either the depreciation in experience or in knowledge. As before, we measure knowledge using patents or RD&D. The varying depreciation rate in each scenario is reflected on the horizontal axis, using steps of 2.5%. For instance, in the first scenario (EXP base, PAT varies), the graph depicts LBD rates when holding the depreciation rate for experience at its base of 3% and varying the depreciation rate of knowledge from 0 to 20%. The right graph shows the corresponding *LBS* rates.

Figure 2.3 illustrates the results.[32] We observe two important patterns. First, learning rates remain relatively stable when using the patent-based knowledge stock, no matter if varying the depreciation rate for knowledge (EXP base, PAT varies) or for experience (EXP varies, PAT base). As can be seen in the left panel of Figure 2.3, LBD rates are approximately constant. In the right panel of Figure 2.3, depreciating cumulative patents at a higher rate decreases LBS to a minimum of 5.5%, i.e. only about 1.5 and 1.8 percentage points lower than the estimated base case in Table 2.2 and the zero depreciation case, respectively.

Second and more importantly, LBS rates strongly react to variations in the RD&D-based knowledge stock depreciation rates. As can be seen in the right panel of Figure 2.3, LBS rates vary between 17.7% in the zero depreciation case and 4.8% when using a depreciation rate of 20% (EXP

[32]Varying both forgetting and depreciation rates simultaneously produces similar point estimates.

base, RD&D varies). The sensitivity is particularly pronounced in the first steps after starting with a zero depreciation rate, i.e. around values frequently used in prior studies (Klaassen et al., 2005). Overall, the RD&D-based knowledge stock depreciation rate, and with it the choice of RD&D versus patents as measure for knowledge, appears to contribute to explaining parts of the previously reported range in learning rates.

In untabulated analyses, we also vary the lag structure from two to seven years but do not find large impacts on our results. In sum, the sensitivity analysis supports our initially reported LBD rates. We find that the measurement and the assumed depreciation rate of the knowledge stock have larger implications on the learning rates than the depreciation of experience. However, our result that LBS rates are significantly higher than LBD rates remains robust.

2.4.4 Decomposing LCOE

That LBS is highly significant in terms of magnitude suggests that research and development drive technology cost. To further gauge into what parts of LCOE are driven by knowledge creation, and what parts are driven by experience, we decompose LCOE and estimate the impact of knowledge and experience separately for installment costs and capacity factor. Importantly, this decomposition also aids the setup of energy system models in that it sheds light on how researchers can endogenize technological change, i.e, via endogenizing upfront installment costs or capacity factors. Table 2.3 shows the corresponding regression results of this decomposition into installment costs and capacity factor.

As shown in columns 1 and 2, we do not find any significant learning when we measure costs with total installed costs. These findings are in stark contrast to our results on LCOE. Yet, note that EOS are still significantly negatively related to costs and the commodity index is positively associated to costs, as can be expected.

In columns 3 and 4, we use capacity factor and estimate a statistically significant LBS rate of 3.9% to 5.2%. LBD rates vary between 0.3% to 0.8%, albeit insignificant in this multi-factor model. While EOS again show a significant relationship to the dependent variable, changes in

TABLE 2.3: Regression Results for Wind Installment Cost and Capacity Factor

	(1) IC	(2) IC	(3) CF	(4) CF	(5) CF
EXP	−0.005	−0.002	0.011	0.004	0.039***
	(0.013)	(0.013)	(0.011)	(0.012)	(0.015)
KS^{PAT}	−0.007		0.055***		0.054***
	(0.013)		(0.011)		(0.012)
KS^{RDD}		−0.030		0.073**	
		(0.032)		(0.030)	
CI	0.252***	0.248***	−0.046	−0.040	−0.053*
	(0.035)	(0.036)	(0.031)	(0.033)	(0.032)
EOS	−0.096***	−0.098***	0.050***	0.090***	0.028
	(0.021)	(0.018)	(0.018)	(0.016)	(0.020)
LA	0.105	0.097	−0.288**	−0.369***	−0.248*
	(0.151)	(0.149)	(0.131)	(0.137)	(0.135)
Constant	6.637***	6.811***	−0.634	−0.668	−0.626
	(0.705)	(0.741)	(0.613)	(0.683)	(0.622)
Country FE	Yes	Yes	Yes	Yes	Yes
LBD (in %)	0.36	0.14	−0.75	−0.26	−2.72
LBS (in %)	0.50	2.04	−3.85	−5.21	−3.80
Adjusted R^2	0.35	0.35	0.67	0.63	0.61
N	147	147	147	147	147

This table presents regression results for installed costs and capacity factor as proxies for technological change. We estimate each model twice, first with patents (columns 1 and 3), then with RD&D as the knowledge variable (columns 2 and 4). Column 5 shows results of the instrumental variable model using the two-stage least squares (2SLS) estimator. All variables are on log scale. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

the commodity index have, as expected, no effect. Note that the learning rates are negative because an increase of capacity factors indicates technological progress.[33]

As argued, since bias due to simultaneity could also affect inference when using installment costs or capacity factor as proxies for technological change, we repeat our instrumental variables estimation of section 2.3.2. Column 5 of Table 2.3 shows the results.[34] As in the case of LCOE, the IV approach produces almost identical LBS rates compared to the base OLS case. LBD rates increase by approximately two percentage points to 2.7%.

[33]We also re-run equation 2.2 using total installed costs scaled by full load hours as the dependent variable. This constitutes a further robustness check as well as a potential alternative cost measure to incorporate into energy system models. We do not tabulate the results because they are conceptually similar to using capacity factors and only show slightly higher learning rates compared to those of the capacity factor.

[34]We do not tabulate results of the IV approach for total installed costs because learning rates hardly change and remain insignificant.

Overall, our decomposition of LCOE illustrates that a mere modeling focus on installed costs does not provide a complete picture of progress in onshore wind technology. Instead, to achieve results much closer to the technical reality and the progress in LCOE, the capacity factor with its significant LBS rates should likewise be modelled.

2.5 Discussion

Our results above suggest that, first, LBS has larger effects on technology costs than LBD. Second, LBS estimates depend heavily on the assumptions on the depreciation of the knowledge stock. In particular, LBS rates react sensitively to changes in the depreciation rate when measuring knowledge with RD&D. In contrast, learning rates are more stable across different depreciation rates when using patents as measure for knowledge instead.

One reason for the high sensitivity in learning rates when using RD&D as proxy for knowledge is that RD&D is an input-oriented measure. Arguably, RD&D is subject to diversion and failure, which the depreciation rate must adequately account for. Hence, using insufficiently low depreciation rates can result in inflated knowledge stocks. In line with Figure 3 above, inflating knowledge stocks can in turn lead to high estimated learning effects from RD&D expenditures.

Patents on the other hand are an output measure of knowledge, verified by the patent examiner as unique and new.[35] As our findings show, using patents to proxy for knowledge is hence more robust to different assumptions on the depreciation rate.

Overall, our findings indicate that energy system models that incorporate ETC should not be confined to LBD only, and include LBS. Public RD&D lends itself to being used as the knowledge measure in systems models (Gillingham et al., 2008, Rubin et al., 2015) because it is a policy variable, unlike patents. In order to deal with the lower robustness of RD&D, validating LBS rate assumptions using patents or including a sufficiently high depreciation rate for RD&D in the range of 6-10% appears reasonable.

Furthermore, we find that LBS in particular channels into improvements in quality rather than in mere cost reductions. This is, we find no significant effects on total installed costs but mostly in terms of capacity factor. Last, the assumed time lags until which new experience or new

[35]Patents have the additional benefit of measuring both public and private knowledge whereas public RD&D spending does not.

knowledge adds to the existing stocks has only small or no effects on learning rates. Thus, system models can adapt time lags for learning such that it fits modelling needs for investment decision frequency.

In closing, we present a short projection model where we employ our main LBD and LBS estimates for LCOE and capacity factor. The aim of this brief projection is to use and compare our estimates with expected capacity factors for 2050.

According to a projection by IRENA (2019), European onshore wind capacity is to reach 215 GW in 2030 and 482 GW in 2050, starting from 162 GW in 2018. We combine our model assumptions and results (3% forgetting without lag, 6% knowledge depreciation rate with five year lag, average European 2018 LCOE (capacity factor) of 0.062 $/kWh (35.41%), LBD and LBS from Table 2.2 with four new assumptions: First, Europe adds capacity constantly each year to reach the 2030 target and then the 2050 target, second, future yearly European wind RD&D expenses correspond to its 2019 value of $364.59 million, third, learning rates are applicable to Europe as a whole, and, fourth, there are no changes in commodity prices, manufacturing EOS and labor costs.

Our computed projections show that the LCOE declines by 6.19% until 2030 and 10.50% until 2050, then amounting to 0.055 $/kWh, highly competitive with current generation costs of conventional technologies even in the absence of any carbon pricing. In the same period, the average capacity factor of a European onshore wind farm increases by 6.01% to 37.57%. This capacity factor approaches the 2018 level of Great Britain and Denmark, the two countries with the highest average capacity factor. The projection in IRENA (2019) suggests capacity factors between 30% and 58%. Our estimate of 37.57% is at the lower and more conservative end of this projection, yet well within this range.

2.6 Conclusion

This study uses recent country-level data to estimate learning rates of onshore wind power. We identify relevant cost drivers and learning channels for different measures of technological progress of wind turbines, i.e., LCOE, installment cost, and capacity factors. Our goal is to show what cost drivers and learning channels are robust across different specifications and *where* learning takes place, i.e., what cost components experience technological progress. In decomposing LCOE into installment costs and capacity factor, we also aim at guiding energy system models in how they can incorporate endogenous technological change into equilibrium market analyses and corresponding projections.

First, we find learning by doing rates of 2%-3% and learning by searching rates of 7%-9% when estimating effects for LCOE. These estimates are robust against a variety of additional controls as well as when using instrumental variables. Yet, we show that estimates depend on assumptions on depreciation rates and the measurement of the knowledge stock, explaining parts of the huge variation observed in previous learning rate studies. Importantly, learning rates are most robust when measuring knowledge creation by using the patent stock, instead of relying on RD&D data.

To explore the relevant cost components that are subject to learning, we then decompose LCOE into installment costs and capacity factor. For installment costs, we find learning rates close to zero. In contrast, for the capacity factor, we find insignificant LBD rates but significant LBS rates of 3.9%-5.2%, depending on the specification.

We therefore recommend to extend system modeling of ETC with capacity factors. In so doing, energy market models can account for the fact that onshore wind is not necessarily becoming less expensive in terms of upfront costs, but better in terms of quality and efficiency. In other words, traditional learning channels, such as learning by doing, become less important for upfront installment costs the more mature the technology gets. Instead, learning by searching becomes more relevant, in particular for advancing the quality or efficiency of wind turbines.

Notably, we also find significant and economically strong effects of economies of scale and commodity prices. Hence, future costs of onshore wind also depend on sufficiently competitive supply as well as technological progress both in upstream industries and in the wind industry.

In conclusion, our results highlight the benefits of shifting from a mere focus of installment costs to capacity factors when researching future cost developments and integrating learning curves into power system models. When implementing and estimating learning rates, in particular for learning by searching, researchers have to carefully introduce assumptions on depreciation for knowledge creation via RD&D and patent filings that can significantly drive learning in onshore wind technologies.

3 | System Price Dynamics for Battery Storage

by Magnus Schauf and Sebastian Schwenen[36]

While steep learning curves have been documented for lithium-ion battery packs, little evidence exists on whether total system prices for end-users reflect this decline. We use project-level data from California to estimate system price dynamics and experience rates for battery storage systems. We document low experience rates of about 1.3%, i.e., with every doubling in cumulative projects, system prices fall by 1.3%. Larger systems show higher experience rates of up to 11%, while smaller systems show slightly negative experience rates. We find that limited competition among installers is restraining price declines for small systems. Moreover, learning is driven by industry (rather than firm) experience and is significantly lower for non-battery pack prices. In sum, our results suggest that price dynamics relevant to end-users fall behind the pace of reported cost declines for battery packs, and warrant policy focus on installer competition and non-battery pack prices.

[36] This essay is based on joint work with Sebastian Schwenen. My contributions are as follows: development of the research idea, literature review, formulation of the statistical model, data curation, performing the analysis, creating the visualizations, and writing the original draft.

3.1 Introduction

Battery storage is a key ingredient for decarbonized energy systems (Arbabzadeh et al., 2019). When widely distributed across the system, battery storage facilitates the growth of wind and solar energy (Zerrahn et al., 2018, Schill, 2020, Tong et al., 2021), provides grid stabilization services (Davies et al., 2019), and supports off-grid electricity provision (Jaiswal, 2017, Lee and Callaway, 2018).

The growing relevance of battery storage (Schmidt et al., 2019, Beuse et al., 2020) coincides with a massive increase in R&D and patenting, aiming to reduce battery costs (IEA, 2020a, 2022). However, the economics of battery storage remain challenging for end-users and often dependent on subsidies (Comello and Reichelstein, 2019). As a consequence, understanding learning and potential price reductions for battery storage is important for predicting future market shares and for designing effective support policies.

To analyze and forecast learning and cost reductions, previous studies estimate learning or experience rates for battery storage. Typically, learning rates indicate the change in technology costs associated with a doubling of experience, where experience is measured as cumulative installed capacity or cumulative production. The literature finds learning or experience rates for batteries mostly between 12% and 30% (Kittner et al., 2017, Schmidt et al., 2017, Hsieh et al., 2019, Kittner et al., 2020, Ziegler and Trancik, 2021). Yet, while these results are largely confined to analyzing global averages of scarce annual data for battery cells and packs, less is known on the dynamics of *total system prices* for distributed storage systems, i.e. what drives prices relevant to end-users. Importantly, although evidence for solar photovoltaics (PV) shows that market structure matters (Gillingham et al., 2016), there are no documented experience rates for local battery storage markets that take into account the degree of installer competition. A further consequence of scarce data is that little attention has so far been paid to estimating the price dynamics for the different applications of distributed battery storage (e.g. for small residential and larger non-residential systems) as well as its different price components, such as balance-of-system (BOS) prices.

In this article, we provide several contributions to the literature on learning by doing and technological progress of battery storage. First, we use rich project-level data from California to provide an empirical analysis of total system price dynamics in battery storage markets. We estimate experience rates of about 1.3%, implying that, on average, experience rates for system prices fall behind the majority of reported experience and learning rates for battery packs and cells (Kittner et al., 2017, Schmidt et al., 2017, Ziegler and Trancik, 2021). Second, we document substantial heterogeneity in total system prices and show that experience rates for larger systems are significantly higher than for smaller residential systems (11% vs. -2%). Third, we show that besides experience and system size, market structure matters. In particular for small storage systems, we find that less competition among installer firms is associated with lower experience rates and thus, on average, higher system prices. Fourth, we report that the non battery-related share of the total price, i.e. the BOS price, shows lower experience rates than total prices. Lastly, we explore experience spillover effects and find a price-reducing effect of industry-wide experience. In contrast, we find that firm-specific experience does not explain observed reductions in system prices.

Overall, our analysis reveals that total price dynamics and specifically BOS prices do not match the pace of cost and price reductions for battery packs. Learning effects play a minor role especially for small system prices, which are rather driven by the economics of installer firms and the degree of competition among them. Because we find marked differences in learning for small residential and larger systems, the results of this article further highlight the relevance of tailoring support policies for battery storage to the different use cases. In addition, our findings stress the policy potential for reducing BOS prices and increasing installer competition to further accelerate investment in distributed storage.

3.2 Battery Storage Trends in California

To analyze technological progress and its determinants, we require detailed data on the total prices of individual storage systems. To this end, we conduct our analysis using the case of California and rich project-level data provided by the California Public Utilities Commission (CPUC). More specifically, the data are from the CPUC's Self Generation Incentive Program (SGIP), which administers the vast majority of subsidized battery storage systems in California. SGIP data include, amongst others, information on location, involved firms, system size, and "total eligible costs", i.e. total system prices.

Although other states in the US have started to promote battery storage, California represents the vast majority of distributed storage capacity (82% in 2019 for systems below 1 MW) in the US (EIA, 2021). The SGIP data hence offer a well representative sample. Moreover, cost and growth dynamics are comparable to markets outside the US, e.g. to the German market (Figgener et al., 2021, 2022).

Figure 3.1 shows the growth of SGIP supported storage projects over time. The program has supported about 8,000 systems (panel a) or about 250 MWh of storage capacity (panel b) annually over the recent years. In total, the program supports almost 1.1 GWh of cumulative storage capacity until 2021. The SGIP data, i.e. our sample, starts in 2008 and ends in December 2021 (because there are very few observations in the early years, Figure 3.1 shows data beginning in 2014).

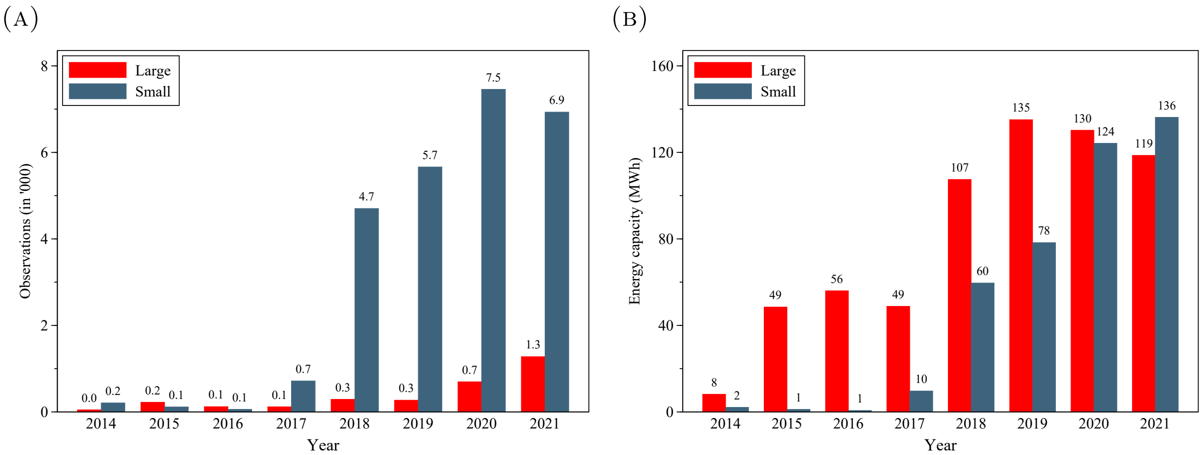


FIGURE 3.1: SGIP Battery Systems and Installed Capacity in California. (A), number of subsidized storage systems. (B), installed storage capacities. We show systems and capacity by size segment, where "small" refers to systems with a power rating of 10kW or less and "large" refers to systems with more than 10kW. Data as of February 2022.

As further shown in Figure 3.1, the bulk of capacity additions until 2017 came from larger systems (above 10kW). From 2017 onward, the number of small systems (below 10kW) surged to several thousand new installations per year. In parallel, this increase led to a rising share of residential storage capacity, which in 2021 represents more than 50% of total interconnected capacity. Among the reasons for this strong uptake of residential storage are wildfire-related power shutoffs, a gradual phase-out of net metering policies, new product launches, and government subsidies for adopters (Barbose et al., 2021).

Similar to distributed solar generation (Gillingham et al., 2016), battery storage prices vary substantially across regions. Figure 3.2 illustrates this price dispersion for battery storage by county for large (panel a) and small systems (panel b). As can be seen, prices differ considerably by county, ranging from about 900 to 2800 USD per kWh.

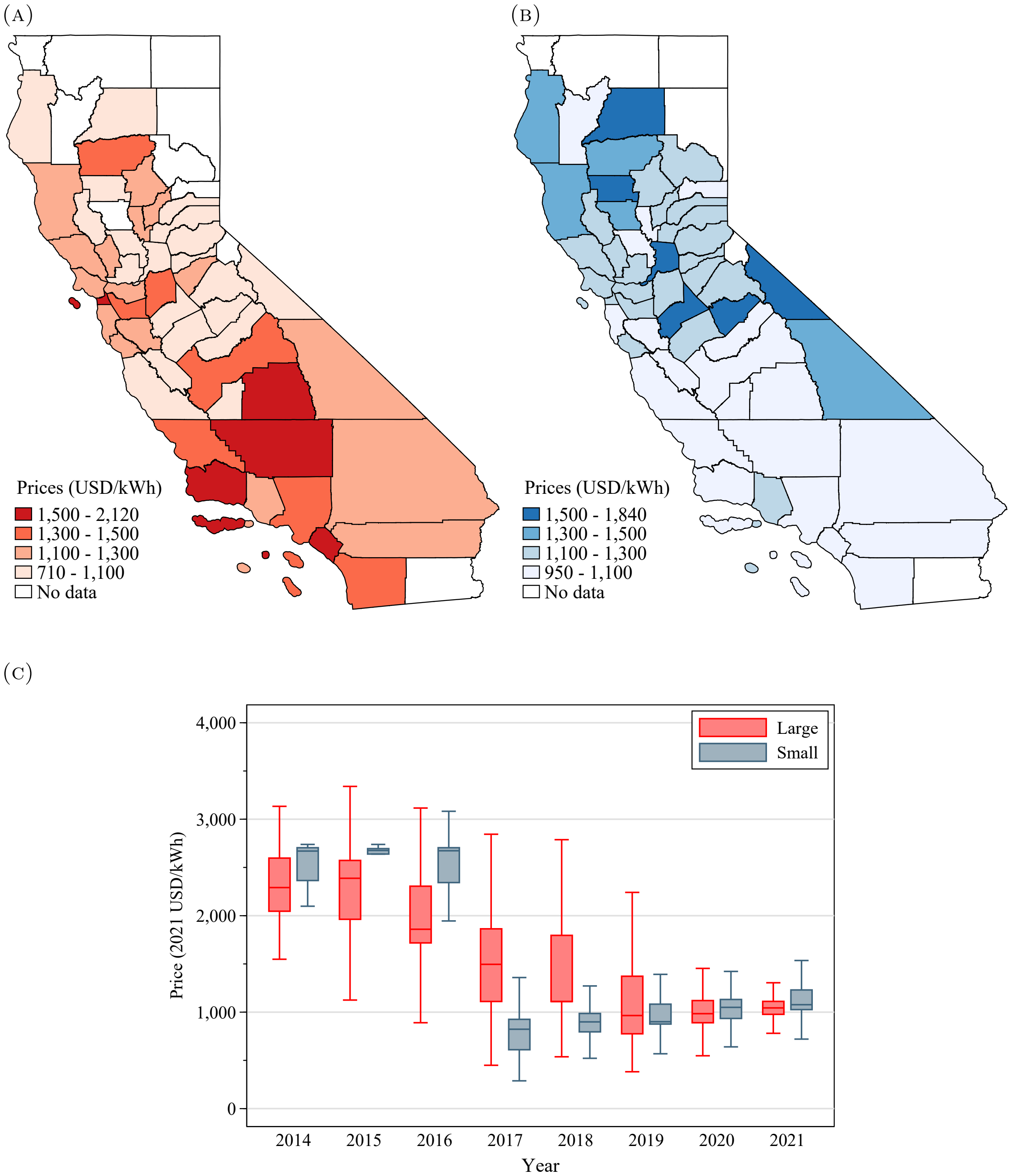


Figure 3.2: System Prices. (A), mean prices for large systems by county. (B), mean prices for small systems by county. (C), by size segment and year.

Finally, as shown in panel c of Figure 3.2, average storage prices decline significantly especially in the early years of our sample, with a parallel decline in variance. The strong decline for small systems in 2017 coincides with the launch of a new and aggressively priced product from Tesla, a firm that acts both as installer and battery technology provider. While average prices of small systems tend to slightly adjust upwards thereafter, this price decline suggests to include the role of competition, amongst other drivers, to explain the heterogeneity and dynamics in system prices as observed in Figure 3.2.

3.3 Estimating Experience Rates for Battery Storage

A well-established approach to measuring technological progress is to use learning rates, that indicate percentage changes in technology costs associated with a doubling of experience (Wright, 1936, Arrow, 1962). While experience is measured differently in the literature, a common approach is to proxy experience with cumulative installed capacity, namely cumulative kilowatt-hours (kWh) in the case of energy storage (Schmidt et al., 2017, Way et al., 2022). Similar to other energy technologies, such as wind power (Schauf and Schwenen, 2021), lithium-ion battery learning and experience rates as reported in the literature differ substantially, depending on the technology variant, definition of experience, model specification, and the sample period. Reported experience rates for electric vehicle battery packs are between 6% and 21% (Nykvist and Nilsson, 2015, Schmidt et al., 2017, Hsieh et al., 2019, Kittner et al., 2020). Experience rates for batteries range from 15% to 30% (Kittner et al., 2017, Schmidt et al., 2017, Kittner et al., 2020, Ziegler and Trancik, 2021), or even higher when accounting for performance improvements beyond cost declines (Ziegler and Trancik, 2021).

Our methodological approach relies on one-factor experience curves (Schmidt et al., 2017). In particular, we use SGIP data and predict total prices per kWh for battery storage systems (in logs) with experience (measured as cumulative projects, likewise in logs). Since learning on total system prices typically does not depend on the energy storage capacity of the system, we use the natural log of cumulative projects to proxy for experience. In additional analyses, we validate our results using cumulative capacity in kWh. We use least squares regression with standard errors clustered at the county level. Additional information and summary statistics for the underlying data are presented in the Methods section and in the Appendix (Tables A.4 to A.6).

Table 3.1 reports the estimated coefficients and corresponding experience rates. We compute the experience rates as $1 - 2^{\beta}$, where β is the estimated coefficient for experience. As shown in column (1), a doubling of experience, when measured as the cumulative number of projects, is associated with a decline in system prices of 1.29%. In column (2), we proxy experience by cumulative installed capacity and find slightly higher experience rates of about 3.33%. These estimates for project-level data are significantly below the previously reported experience rates (Schmidt et al., 2017, Hsieh et al., 2019, Kittner et al., 2020, Ziegler and Trancik, 2021).

Table 3.1: Estimated Experience Rates

Dependent variable: Price in 2021 USD/kWh	All observations	
	(1)	(2)
EXP #	-0.019^{*}	
	(0.011)	
EXP kWh		-0.049^{***}
		(0.015)
Experience rate %	1.29	3.33
Adjusted R^2	0.003	0.01
N	28,299	28,299

All variables are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

3.4 Scale and Installer Competition

To further probe into the markedly low experience rates for system prices, we explore whether learning effects differ when splitting the sample according to different storage applications. We split the sample in residential (i.e. small, 10 kW or less) and non-residential (i.e. larger, above 10 kW) systems. This scale threshold is consistent with the definition of the CPUC (CPUC, 2016).

Table 3.2 presents the results for small and large storage systems. As shown in column (1), large systems show experience rates of about 11.11%. In column (2), we control for the market concentration in each county, as measured by the county-specific Herfindahl-Hirschman Index (HHI), which impacts prices with marginal significance. The specification in column (2) further controls for system size in kWh and duration in hours. We add these controls to account for installation-related economies of scale within CPUC's classification of large and small segments. In this specification, we also control for unobserved, time-invariant county and installer firm heterogeneity by including corresponding fixed effects. We find an experience rate of 8.44%. In sum, the experience rates for large systems are much higher than for the sample including all systems and closer to the experience rates as reported in previous studies.

TABLE 3.2: Regression Results by Segment

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.170^{***}	-0.127^{***}	0.028^{*}	0.021^{***}
	(0.008)	(0.017)	(0.014)	(0.007)
HHI		0.148^{*}		0.577^{***}
		(0.088)		(0.107)
Size kWh		-0.039^{**}		-0.173^{***}
		(0.019)		(0.013)
Duration		-0.123^{*}		-0.426^{***}
		(0.072)		(0.031)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	11.11	8.44	−1.93	−1.49
Adjusted R^2	0.39	0.66	0.01	0.67
N	2,957	2,957	25,331	25,331

All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Column (3) of Table 3.2 shows results for the sample of small systems, which are in stark contrast to the results for larger systems. Learning for small systems is close to zero with an estimated negative experience rate of approximately 2%. In addition, the relatively good model fit (adjusted R^2) of the one-factor model for large systems does not apply to small systems.

We again extend the basic model to control for the county-level HHI, for scale effects, and for county and installer firm heterogeneity. The results for this specification are shown in column (4) and indicate that scale effects play a significant role for small systems, too. For instance, an increase of a small storage system's capacity by ten percent associates with a decrease in system price per kWh of about 1.7%.

Importantly, we find that also the level of installer competition significantly determines the system price. Specifically, a more concentrated installer market (a higher HHI) is associated with higher prices. In other words, an increase in the HHI by 0.12 (one standard deviation) is associated with an increase in system prices by 5.3%. Notably, the model in column (4) that accounts for the HHI and system scale characteristics explains a relevant part of the variation in system prices (as shown by the relatively high R^2).

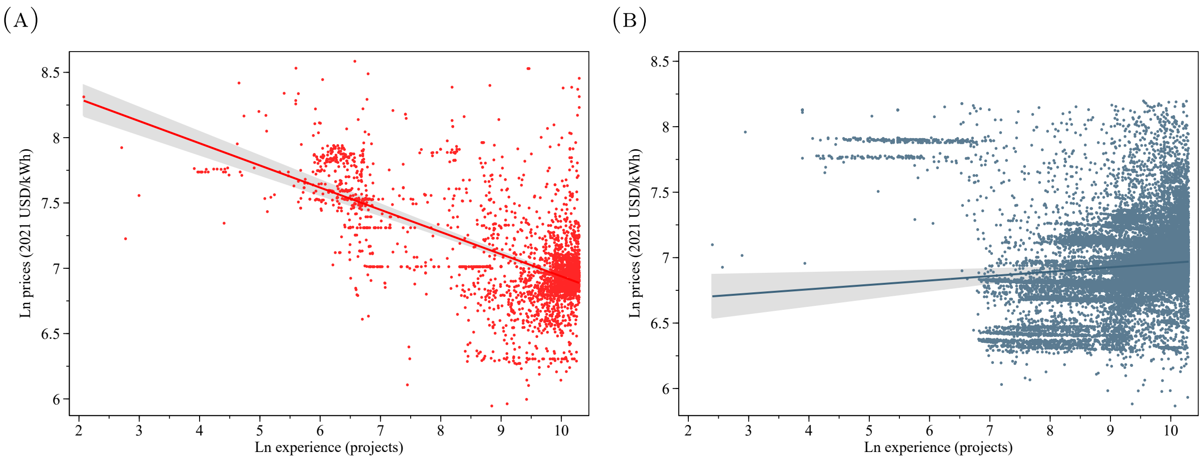


Figure 3.3: Experience Curves. (A), for large systems above 10 kW. (B), for small systems below 10 kW. 95% confidence intervals are shown in grey.

Figure 3.3 illustrates the experience curves for small and large systems graphically. Panel a of Figure 3.3 shows the experience curve for larger systems as estimated in column (1) of Table 3.2. In line with the relatively high R^2 for larger systems, the model describes the data well. In contrast, panel b of Figure 3.3 shows the experience curve for smaller systems (that correspond to the estimates in column (3) of Table 3.2). As can be seen, there is significant heterogeneity in system prices for small systems. The above findings indicate that, first, learning follows strongly different magnitudes for large and small systems, and second, experience alone does not describe the data well, especially for smaller storage systems. As we have shown in our regression results above, further factors such as market concentration, system size, and duration play a significant role for total system prices, and in particular for small storage systems.

3.5 Balance-of-System Prices

So far, our results point to significant learning in total system prices of larger battery storage systems but not for small systems. Next, we explore which price components are driving these results. In particular, we investigate whether observed price declines can be attributed to the prices of battery packs or rather to non-battery, i.e. BOS prices.

Whereas battery packs are arguably a globally traded commodity, BOS prices primarily encompass components with mostly local learning, such as installation, permitting, customer acquisition, and mark-ups. In addition to these "soft cost" components (O'Shaughnessy et al., 2019), BOS also entails inverters and other auxiliary hardware like cables.

Specifically, we proxy BOS prices by deducting battery pack prices from total system prices. Since the SGIP data only provides system prices, we use yearly averages for battery pack prices from Bloomberg's battery price survey to compute BOS prices. This approach is consistent with earlier studies in the context of solar PV, that examine learning in non-module (i.e. BOS) or soft costs after subtracting module (and inverter) costs (Shum and Watanabe, 2008, Strupeit and Neij, 2017). Hence, our BOS measure includes the potentially missing ability of installer firms to purchase battery packs at prices published by Bloomberg, e.g. because of low order volumes or a lack of trading networks.

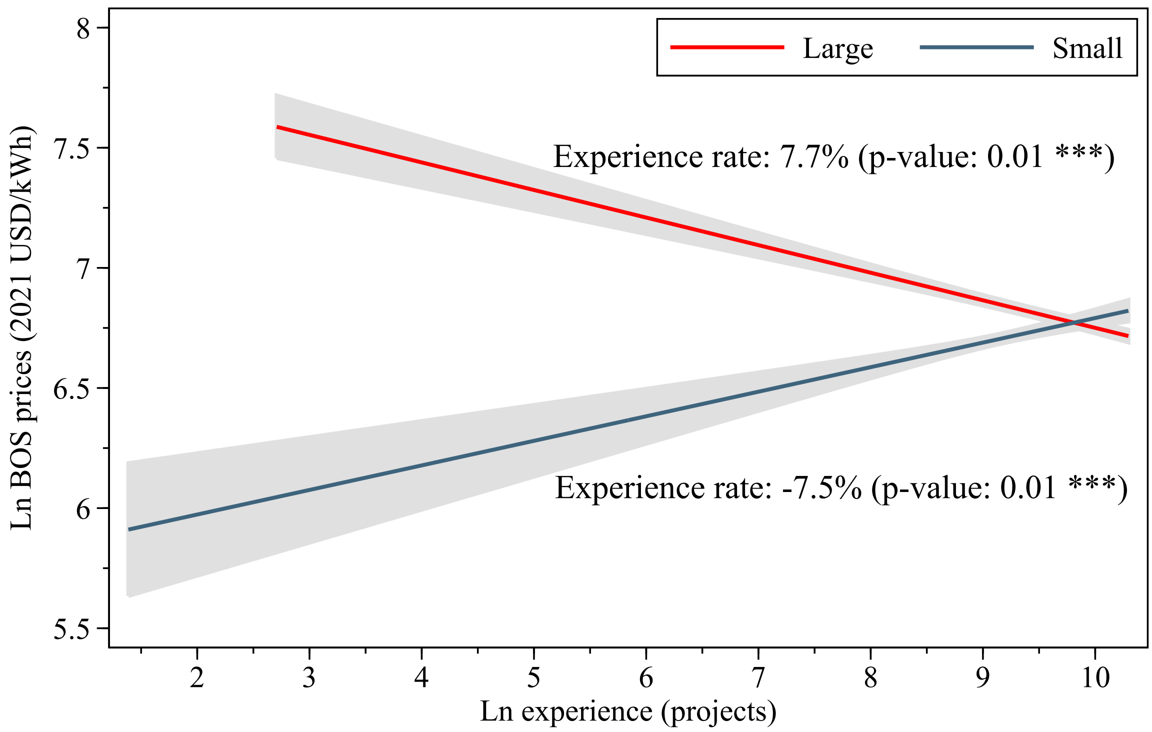


FIGURE 3.4: BOS Experience Curves, with 95% confidence intervals in grey.

To estimate learning in non-battery pack prices, we rerun our one-factor experience curve model using BOS prices as the dependent variable. Figure 3.4 depicts the resulting experience rates, again for the small and large segment without further controls. As shown, BOS learning is less strong than total system price learning. This holds for both segments, but in particular for small systems, where we estimate negative BOS learning of about 7.5%. Because BOS learning is slower or negative as compared to total prices, BOS prices make up for an increasing share of total battery system prices.

To illustrate the increasing relevance of non-battery price components, Figure 3.5 plots the share of BOS prices over time. As shown, at the end of our sample in 2022, BOS prices account for more than 80% of stationary system prices.

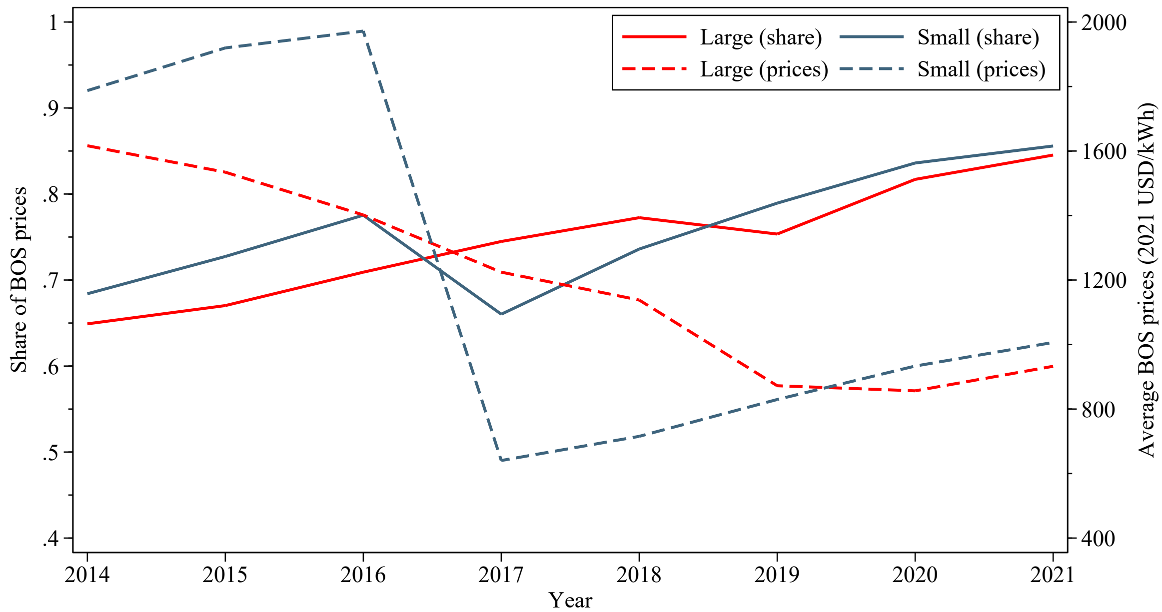


FIGURE 3.5: BOS Prices and BOS Percentage of Total Prices.

Overall, our findings suggest that local BOS price learning cannot match the pace of upstream battery technology learning. The detrimental dynamics of BOS prices hence attenuate learning effects for total system prices. In Appendix Table A.7 we show that our results hold when running the extended model with additional controls, e.g. for HHI.

3.6 Separating Industry from Firm Learning

The previous analysis assumes homogeneous experience spillover effects within California, i.e. capacity added by one firm directly factors into the entire experience stock across the industry. This assumption is implicit to the vast majority of experience curve studies, and is impossible to test without project-level and installer firm-level data. In closing, we exploit our data to explicitly investigate the prevalence of spillover effects by separating industry from installer firm learning (Irwin and Klenow, 1994, Bollinger and Gillingham, 2019, Nemet et al., 2020). Because our earlier findings indicate that reductions in total system prices are primarily driven by global progress in battery packs rather than installer-specific BOS prices, we expect industry-wide learning to dominate intra-firm learning. We conduct our analysis by computing separate experience stocks for the industry and installer firms, and include both as explanatory variables (see Methods).

Table 3.3: Industry versus Firm Learning by Segment

Price, BOS in 2021 USD/kWh	Price		BOS	
	Large (1)	Small (2)	Large (3)	Small (4)
SPILL #	-0.161^{***}	-0.089^{***}	-0.127^{***}	-0.055^{***}
	(0.021)	(0.013)	(0.020)	(0.018)
EXP Firm #	0.035^{***}	0.074^{***}	0.034^{**}	0.085^{***}
	(0.012)	(0.006)	(0.014)	(0.008)
HHI	0.160^{*}	0.434^{***}	0.110	0.499^{***}
	(0.090)	(0.095)	(0.101)	(0.116)
Size kWh	-0.039^{*}	-0.180^{***}	-0.047^{**}	-0.217^{***}
	(0.020)	(0.012)	(0.023)	(0.014)
Duration	−0.119	-0.416^{***}	-0.163^{*}	-0.490^{***}
	(0.077)	(0.031)	(0.093)	(0.036)
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry experience rate %	10.57	5.96	8.45	3.71
Firm experience rate %	−2.45	−5.30	−2.40	−6.10
Adjusted R^2	0.66	0.68	0.54	0.69
N	2,957	25,331	2,957	25,331

All variables except HHI are on log scale. The variable SPILL captures learning from industry-wide experience, i.e. spillover learning. The variable EXP Firm captures learning from firm-specific experience. For each observation, we compute SPILL as the industry-wide cumulative number of projects excluding the firm that has installed the observed system. For each observation, we compute EXP Firm as the cumulative number of projects by the firm that has installed the observed system. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table 3.3 shows the results. In the large segment, industry learning is significant while firm learning is negative (column (1)), with attenuated industry learning effects for BOS (column (3)). The results for small systems show similar patterns. The magnitude of industry learning is lower than for larger systems, with an industry experience rate of 6% for system prices (column 2) and 3.7% for BOS (column 4). However, negative firm learning is more than twice as large when compared to larger systems. In terms of magnitude, a doubling of firm experience is related to an increase in system price by 5.3% and an increase in BOS by 6.1%.

Put differently, firms with more experience ask for higher prices, on average. This effect is more pronounced for small systems, where, as shown earlier, competition is a relevant driver for system prices. These findings indicate that both commercial and especially residential customers are willing (or required) to pay for previous experience, e.g. because it is signaling market share, reputation, and reliability. Furthermore and as expected, industry learning plays a bigger role in explaining system price reductions than intra-firm learning, since the latter reflects less dynamic BOS prices and positive margins for experienced installers. Lastly, even after controlling for firm learning and a range of further variables, experience rates for total system prices and especially for BOS remain much lower than for battery cells and packs.

3.7 Discussion

Our results have several findings relevant to scholars, policy makers, and investors in distributed energy storage. First, we provide robust evidence of low learning by doing in system prices for battery storage based on rich project-level data. We estimate experience rates of about 1.3%, implying less learning than previously reported. When separating experience curves for small (below 10kW) and large (above 10kW) systems, we document significant heterogeneity in experience rates, with up to 11% for larger and -2% for smaller systems. These results highlight the benefit of more differentiated projections. Projections that do not account for the relatively stronger learning for large systems may understate future capacity additions, in particular in markets where large systems dominate.

Second, our results show statistically significant and economically relevant effects of market competition on system prices. To increase market penetration, regulators should hence facilitate installer competition, in particular for the smaller residential systems. Furthermore, we find a large effect of system size on system prices, consistent with bottom-up cost modeling (Ramasamy et al., 2021). Further scaling up both large and small systems is associated with lower system prices per kWh. To harness scale economies, regulators should remove barriers for the operation of larger storage systems, e.g. by allowing for additional revenues from providing grid services and trading in peer-to-peer markets.

Third, we report slower learning in BOS prices compared to total system prices, eventually leading to high shares of BOS versus battery pack prices. Battery storage hence faces a “BOS price challenge”, as found in the context of soft costs for distributed solar PV (O’Shaughnessy et al., 2019). Future policies should therefore focus on reducing BOS prices. Potential levers for reducing BOS prices include increased price transparency, e.g. by further expanding quote platforms for installers, as well as standardizing permitting and regulatory processes. Given the stickiness of BOS prices, our analysis at the same time underscores the importance of global cost-reductions of battery packs through innovation and production scale-up.

Fourth, learning at the installer level is negative (reflecting positive margins for experienced installers). Hence, observed price reductions are largely driven by industry-wide experience with again relatively low experience rates of 4-10%. The presence of industry-wide (as opposed to firm-specific) learning indicates little within-firm appropriability of experience, and instead points to the existence of spillovers across the industry. As such, positive externalities of experience add to the potential benefits of battery storage for decarbonized energy systems. From a policy perspective, these positive externalities provide a rationale for continued public support for battery storage.

3.8 Methods

3.8.1 Experience Curve Model

To model cost reductions for distributed battery storage systems, we utilize a simple mathematical power law known as the “learning curve” (Wright, 1936). Since we are interested in learning curves for the total system, we predict prices rather than costs. Using prices instead of costs is common in the literature because cost data are often not available. Learning curves based on price data are commonly referred to as experience curves (Schmidt et al., 2017), which we follow in this paper.

Formally, let P_t^{store} be the deflated price per unit of capacity (kWh) for stationary storage systems, P_0^{store} be the price of the first unit of experience EXP, and b be the learning parameter. Then, we can write

$$P_t^{store} = P_0^{store} * EXP_t^b. \tag{3.1}$$

Assuming a multiplicative error term ϵ, we can log-linearize the relationship to

$$ln(P_t^{store}) = P_0^{store} + \beta_1 ln(EXP_t) + \epsilon, \tag{3.2}$$

where β is the estimator for b and represents the learning elasticity. We then obtain the learning by doing, i.e. experience, rate as $1-2^{\beta}$. Equation 3.2 estimates a standard one-factor experience curve.

In our extended model, we add competition (HHI), installation-level economies of scale ($SIZE$ and DUR), and fixed effects (ϕ) as further variables to the basic one-factor experience curve. Formally, we estimate

$$ln(P_t^{store}) = P_0^{store} + \beta_1 ln(EXP_t) + \beta_2 HHI_{j,t} + \beta_3 ln(SIZE_i) + \beta_4 ln(DURi) + \phi + \epsilon, \tag{3.3}$$

where HHI captures the Herfindahl-Hirschman index in county j at time t, $SIZE$ and DUR represent system size in kWh and duration in hours of project i, and ϕ are county and installer firm fixed effects. Duration is defined as the ratio of storage capacity (kWh) to power rating (kW).

Finally, we formalize the spillover model as

$$ln(P^{store}) = P_0^{store} + \beta_1 ln(SPILL_t) + \beta_2 ln(EXP_{k,t}) + \delta + \phi + \epsilon, \tag{3.4}$$

where the first factor $SPILL$ captures industry experience at time t and the second factor, EXP, captures experience of firm k at time t. We likewise extend this model to include the HHI, system size, duration, and fixed effects, as indicated by δ and ϕ. In all our models, we cluster standard errors at the county level to correct for heteroskedasticity.

3.8.2 Experience and Competition Variables Construction

We construct experience, our main explanatory variable, on a per day basis using each system's interconnection date. We use cumulative projects as our main experience proxy to reflect our project-level data where most of the learning, if present, arguably realizes per installed project, regardless of the exact storage capacity. Accordingly, we calculate the cumulative capacity by each firm at any given installation date. In the spillover model, we subtract this firm experience from total experience to obtain our industry experience measure $SPILL$ Nemet et al. (2020). Following previous literature, we accumulate energy storage capacity in kWh (Schmidt et al., 2017, Kittner et al., 2017, Ziegler and Trancik, 2021) as a robustness test.

We use the Herfindahl-Hirschman Index (HHI) to measure competition by county. The HHI shows the sum of squared market shares of all firms in the market and is capped at one for a monopoly. For every county, we define market share as the share of cumulative installations per installer in the previous year (Gillingham et al., 2016).

3.8.3 The California SGIP Data and Further Data Sources

The main dataset used in our study is a public export of California's Self-Generation Incentive Program (SGIP) database. This database contains applications for a variety of technologies on plant level between 2000 and today. The first battery storage system is recorded in 2008 (see discussion surrounding Figure 3.1 and Appendix Figure A.1). Variables include system power and energy capacity, county, eligible costs, incentives, involved firms, and application process and status characteristics. In order to remove outliers in terms of price or system design and address potential data errors, we only include systems within a price range of 200 to 6,000 USD per kWh (400 to 12,000 USD per kW). We also exclude systems with a duration (energy storage capacity divided by power) smaller than one or larger than ten. Overall, these cleaning steps affect less than 1% of observations and, in untabulated analyses, do not materially impact our results. Importantly, we apply a thorough string clean algorithm on firms and counties that adjusts spelling, abbreviations, and typos.

We merge in publicly available battery price data from Bloomberg to compute BOS prices from total system prices. To get average prices for batteries used in stationary storage systems, we adjust the Bloomberg data in all years as follows. Given the relationship between average prices and average prices for stationary storage systems in 2021, we add 15.15% to the price index in order to reflect higher average prices for batteries used in stationary storage applications (as compared to the raw battery packs prices). Finally, we extract Consumer Price Index data from FRED to deflate all monetary variables to 2021 values.

3.8.4 Robustness Checks

To test the sensitivity of our results to our modeling assumptions, we run a battery of robustness checks. Specifically, we (i) alter the definition of experience to cumulative installed capacity in kWh, (ii) change the sample period to start in 2014, (iii) consider only systems which the program administrator marked as paid, (iv) drop systems installed by SolarCity/Tesla as the corresponding price data might represent appraised values (Barbose and Darghouth, 2019), (v) exclude installations by firms with less than 20 observations, (vi) set a different size threshold of 50 kWh that defines the segments (small/large), and (vii) use unadjusted Bloomberg battery prices to calculate BOS prices. Appendix Tables A.8 to A.20 contain the results. Our experience rates and further results remain robust and largely similar in terms of magnitude.

4 | Better Safe than Sorry? Toxic Waste Management after Unionization

Magnus Schauf and Eline Schoonjans[37]

How do unions protect workers from toxic waste? This paper studies the impact of organized labor on toxic waste management at US facilities between 1991 and 2020. When unions bargain for worker benefits such as workplace safety and member health, their effect on toxic releases remains unclear. Reducing toxic waste releases has positive health and environmental effects but requires more and dangerous activities to treat waste after production. Using a regression discontinuity design on close-call union elections, we find a significantly positive effect of unionization on toxic releases at the facility site. In contrast, end-of-pipe (EOP) treatment of toxic waste increases after unionization. These effects are more pronounced in states without right-to-work laws, for less toxic chemicals, and for non-heavy industries. Finally, we show that unionized facilities increase waste prevention activities through innovative product and process modifications and have less catastrophic releases. However, these effects cannot offset the reduction in waste EOP treatment, resulting in more waste releases. Our findings suggest that unions prioritize safety over ecology and call upon managerial and governmental action to better align these two objectives.

[37] This essay is based on joint work with Eline Schoonjans. My contributions are as follows: development of the research idea, partial literature review, formulation of the statistical model, TRI data curation, performing the analysis, creating visualizations, writing large parts of the original draft, and reviewing and editing.

4.1 Introduction

Each year, US manufacturing facilities produce about 30 billion pounds of hazardous chemical waste, 10% of which end up in the environment through air, land, and water releases (EPA, 2022d). Such toxic chemical releases have a multitude of negative effects on human health, our planet, and the economy (Currie et al., 2015, Levine et al., 2020).

Workers represent a stakeholder group highly affected by toxic waste (Dietz et al., 2015). On one hand, workers are exposed to toxic chemical releases at the workplace and possibly as members of local communities. On the other hand, workers are also most affected by performing dangerous and costly tasks that avoid releases of these chemicals. Hence, workers face an ecology-safety tradeoff between protecting themselves, the community, and the society at a larger scale from releasing toxic waste and protecting themselves from handling toxic waste.

While mechanisms are often not well understood (Ertugrul and Marciukaityte, 2021), recent research suggests that workers' interests and the interests of other stakeholders like society or nature diverge (Ertugrul and Marciukaityte, 2021, Heitz et al., 2021). Yet, little research causally examines whether pollution that is particularly detrimental on a local level (Currie et al., 2015) leads to better alignment of interests between workers and society. Toxic waste management provides a context for disentangling mechanisms by directly comparing qualitatively different worker benefits. Although benefits of lower pollution at the workplace also improve welfare for other, especially local, stakeholders, it is unclear whether unions prioritize this benefit in light of associated costs borne by workers.

This paper empirically studies how a shift in stakeholders' bargaining power toward workers following unionization affects the ecology-safety tradeoff and associated toxic waste externalities. Specifically, we test whether facilities rather release (less ecology, more safety) or treat (more ecology, less safety) their toxic waste. Toxic waste treatment refers to end-of-pipe (EOP) procedures, which include recycling, energy recovery, and other, typically chemical, treatment. Releases entail chemical emissions and disposals to the environment, i.e. air, land, and water.

We formulate unions' stance on the ecology-safety tradeoff as a bidirectional hypothesis. If ecology concerns dominate, unionization will lead to less releases and possibly more treatment. If safety concerns dominate, unionization will lead to more releases and less treatment.

The *collective voice* view stipulates that unionized workers bargain more easily for their interests than non-unionized workers (Freeman and Medoff, 1979). Basic interests are securing labor and reasonable pay (McDonald and Solow, 1981). Both translate into a distaste for EOP waste treatment which is often costly (King and Lenox, 2002, Frondel et al., 2007). Saving these costs could permit unionized workers to extract part of the rent surplus in the form of higher pay or better employment conditions.

Furthermore, labor unions' interests extend to additional dimensions of member welfare, such as workplace safety and worker health (Freeman and Medoff, 1979). Given the high risk for fatal injuries when performing waste treatment activities (BLS, 2021), pursuing workplace safety could also align with decreasing waste treatment. On the contrary, welfare maximization arguably implies protection from pollution and its negative effects at the workplace and in local communities, be it for selfish or altruistic motivations. Moreover, since environmental protection can represent an investment in human capital, which is stickier following unionization (McDonald and Solow, 1981), managers might strive to reduce toxic releases to increase their workers' health and thereby productivity (Graff Zivin and Neidell, 2012). This reduction can be achieved with more EOP waste treatment but also by means of other pollution prevention activity.

Consequently, we argue that innovation activities and better training could align interests between different stakeholder groups and relax workers' ecology-safety tradeoff. In light of this multi-win character, we hypothesize that such activities should increase following unionization. Stimulating innovation environments require short-term failure tolerance and long-term reward mechanisms (Manso, 2011). Unionization facilitates the former through better employment protection while the reduction of negative waste effects might represent sufficient long-term motivation. Whether and to what extent unions can realize all of these interests depends on their bargaining power which can be restricted by, i.a., right-to-work (RTW) legislation (Chava et al., 2020).

For estimation, we rely on a local regression discontinuity design (RDD) using union elections that narrowly pass or don't pass the majority cutoff of 50 percent plus one vote. The local RDD establishes causality under verifiable assumptions, addressing endogeneity concerns of unobservable differences between unionized and non-unionized facilities (Hahn et al., 2001, Lee and Lemieux, 2010). We consider chemical-facility-level data reported annually by manufacturing facilities to the Toxic Release Inventory (TRI), a program of the US Environmental Protection Agency (EPA). By means of thoroughly cleaned facility names, we match this detailed source of toxic waste management data to US union elections between 1990 and 2017. Our final sample contains 5,583 chemical-facility-year observations related to 605 union elections.

Our main result provides evidence of a shift in waste management practices after a shift in stakeholder power toward unionized workers. Specifically, we find that, on average over three years after unionization, releases increase and treatment decreases at facilities with close-call union wins. The effect is statistically significant and economically large for *on-site* release and treatment in particular, i.e. at the location where unions have most interest in. Year-to-year changes in on-site releases (treatment) are 14.7 (59.3) percentage points higher (lower) in facilities with a marginal union victory compared to facilities with marginal union losses, on average. We do not find significant evidence of "outsourcing" releases or treatment to other facilities (off-site). As such, our findings indicate unions' preference for safety when facing an ecology-safety tradeoff.

This main effect survives a battery of contextual and RDD-specific robustness tests and remains significant in a global RDD using all elections. In cross-sectional analyses, we examine whether union power as determined by the presence of RTW laws, chemical toxicity, and industry affiliation play a role for the unionization effect. We find that facilities reduce treatment especially in non-RTW states where unions have higher bargaining power and for less toxic chemicals. Similarly, facilities from non-heavy industries primarily drive the observed decrease in waste treatment. We argue that operative flexibility and worker expectations might explain this heterogeneity.

Next, we probe into two possible explanations behind our main effect. Specifically, we investigate the impact of production output and financial constraints. First, consistent with DiNardo and Lee (2004), we do not find a significant effect of unions on productivity and rule out that changes in production output explain increasing releases or decreasing treatment. Second, since waste treatment is costly, financially constrained facilities might not be able to afford waste treatment. However, we also rule out that financial constraints drive our results. This finding emphasizes the ecology-safety tradeoff and unions' welfare extraction rather than purely monetary motivations as drivers behind the observed changes in waste management practices.

Lastly, we investigate two mechanisms, catastrophic releases and innovative pollution prevention activity, that could relax the ecology-safety tradeoff. We show a decrease in catastrophic releases which might result from better training. Moreover, we show an increase in innovative pollution prevention activity. Together, these findings suggest that unionization motivates facilities to focus on multi-win outcomes.

Our paper contributes to the literature in several ways. First, we identify labor unions as significant drivers of facilities' environmental performance in general and waste management strategy in specific. Other important determinants of firms' environmental performance entail environmental and liability regulation (Shapiro and Walker, 2018, Akey and Appel, 2021), pressure by community stakeholders (Kassinis and Vafeas, 2006), financial constraints (Dutt and King, 2014, Cohn and Deryugina, 2018, Xu and Kim, 2022), corporate governance (Kim et al., 2019, Shive and Forster, 2020), and innovation (King and Lenox, 2002). We add to this literature by highlighting that unions represent an obstacle in reducing environmental impact because of their lower willingness for curing toxic chemicals.

Second, we contribute to the literature on real effects of unionization. Previous literature reports unionization effects on investment (Connolly et al., 1986, Machin and Wadhwani, 1991), innovation (Haucap and Wey, 2004, Bradley et al., 2017), and corporate governance (DeAngelo and DeAngelo, 1991, Chyz et al., 2013, Chung et al., 2016). While the evidence is sometimes mixed, a commonly shared conclusion is that unions and their members extract welfare at the expense of shareholders. A particularly recent stream investigates the effect of unionization on other stakeholders, e.g. using environmental, social, and governance scores (Ertugrul and Marciukaityte, 2021, Heitz et al., 2021) or product recalls (Kini et al., 2021). These studies corroborate the general consensus of unionization being detrimental to other stakeholder groups. We add to this literature by exploiting the various advantages that the context of waste management offers. Most importantly, unionized workers in our setting face a tradeoff between being exposed to pollution or to dangerous jobs. As such, we can study a setting where negative externalities from pollution take place and partially realize at the same level as unionization and decisions on waste management: the facility. Moreover, we establish our effects using quantity-based measures rather than methodology-based and often controversial ESG scores (Chatterji et al., 2016, Berg et al., 2022).

Overall, we show that real effects of unionization extend to toxic waste management and provide new insights into how unionized workplaces operate on the local facility level. Our results highlight that the utility of being in a labor union goes beyond purely monetary incentives. Finally, the tendency for unions to value safety over ecology highlights the need for policymakers and managers to increase standards of and trust in waste management practices while augmenting efforts toward multi-win outcomes, e.g. via green innovation and training.

The rest of this paper is organized as follows. Section 4.2 develops our hypothesis from reviewing the literature on unionization in the context of workplace and environmental protection. Section 4.3 describes our data and econometric approach. Section 4.4 presents main results, Section 4.5 shows cross-sectional heterogeneity, and Section 4.6 investigates possible underlying mechanisms. Section 4.7 concludes.

4.2 Hypothesis Development

This section discusses the role of labor unions in influencing environmental externalities generally and toxic waste management at manufacturing firms specifically. As the organized voice of individual workers, labor unions assist in internalizing employment-related external costs and reduce transaction costs through *collective bargaining* (Freeman, 1976). They lobby for their interests when bargaining with managers or when interacting with policymakers. Unions' main interests are employment and employment conditions, such as wages, job security, and safety (Freeman and Medoff, 1979, McDonald and Solow, 1981).

4.2.1 Ecology-Safety Tradeoff

Empirical evidence on whether unions' interests align with those of other stakeholders beyond their bargaining unit, including the general workforce, communities, and society at large, is somewhat mixed. A particularly recent stream investigates the effect of unionization on non-shareholding stakeholders, e.g. by means of environmental, social, and governance scores (Ertugrul and Marciukaityte, 2021, Heitz et al., 2021) or product recalls (Kini et al., 2021). They find that unions extract welfare for their members at the expense of external stakeholders. However, anecdotal evidence shows union support for environmental protection policies, despite their potential negative impact on member jobs. In the 1950's and 1960's unions lobbied for environmental regulation to reduce air, land, and water pollution (Dewey, 1998). The passing of these regulations (Clean Air Act and Clean Water Act) led to significant costs for workers due to lower wages and unemployment (Walker, 2011, 2013). Yet, their positive impact on member and community health seemed to outweigh these costs, as workers and their families are arguably most exposed to detrimental effects of pollution on the local level (Dietz et al., 2015).

Health effects resulting from contamination with or exposure to pollution, as well as resulting economic effects, are empirically well-documented. Adverse inter-generational health impacts (for a review, see Graff Zivin and Neidell, 2013), including pronounced elderly mortality (Deryugina et al., 2019), higher respiratory and heart-related hospital admissions (Schlenker and Walker, 2016), and increased probability of low birthweight (Currie et al., 2015), lead to ripple effects throughout the whole economy: Housing prices decrease (Currie et al., 2015), workers lower labor supply and become less productive (Hanna and Oliva, 2015, He et al., 2019), investors trade worse (Huang et al., 2020), and managers and their human capital migrate away from polluting plants (Levine et al., 2020).

Consequently, pollution from facilities' releases of toxic chemical waste directly impacts worker well-being. Workers are exposed to pollution directly at the workplace and potentially also as inhabitants of neighboring communities (Currie et al., 2015, Dietz et al., 2015). Put differently, a firm's toxic releases essentially reduce workers' welfare non-monetarily through its negative health impacts and monetarily because workers might lower their labor supply and spend more on pharmaceuticals or other "defensive investments" to mitigate pollution effects (Hanna and Oliva, 2015, Deschênes et al., 2017). Therefore, a union that maximizes member welfare should also pursue ecological objectives through lower toxic releases. Moreover, if unionization leads to costlier and stickier human capital (McDonald and Solow, 1981), managers can have incentives to reduce releases and increase workers' productivity. As such, environmental protection is an investment in human capital (Graff Zivin and Neidell, 2012).

However, industrial ecology scholars argue that workers partially carry the burden of lower toxic releases to the environment through higher exposure and higher risks at their jobs, without reasonable accounting for associated health and safety effects (Ashford, 1997, Armenti et al., 2011, Scanlon et al., 2015). Workers perform waste treatment jobs, namely recycling, use for energy recovery, and other treatment that typically destroys the chemical in order to reduce releases. These waste treatment practices are usually the final step in the production process (end-of-pipe). Official statistics for workplace safety underscore that unions could directly bargain to treat less waste because it is dangerous. For instance, "refuse and recyclable material collector" is the sixth most fatal work-injury related occupation with 33 fatalities per 100,000 full-time equivalent workers, which is ten times higher than the average over all occupations in the US (BLS, 2021). Recent empirical studies report a downward shift in the distribution of accident-case rates and injuries after unionization (Zoorob, 2018, Heitz et al., 2021, Li et al., 2022), supporting the argument that unions address workplace safety. Potential channels might be better training of employees (Heitz et al., 2021) and protection from dangerous tasks such as waste treatment.

Besides concerns for member safety, unionization might lead to less waste treatment because of cost saving incentives. Infrastructure to treat waste is costly to install and operate (Frondel et al., 2007). Further, King and Lenox (2002) argue that on-site waste treatment often results in unexpected additional costs. Finally, unionization could indirectly lead to less waste treatment through greater employment protection, inducing “shirking” or a less thorough work attitude (Bradley et al., 2017).

Manufacturing facilities can also cooperate with special third-party waste management plants to relocate waste before managing it. Since such off-site waste management essentially avoids unionized workers to be exposed to or treat waste on site, our reasoning above applies for *on-site* waste management in particular.

Taken together, we posit that workers face a tradeoff between increasing ecology (through lower toxic releases) and increasing safety (through less dangerous waste treatment practices). Since unionization shifts the weights of stakeholder interests, workers should have more power to impact the ecology-safety tradeoff according to their interests. We hypothesize that it is ex ante unclear whether these interests relate to less releases but more treatment or more releases but less treatment. While we so far assumed the decision at stake to be ecology *versus* safety, we next argue how facilities could relax this tradeoff.

4.2.2 Relaxing the Ecology-Safety Tradeoff

Several mechanisms exist to reduce both the need to release and treat waste. First, a mechanical lever for unions to decrease waste that needs to be managed, is by decreasing production output. In light of stronger employment protection, previously mentioned “shirking” behavior might not only refer to unpleasant waste treatment but also extend to other, production-related, job duties (Bradley et al., 2017). On the contrary, unionization can enhance productivity through its bundling of worker interests and reduction of transaction costs (Freeman, 1976). Empirical evidence reports little changes in productivity due to unionization (DiNardo and Lee, 2004)

Second, a theoretically more appealing mechanism is to increase investment in source reduction or pollution prevention activities such as training, innovation, and improvement of operations. Traditional hold-up theory would predict investments to decline after unionization because managers anticipate excessive rent capturing by unions (Grout, 1984, Connolly et al., 1986). However, in our setting the character of these investments is different. Firm investment in pollution prevention implies positive externalities (or reduced negative externalities) that directly benefit workers through higher workplace safety and better environmental protection. As such, firms can share non-monetary benefits from these investments with their workforce. These benefits could represent long-term rewards which, combined with short-term failure tolerance of union contracts, often stimulate innovation activity (Manso, 2011).

Third, pressure due to the unionization shock on labor costs can also play a role. Higher labor costs might induce managers to save costs. Reportedly, cost savings are the major influencing factor for pollution prevention earlier during the production process, rather than end-of-pipe waste treatment (Frondel et al., 2007). Moreover, pollution prevention increases process control, stimulates process innovation, and encourages the development of worker problem-solving skills, which in turn leads to higher financial performance (King, 1999, King and Lenox, 2002). Nevertheless, King and Lenox (2002) argue that managers have systematically overlooked innovative pollution prevention as a green and profitable opportunity. Taken together, the multi-win character of pollution prevention investment should dominate managerial hold-up concerns. Consequently, we expect that unionization relaxes the ecology-safety tradeoff through innovative pollution prevention policies and less failures in operations.

4.3 Methodology and Data

4.3.1 Data and Sample

Our sample consists of industrial facilities that are mandated to report toxic waste by chemical to the US Environmental Protection Agency (EPA) and had a union election between 1990 and 2017. Specifically, we use data of hazardous chemical usage and waste submitted to EPA's Toxic Release Inventory (TRI) under the Emergency Planning and Community Right to Know Act (EPCRA) of 1986. The EPCRA and subsequent amendments require a facility to report chemical-level data for currently about 600 chemicals. TRI data items include chemical information, production waste quantities, waste management practices, and the geographic location of these management practices (on-site versus off-site).

We add toxicity data, namely reportable quantities for chemicals according to the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), using the Chemical Abstracts Service Registry Number (CAS) for merging (King and Lenox, 2000, 2002, Kim et al., 2019). Reportable quantities represent the threshold value in pounds that determines necessary emergency reporting and action in case of an accidental spill. These quantities are in a range of 1 to 5,000, with the lowest value of 1 indicating a highly toxic chemical for which spilling one pound or more already requires emergency action.[38] Further, by means of the CAS, we supplement our TRI data with a chemical's listing period in the TRI, obtained from the EPA. In robustness tests, we exclude chemicals based on their listing period not covering our entire sample period to control for regulatory changes (see Section 4.4.3).

Although not free of flaws,[39] the TRI does not seem to be subject to systematically manipulated reporting (Bui and Mayer, 2003). Moreover, the EPA checks submitted reports and can fine misreporting facilities. Consequently, academic literature exploits the rich TRI data in many different applications (e.g. King and Lenox, 2002, Currie et al., 2015, Shapiro and Walker, 2018, Akey and Appel, 2021). Following previous literature (Dutt and King, 2014, Akey and Appel, 2021), we exploit the empirical advantages of this detailed chemical-level data, e.g. more precise estimates of toxic waste quantities, more precise controls for changes in production output at multi-product facilities, and accounting for chemical fixed effects in further analyses.

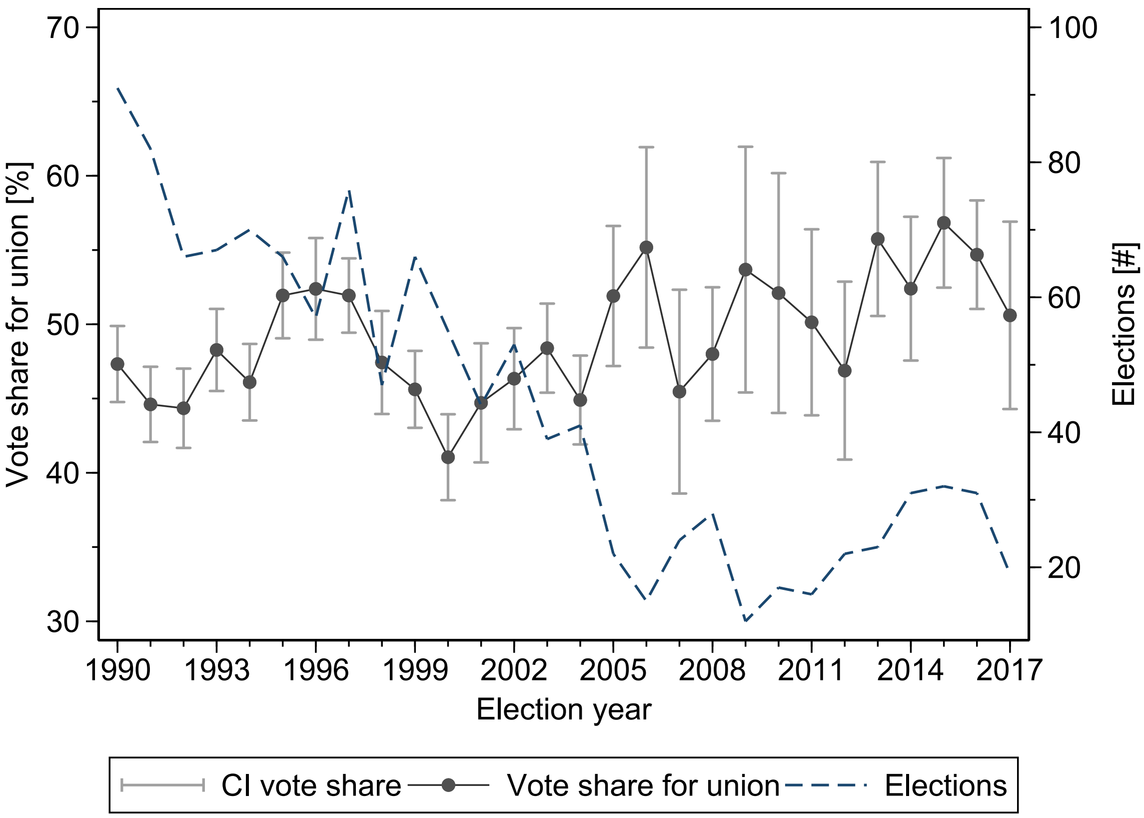
The US authority supervising and validating facility-level union elections, the National Labor Relations Board (NLRB), provides union election data. Per election case, the data contain facility and union information as well as election characteristics, most importantly the number of eligible voters and the valid votes pro and contra joining the respective union. We only keep certification cases, i.e. elections for union representation at a facility. Figure 4.1 shows the trends in union elections over our sample period. Consistent with other studies (Bradley et al., 2017, Campello et al., 2018, Heitz et al., 2021, Kini et al., 2021), the number of elections

[38] We also merge in alternative chemical-level toxicity data, namely the human toxicity potential (HTP) published by Hertwich et al. (2001). By providing separate toxicity values for the two key exposure routes – air and water – of pollution on humans, the HTP enables robustness tests with an explicit focus on human health.

[39] These flaws relate to the self-reported nature of the data and inconsistency over time due to frequent regulatory changes (e.g. Currie et al., 2015).

gradually declines while the vote share, i.e. the success rate of unionization, fluctuates more, with a tendency to increase in more recent years.

FIGURE 4.1: Number of Union Elections and Vote Shares by Election Year



Notes: This figure shows trends in union elections from 1990 till 2017, certified by the NLRB and matched to the TRI data. The dashed line represents the number of elections certified by year. The line with dots depicts the average vote share in a year and the gray vertical lines indicate the 95% confidence interval for this average vote share.

Since NLRB and TRI data do not share a common identifier, we must string-match facility names. Before, we perform a meticulous string cleaning procedure in order to increase the number and quality of exact and fuzzy matches. Our string cleaning algorithm harmonizes facility names across both data sets for instance by adjusting abbreviations or removing legal forms.[40] We are careful to ensure accurate matches by requiring that the facilities' states and cities always match. We complement all exact matches with manually checked fuzzy matches of distance 1 or 2 as calculated by the Optimal String Alignment method.

[40]Similar, though sometimes more compact string cleaning algorithms are commonly used in the literature, including for TRI and unionization data (Lee and Mas, 2012, Akey and Appel, 2021, Xu and Kim, 2022).

In order to arrive at our main sample, some additional cleaning steps are necessary. First, as small union elections are less suitable for our research design (DiNardo and Lee, 2004, Frandsen, 2017), we exclude elections with less than 50 eligible voters.[41] Second, we only include observations which we can merge to the National Establishment Time Series (NETS) using the TRI facility identifier. NETS, a commercial database by consultancy Walls & Associates based on data from Dun & Bradstreet, provides facility-level sales, employees, and the "Paydex" business credit score,[42] amongst others. These variables allow for testing one of the key identifying assumptions of our empirical design more thoroughly (see Section 4.3.3). Our main sample contains 605 unique union elections and 5,583 chemical-facility-year observations consisting of 283 different chemicals.

4.3.2 Variables

Having introduced our data sources and sample, we next briefly describe variables relevant for estimating our effects and for testing the validity of our design.

In our main analysis, we estimate direct and medium-term effects of unionization on several measures of waste management at the facility-chemical-year level.[43] We consider waste management variables up to three years post union election, because the certification and bargaining process as well as potentially resulting real effects are not immediate. First, we calculate releases as the sum of chemical releases to air, land, and water, on-site, off-site, and in total. Second, we construct EOP waste treatment as the sum of waste that is recycled, used for energy recovery, or otherwise treated. Again, this measure can be a total as well as separated for on-site versus off-site. Importantly, we process waste releases and waste treatment to ratios that indicate the change in the outcome variable on a year-by-year basis. The benefits of using ratios instead of level variables are fourfold. First, we decrease the skewness of our outcome variables. Second, we avoid potentially inconsistent estimates produced by a common alternative, log-transformation (Cohn et al., 2022). Third, we facilitate the comparability of otherwise very heterogeneous chemical quantities and facility sizes (Dutt and King, 2014). Finally, we align with the reporting of production output in the TRI.

[41] Smaller elections can be more easily manipulated during the election and seem to occur in a more selective way given their notably higher vote share.

[42] The Paydex score is a business credit score between 0 and 100, calculated from previous transaction data. A high score indicates a high probability for the focal firm to pay back its debt on time.

[43] We eliminate some rare cases of partial facility reports where two or more entries per chemical exist for a given year and facility by aggregating the individually reported quantities.

We formally define the change in the outcome variable as

$$\Delta Y_{i,j,t} = Y_{i,j,t}/Y_{i,j,t-1}, \tag{4.1}$$

where Y represents waste treatment or releases, on-site, off-site, or in total, in pounds of chemical i at facility j in year t (Dutt and King, 2014). We exclude observations with ratios exceeding a threshold of three as these are either data errors or evidence of extraordinary transformations at the facility (Akey and Appel, 2021). In robustness checks, we adjust this threshold to either two or four and also take the natural log to further reduce the impact of extreme values (Dutt and King, 2014).

Throughout our analysis, the vote share, i.e. the number of votes in favor of the union divided by the total number of valid votes cast, constitutes our main independent or "running" variable. A vote share of 50% plus one vote implies a successful union election and thus establishes treatment in our analysis. Since vote share has finite, discrete, and asymmetric support, which changes with the number of votes cast, we adjust the vote share such that 50% constitutes the homogeneous and symmetric cutoff. For all even numbers of votes cast, we subtract an amount equal to $^{0.5}/_{\text{number of votes cast}}$ from the vote share. Cases with odd numbers of votes cast are not adjusted (DiNardo and Lee, 2004).

In our further analyses and for testing one identifying assumption of our empirical approach, we require additional facility-level and chemical-level variables. Facility-level variables encompass sales, number of employees, and the Paydex score from NETS (Akey and Appel, 2021). Chemical-facility-level variables include information on (i) production output, (ii) pollution prevention measures, also termed "source reduction activities", and (iii) catastrophic releases from TRI.

First, we proxy production output with the production ratio that facilities report to the TRI. The production ratio indicates changes in the output of a manufactured product or a supporting operational procedure related to the use of a specific chemical. Following Akey and Appel (2021) and the construction of our dependent variables, we exclude observations with ratios larger than three. Second, to measure facilities' engagement in chemical-level pollution prevention, we construct an indicator variable from the approximately 50 codes that facilities can report as performed pollution prevention activity. This variable, "innovative prevention", is equal to one if a facility, for a given chemical, reports prevention activities related to product and process innovations and zero otherwise.[44] Finally, we examine catastrophic releases because we assume that better trained employees commit less mistakes leading to such releases.[45] Given the rarity of catastrophic releases, we construct an indicator variable equal to one if a facility reported catastrophic releases of a specific chemical and zero if not.

We describe all variables in Appendix Table A.21. Appendix Table A.22 contains summary statistics and Appendix Figure A.2 illustrates spatial heterogeneity across US states for several variables characterizing our sample.

4.3.3 Empirical Strategy

We identify the causal effect of unionization on waste management practices at manufacturing firms by means of a regression discontinuity design (RDD). Due to endogeneity, a simple OLS regression could provide inconsistent and biased estimates. Endogeneity arises when unionization depends on factors that also influence our variables of interest. For example, workers at facilities that have unsatisfying and dangerous waste management practices or other unobservable grievances may be more likely to unionize, which could imply over- or underestimation of the unionization impact.

The RDD establishes causality and exploits the election character of unionization, where a simple majority separates the treatment (i.e., successful union certification) from the control group (DiNardo and Lee, 2004). Specifically, considering close-call union elections around the majority cutoff represents a quasi-experimental approach which supports causal interpretation of the local treatment effect.

Formally, in our main empirical analysis, we estimate the following non-parametric local-linear equation (Lee and Lemieux, 2010):

$$\Delta Y_{i,j,t+n} = \alpha + \tau D_{j,t} + \beta_l (X_{j,t} - c) + (\beta_r - \beta_l) D_{j,t} (X_{j,t} - c) + \varepsilon_{i,j,t+n}, \tag{4.2}$$

where Y represents released or treated waste in pounds of chemical i at facility j in year $t+n$, with $n \in [1, 2, 3]$. Our running variable X, adjusted vote share, splits our observations into

[44] This innovation measure captures TRI reporting codes W50, W51, W59, W80, W82, W83, W84, W89.

[45] Catastrophic releases refer to a "major uncontrolled emission, fire, or explosion, involving one or more highly hazardous chemicals, that presents serious danger to employees in the workplace" (OSHA, 2012). In about 2% of facility-chemical-year observations, facilities report a catastrophic release.

Table 4.1: Pre-Treatment Balance

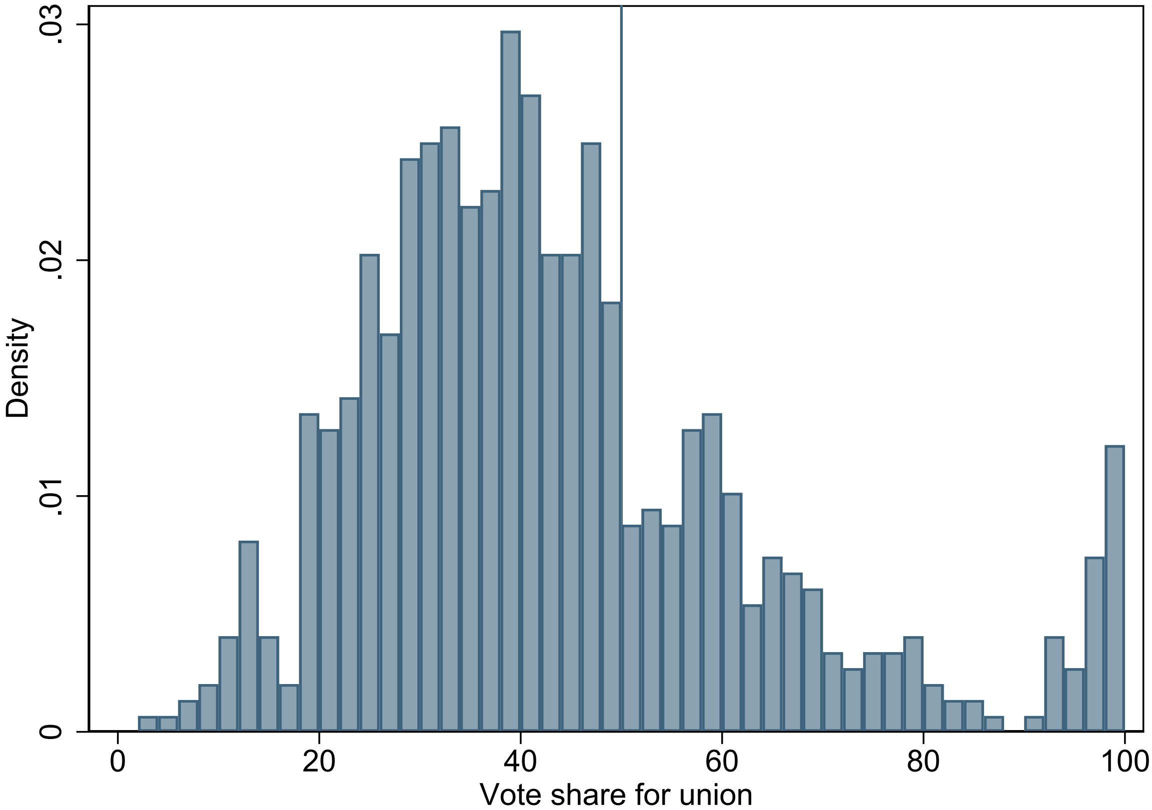
	No Union	**Unionization**		**Difference**	
	Mean	Mean	Diff	T-stat	p
Total waste release ratio	0.912	0.958	−0.046	−0.819	0.414
On-site release ratio	0.887	0.962	−0.075	−1.434	0.153
Off-site release ratio	0.884	0.788	0.096	0.846	0.400
Total waste treatment ratio	0.934	0.923	0.011	0.162	0.871
On-site treatment ratio	0.998	0.946	0.052	0.507	0.613
Off-site treatment ratio	0.865	0.734	0.130	1.599	0.112
Catastrophic releases	0.018	0.019	−0.001	−0.037	0.970
Prevention count	0.201	0.281	−0.081	−1.304	0.193
Innovative prevention	0.022	0.019	0.003	0.222	0.825
Production ratio	1.031	0.927	0.104	2.810	0.005
Ln (Sales)	17.045	17.026	0.020	0.110	0.913
Ln (Employees)	5.014	5.155	−0.140	−0.878	0.380
Paydex score	67.047	68.274	−1.227	−1.030	0.304

Notes: This table presents the pre-election variable balance between the treatment and control group in the MSE-optimal bandwidth of our main specification in the year before unionization. All variables are defined in Appendix Table A.21.

treatment ($D = 1$) and control ($D = 0$) groups at the cutoff c of 50%. We include observations, where X is within the mean-squared-error optimizing (MSE-optimal) bandwidth h on each side of the cutoff (Imbens and Kalyanaraman, 2012). For statistical inference, we correct for the estimation bias with bias-corrected confidence intervals and robust standard errors clustered at the facility level (Calonico et al., 2014, 2019). We choose a triangular kernel for weighting observations, but test robustness of our results to alternative choices.

In order to qualify as an econometric method estimating causal effects, an RDD requires two identifying assumptions: (i) ex ante comparability between treatment and control group observations as well as (ii) exogeneous election outcomes that no party can manipulate (Hahn et al., 2001, DiNardo and Lee, 2004, Lee and Lemieux, 2010). Table 4.1 shows the results for testing the pre-election balance of dependent variables and covariates in the vote share bandwidth of 9% around the cutoff. This bandwidth corresponds to the average MSE-optimal bandwidths of our main analyses. Most importantly, our main dependent variables, changes in (on-site) waste releases and treatment are balanced in treatment and control group prior to the union election. Both treatment and control group are also comparable in terms of adoption of pollution prevention activities, sales, employees, and financial constraints, amongst others. Prior to

Figure 4.2: Distribution of Vote Shares



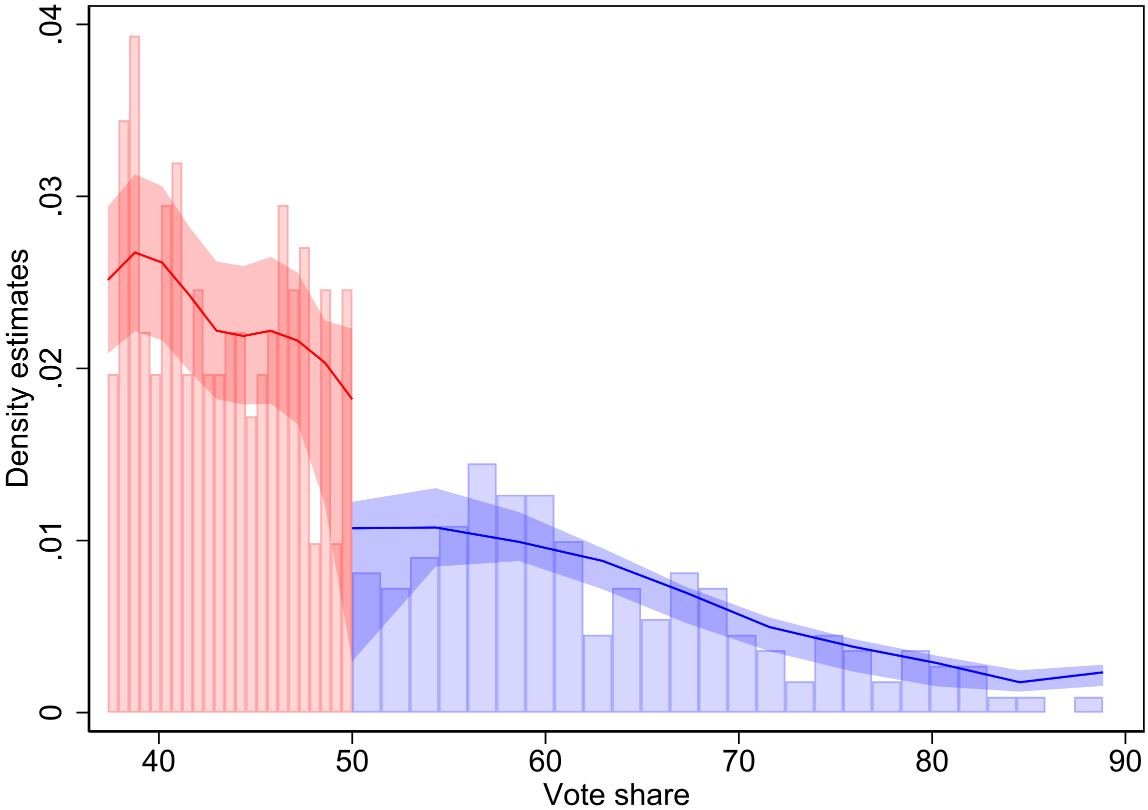
Notes: This figure plots a histogram of the distribution of the adjusted vote shares across 50 equally spaced bins. Each observation represents a unique election in our main sample.

unionization, we observe a significantly lower production ratio among facilities that ultimately unionize. Consequently, we explicitly control for the production ratio in further analyses.

Next, we perform diagnostic tests for the second identifying assumption, absence of manipulation. First, Figure 4.2 illustrates the distribution of vote share in favor of joining the union in 2% steps, i.e. 50 bins. As can be seen, the density of unions that fail is generally larger but decreases closer to the cutoff. This decline continues further on the treatment side of the cutoff. Overall, vote share is fairly distributed across the range of 0% to 100% but further manipulation tests are warranted.

Second, we quantitatively test whether there is a discontinuity in the density of our running variable, vote share. To this end, we present results of the recently proposed test by Cattaneo et al. (2020) in Figure 4.3 and the McCrary (2008) density test in Appendix Figure A.3. While we validate the absence of manipulation under the former test, the discontinuity estimate of

Figure 4.3: Cattaneo (2020) Discontinuity Test



Notes: This figure plots the Cattaneo et al. (2020) discontinuity test for the density of the adjusted vote share variable. The bins plot the distribution of the adjusted vote shares in a histogram. The solid red and blue line estimate the local polynomial density and the shaded red and blue compute bias corrected confidence intervals on each side of the cutoff. Each observation represents a unique election in our main sample.

the latter test marginally rejects the null hypothesis of no discontinuity. Several additional considerations dispel concerns that the discontinuity could imply problematic manipulation in our setting. The McCrary test is not designed for discrete variables like vote share. Therefore, we perform a formal discontinuity test explicitly designed for discrete variables using vote share rounded to the nearest integer (Frandsen, 2017). With a p-value of 0.23, this test again does not indicate the presence of manipulation. Moreover, we argue that with an increasing number of voters, less precise majority manipulation in the secret ballots is possible (DiNardo and Lee, 2004, McCrary, 2008). This argument additionally supports the restriction of our sample to elections with at least 50 voters. Finally, manipulation occurs primarily through contested ballots (Frandsen, 2017). Longer periods – we assume 30 days – between election and certification increase the likelihood of such contested ballots. For a sample that excludes elections with these longer certification periods, no test indicates manipulation.[46] In sum, we conclude that both identifying assumptions of the RDD are sufficiently satisfied.

4.4 Main Results

This section presents our main empirical results from applying the RDD in Equation 4.2. We discuss our baseline estimates, external validity, and a battery of robustness checks.

4.4.1 Main RDD Results

In our main analysis, we estimate the effect of unionization on changes in toxic chemical releases and EOP treatment. We consider average effects up to three years after the election as well as year-by-year effects to investigate both short-term and medium-term effects.

Table 4.2: Main Analysis - Waste Releases after Unionization

	Changes in waste releases		
	Total	On-site	Off-site
	(1)	(2)	(3)
Unionization	0.096	0.147^{**}	-0.172
	(0.085)	(0.071)	(0.171)
Mean	0.941	0.942	0.880

Notes: This table presents the unionization effect on changes in waste releases up to three years post election. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel. The mean reports the control group's average dependent variable in the MSE-optimal bandwidth below the cutoff of 50%. Union election results are from the NLRB over 1990–2017. Toxic waste data are from EPA's TRI over the 1991-2020 time period. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Table 4.2 reports the corresponding regression discontinuity estimates using local polynomial estimation of order one. We find a positive effect of unionization on changes in releases, i.e. increasing releases. This effect is not statistically significant for the total release ratio in column (1). In columns (2) and (3), we decompose waste releases into on-site and off-site releases. On-site, where unions arguably have greater incentives to influence managerial decisions, the change in waste releases increases significantly by 0.147 for union wins compared to union losses.

[46] For this more restrictive sample, our main results of section 4.4 remain robust (untabulated).

At the 50% cutoff, this estimate reads as follows: facilities with a union loss reduce their on-site releases by approximately 12% whereas facilities with union wins increase on-site releases by 3%, compared to the previous year. Off-site changes in releases are statistically indistinguishable from zero.

Why would unionization cause higher toxic releases that adversely affect the environment at the workplace of union members? We conjecture in section 4.2 that unions are particularly concerned with workplace safety. Increasing releases after unionization can be a consequence of this preference as unions might prefer polluting waste releases over some more dangerous waste treatment activities.

TABLE 4.3: Main Analysis - EOP Waste Treatment after Unionization

	Changes in waste treatment		
	Total	On-site	Off-site
	(1)	(2)	(3)
Unionization	-0.236	-0.593^{**}	-0.085
	(0.179)	(0.244)	(0.125)
Mean	0.943	0.948	0.909

Notes: This table presents the unionization effect on changes in EOP waste treatment up to three years post election. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel. The mean reports the control group's average dependent variable in the MSE-optimal bandwidth below the cutoff of 50%. Union election results are from the NLRB over 1990–2017. Toxic waste data are from EPA's TRI over the 1991-2020 time period. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

We explicitly test our hypothesis in Table 4.3. In column (1), we report a negative, albeit not statistically significant effect of unionization on the change in treated waste. Successful unionization implies an, on average, 0.24 drop in the waste treatment ratio compared to facilities where a union lost in a close-call election. Again, we further validate this finding by decomposing total waste treatment into on-site and off-site treatment. As expected, unionization significantly and strongly impacts on-site EOP waste treatment. On a year-by-year average, unionized facilities reduce on-site waste treatment by 59 percentage points compared to non-unionized facilities. This effect is statistically significant marginally above the 1%-level (column (2)). The economic magnitude of the effect is quite large but should be interpreted with caution considering that it is the local treatment effect at the cutoff. In contrast, column (3) shows that there is hardly any detectable effect on off-site waste treatment where the elected union has less incentive to take action. This finding is in line with our theory because influences and safety concerns of a union should predominantly affect workers' exposure to waste treatment at their facility, i.e. on-site.

To further understand the timing of the apparent negative waste treatment effect coinciding with higher on-site releases over three years after a successful election, we rerun our analysis for each year separately. Table 4.4 contains the results. As can be seen in panel A, changes in total releases increase strongest in the first year but are never statistically significant. In panel B, we show that the on-site release ratio is positive in all years and statistically significant in the year directly following unionization. The results for treated waste in panel C and on-site treated waste in panel D mirror this strong immediate reaction and somewhat lower lagged effects. Specifically, we observe a large reduction in the on-site waste treatment ratio in the year following the election, significant at the 5%-level. Again, the economic magnitude of the effect is quite large.

Table 4.4: Waste Release and Treatment by Year

	(1) t+1	(2) t+2	(3) t+3
Panel A: Changes in waste releases			
Unionization	0.134	−0.022	0.096
	(0.135)	(0.169)	(0.161)
Panel B: Changes in on-site waste releases			
Unionization	0.231*	0.103	0.172
	(0.134)	(0.115)	(0.162)
Panel C: Changes in waste treatment			
Unionization	−0.353*	−0.102	−0.134
	(0.205)	(0.159)	(0.349)
Panel D: Changes in on-site waste treatment			
Unionization	−0.664**	−0.173	−0.493*
	(0.280)	(0.414)	(0.293)

Notes: This table presents the unionization effect on changes in waste releases and treatment for each of the three years post election. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

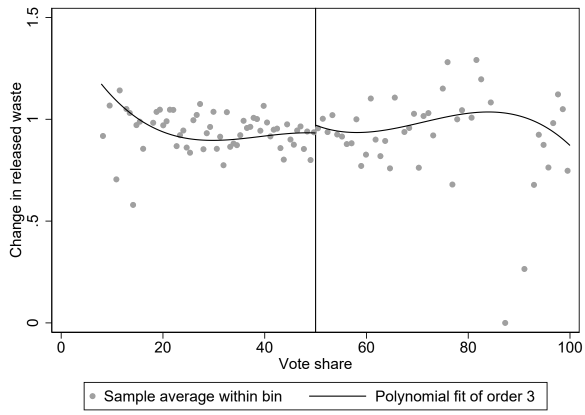
Overall, our results suggest that newly unionized firms have a strong distaste for EOP waste treatment, especially on-site, at the expense of higher on-site releases to the environment. This effect generally is strongest in the year following unionization, but unions' rejections of on-site waste treatment in particular persist in the third year as well. Hence, unions seem to prioritize workplace safety or cost-savings over potentially detrimental effects through increased exposure to chemicals in the environment. In other words, safety dominates ecology. Moreover, the lower magnitude of the release effect might indicate that facilities find other ways than releases to facilitate less treatment.

4.4.2 External Validity

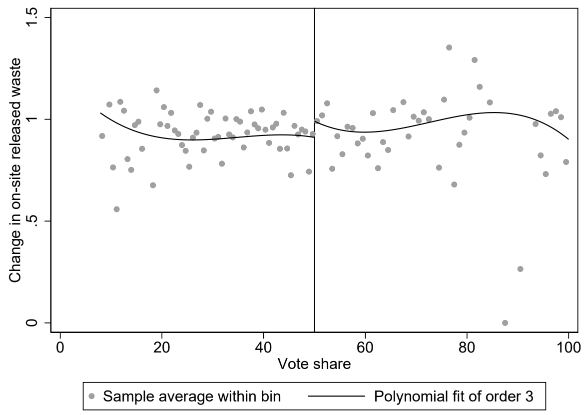
An inherent feature of a local RDD is strong internal validity and limited external validity because only close-call elections are considered. Hence, the local RDD excludes many observations when estimating the treatment effect but for these observations with clearer election outcomes, the relationship between waste management practices and unionization might differ. To probe into the external validity of our results, we estimate a global polynomial RDD using all observations, i.e. including clear wins and losses. Since this global RDD introduces more bias in coefficients, literature suggests using a higher-order polynomial (Dittmar et al., 2020).

Figure 4.4: Global Polynomial Discontinuity Estimates

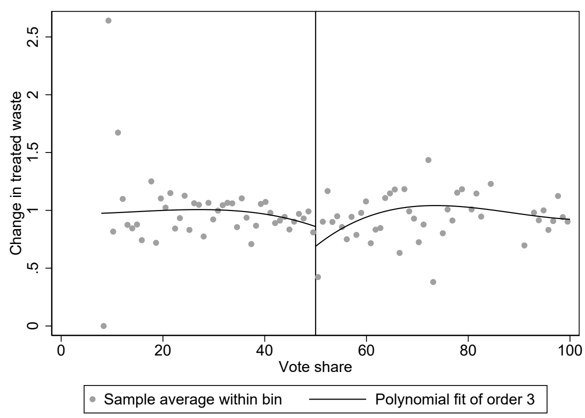
(A) Changes in total waste releases



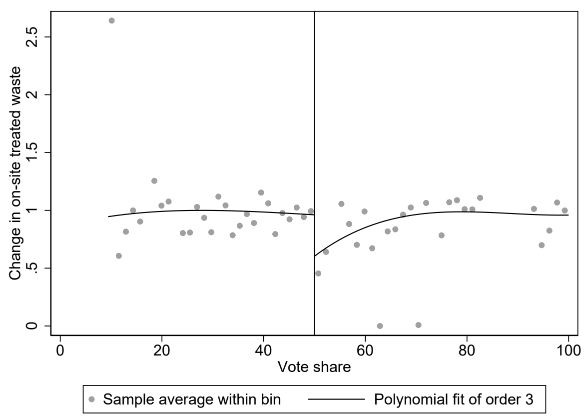
(B) Changes in on-site waste releases



(C) Changes in total waste treatment



(D) Changes in on-site waste treatment



Notes: This figure presents the global unionization effect on waste management practices up to three years post election. Figure A presents changes in total waste releases, Figure B presents changes in on-site waste releases, Figure C presents changes in total waste treatment, and Figure D presents changes in on-site waste treatment. We show third-order global regression discontinuity functions.

Figure 4.4 plots the global third-order polynomial (Dittmar et al., 2020) from a regression of waste release and treatment ratios on vote share at both sides of the unionization cutoff. The effect of unionization on changes in waste releases appears relatively small in this global estimation. On the contrary, there is a drop in the waste treatment ratio at the right side of the cutoff, i.e. when the union election passes with a union win. For both releases and treatment, the effects are stronger on-site than in total.

Table 4.5 reports the conventional estimates of unionization in a global third-order polynomial on our main dependent variables, total waste release ratio (columns (1)-(2)), on-site waste release ratio (columns (3)-(4)), total waste treatment ratio (columns (5)-(6)), and on-site waste treatment ratio (columns (7)-(8)). In columns (2),(4), (6), and (8), we include year and chemical fixed effects to control for unobservable variations across chemicals and over time.

Table 4.5: Global Regression Discontinuity (Third-Order Polynomial)

	Changes in waste releases				Changes in EOP waste treatment			
	Total		On-site		Total		On-site	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unionization	0.098	0.074	0.118*	0.098*	−0.193	−0.265**	−0.399**	−0.479**
	(0.071)	(0.069)	(0.063)	(0.059)	(0.136)	(0.122)	(0.201)	(0.198)
Chemical FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
N	4044	4015	3789	3752	3335	3292	1712	1677

Notes: This table presents the unionization effect on changes in waste releases and treatment up to three years post election. In columns (2),(4), (6), and (8), we include year and chemical fixed effects to control for unobservable variations across chemicals and over time. For estimations with fixed effects, we drop singleton chemical or year observations (Correia, 2019). We report conventional regression discontinuity estimates using the global bandwidth, triangular kernel, and a third-order polynomial. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

As can be seen, the direction and size of our estimates are consistent when using a global polynomial setting.[47] Consequently, we show that our results can be extrapolated to the complete sample of union elections despite our main results from the local RDD having primarily internal validity. The effect sizes of changes in on-site waste releases and treatment remain meaningful, but slightly smaller for all elections compared to close-call elections in our main analysis.

[47] We verify that our results are not driven by particular estimation specifications. Specifically, our results remain virtually unchanged when estimating a second-order or fourth-order polynomial and when using a kernel function (epanechnikov or uniform) that more equally weights observations across the range of our running variable.

4.4.3 Robustness

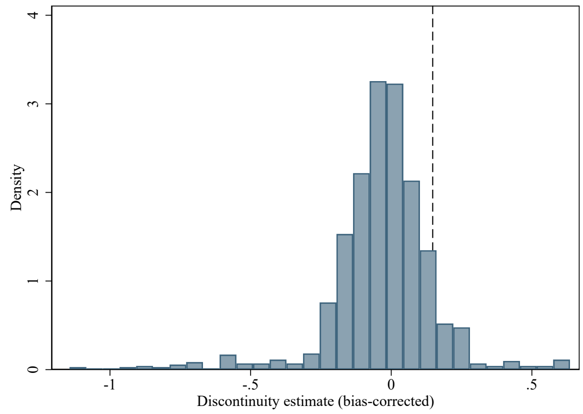
This section examines the robustness of our local RDD findings to assumptions and default econometric model specifications. To this end, we perform several contextual and local RDD-specific robustness checks. First, we change the threshold for including ratios in our analysis from three to two and four (Akey and Appel, 2021). Second, we use the natural logarithm of the ratios, thereby mitigating the effects of outliers while excluding zeros, i.e. observations where facilities do not release or treat a chemical anymore (Dutt and King, 2014). Third, we rerun our analysis using a multiplicative version of the individual ratios in year t+3. We construct this measure by multiplying the ratios in the three years following the election which represents an alternative for testing the medium-term, compound effect of unionization on chemical-level waste management practices (Akey and Appel, 2021). Fourth, we add year and chemical fixed effects as covariates. Fifth, we adjust the number of eligible voters to 25 and 75 (DiNardo and Lee, 2004). Lastly, we only include chemicals for which the EPA consistently mandated reporting during our sample period. Our main result of increasing on-site waste releases and decreasing on-site EOP treatment is robust in all specifications and significant in the vast majority of alternative specifications. Appendix Table A.23 contains corresponding estimation results.

While these robustness tests target contextual assumptions, variables, or sample definitions, a local RDD requires discretionary specifications for estimation. Although we use standard specifications, we still test the sensitivity of our estimates towards alternative specifications. These tests include using a second-order local polynomial to estimate the discontinuity and using an epanechnikov kernel function. Moreover, we also run a “donut” RDD where we exclude observations directly at the cutoff, i.e. those with a vote share or adjusted vote share of 50% (Barreca et al., 2011). As shown in Appendix Table A.24, our results remain virtually unchanged across these robustness checks.

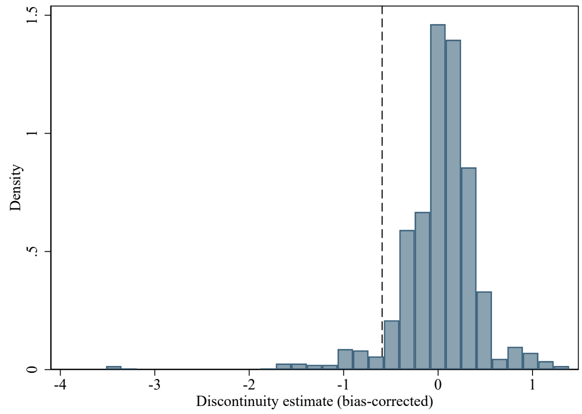
Finally, we perform placebo tests using alternative cutoffs. Thus, by artificially assigning treatment observations to the control group or vice versa, we expect to not find an effect in most cases, implying that our estimated effects are not random. Specifically, we alter the cutoff from vote shares of 20% to 80% in steps of 0.05%, hence running 1,200 iterations of our RDD with 1,200 different cutoffs (Bordignon et al., 2016). Figure 4.5 compares the discontinuity estimates from these false cutoffs to the true estimate of 0.147 for the on-site release and -0.593 for the on-site treatment changes, depicted by the dashed lines. The large majority of these RDD runs

Figure 4.5: Density of Discontinuity Estimates at Placebo Cutoffs

(a) Changes in on-site waste releases



(b) Changes in on-site waste treatment



Notes: This figure plots a histogram of the distribution of the discontinuity estimates from placebo tests with artificial cutoffs between 20% and 80% of the vote share. The dashed vertical line represents the "true" on-site discontinuity estimate from Table 4.2 in the left graph and from Table 4.3 in the right graph.

produces an estimate of zero or close to zero, i.e. does not find a significant effect of unionization on on-site waste releases and EOP treatment. This finding further supports our identification and attribution of our results to the unionization effect.

4.5 Cross-Sectional Heterogeneity

Our main analysis shows that unionization results in increasing on-site releases and decreasing waste treatment, especially on-site. Next, we investigate whether (i) union power as determined by legislation, (ii) chemical toxicity, and (iii) industry affiliation moderate our effects.

4.5.1 Union Power

As of 2022, 27 states in the US have right-to-work (RTW) laws in place. Under RTW legislation, workers at a facility are not obliged to join or pay for the union that represents them. Recent empirical evidence underscores that RTW laws essentially restrict the power of unions with real effects on, i.a., investment and innovation (Bradley et al., 2017, Chava et al., 2020). Consequently, if unions actively bargain for changes in waste management practices, we expect these changes to be stronger for facilities located in a non-RTW law state where unions have more bargaining power. For estimation, we run Equation 4.2 for two samples, namely for observations from RTW versus non-RTW states.[48]

TABLE 4.6: Union Bargaining Power

	Changes in waste releases		Changes in waste treatment	
	Total (1)	On-site (2)	Total (3)	On-site (4)
Panel A: RTW state				
Unionization	0.131	0.160	−0.009	−0.058
	(0.158)	(0.215)	(0.266)	(0.369)
Panel B: Non-RTW state				
Unionization	0.072	0.134*	−0.422***	−1.005***
	(0.107)	(0.072)	(0.116)	(0.191)

Notes: This table presents the unionization effect on changes in waste releases and treatment up to three years post election. We split our sample in observations from US states with right-to-work laws in panel A and US states without in panel B. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel function. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Table 4.6 contains the corresponding estimates. The results in panel A show that unionization does not have a significant effect in RTW law states, neither on changes in (on-site) releases nor in (on-site) treatment. On the contrary, our main effects are significant in non-RTW states (panel B). Especially, we find that the decrease in (on-site) waste treatment is stronger than in RTW states. Some scholars argue that the general attitude toward unions rather than effective RTW legislation determines union power (e.g. Farber, 1984). To proxy for this general attitude, we split the sample into observations from states *eventually* versus *not* adopting RTW legislation. Appendix Table A.25 shows that our results of significant effects in non-RTW states hold. In sum, these findings suggest that unions require sufficient bargaining power to cause real changes in waste management practices.

4.5.2 Chemical Toxicity

So far, our analysis deals with quantity-based measures of toxic waste that implicitly assume a general comparability across chemicals (Kassinis and Vafeas, 2006, Dutt and King, 2014, Wang et al., 2021). However, our chemical-level data also allows for explicit accounting of differing toxicity as done by other scholars (King and Lenox, 2002, Berrone and Gomez-Mejia, 2009, Kim

[48] We assign states according to the year they pass RTW legislation. For instance, chemical-level waste from facilities in Michigan is in the non-RTW split of the sample before 2012 and in the RTW split afterwards.

et al., 2019). As such, we can investigate whether chemical toxicity moderates the ecology-safety tradeoff.

On one hand, union's observed distaste for EOP waste treatment could intensify for extremely toxic materials due to higher safety concerns. Given the proximity of blue-collar workers to production (Bradley et al., 2017) and detailed data provided by EPA and other institutions it is also reasonable to assume that unions could gather this toxicity information. On the other hand, more toxic chemicals are arguably more regulated and have greater negative effects when released. Consequently, waste management practices for these chemicals might be less flexible in general.

For estimation, we use reportable quantities for emergency action to split the sample. All chemical-facility-year observations with a reportable quantity of 1, 10, and 100 pounds constitute the more toxic subsample. Higher, i.e. 1000 and 5000 pounds, or missing reportable quantities hence constitute the less toxic subsample.

Table 4.7: Chemical Toxicity

	Changes in waste releases		Changes in waste treatment	
	Total (1)	On-site (2)	Total (3)	On-site (4)
Panel A: RQ $\leq$ 100 pounds				
Unionization	0.084	0.131	-0.159	-0.448^{***}
	(0.144)	(0.118)	(0.184)	(0.155)
Panel B: RQ $>$ 100 pounds				
Unionization	0.132	0.166^{**}	-0.256	-0.586^{**}
	(0.086)	(0.080)	(0.190)	(0.272)

Notes: This table presents the unionization effect on changes in waste releases and treatment up to three years post election. We split our sample in chemicals that have low reportable quantities (RQ below or equal to 100 pounds), i.e. higher toxicity, and those with high reportable quantities (RQ above 100 pounds or not specified), i.e. lower toxicity. Panel A and B report the respective subsamples which are approximately evenly distributed over the total number of observations. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel function. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

As shown in Table 4.7, accounting for diverging toxicity does not affect the direction of our main result. Panel A and panel B both report increasing release ratios and decreasing treatment ratios. We show that changes in on-site releases are not statistically significant despite their similar magnitude to our main effect, whereas changes in on-site waste treatment drops significantly also for more toxic chemicals (panel A). On the contrary, the coefficients for on-site release and treatment are statistically significant and larger in absolute terms for the subsample of less toxic chemicals (panel B). In Appendix Table A.26, we report further heterogeneity analyses for toxicity subsamples using the human toxicity potential to split the sample (Hertwich et al., 2001). Again, real effects tend to be slightly smaller for more toxic chemicals.

Tighter environmental permits for releasing these chemicals and more detrimental effects of pollution exposure are possible underlying explanations. Nevertheless, this heterogeneity analysis suggests that increasing on-site releases and especially decreasing on-site treatment are present in both toxicity subsamples.

4.5.3 Industry Affiliation

Subsequently, we explore whether a facility being affiliated to a heavy versus a non-heavy industry matters for waste releases and waste treatment. Workers expectations on job risks, such as exposure to dangerous procedures or chemical emissions might depend on the industry affiliation of their employers. Viscusi (1979) finds that workers have no perfect information on job risk and their perception is positively correlated with industry risk.

Specifically, we conjecture that workers in "dirty", i.e. heavy, industries likely expect a certain extent of exposure to hazardous substances and also regard releases and waste management practices as an integral part of performing business. Additionally, industries likely face different possibilities and (regulatory) constraints in adjusting waste management as a response to unions' pressures. To investigate the role of industry affiliation and to approximate corresponding potential preferences of workers, we split our sample into chemical observations from heavy industry (e.g. chemicals, oil and gas) versus non-heavy industry facilities (e.g. food processing, electronics).[49]

Panel A of Table 4.8 shows significant positive effects of unionization in non-heavy industries on changes in total (column (1)) and on-site releases (column (2)) as well as significant negative effects on changes in total (column (3)) and on-site waste treatment (column (4)). Panel B mostly corroborates the direction of these effects also for observations from heavy industries, although only the on-site treatment coefficient is statistically different from zero.

[49] Specifically, we assign facilities with a primary NAICS starting with 21, 221–223, 324–327, 331–332, and 562 to the heavy-industry subsample and all others to the non-heavy industry subsample.

Table 4.8: Industry Affiliation

	Changes in waste releases		Changes in waste treatment	
	Total	On-site	Total	On-site
	(1)	(2)	(3)	(4)
Panel A: Non-heavy industry				
Unionization	0.198**	0.237***	−0.408***	−0.832***
	(0.098)	(0.058)	(0.122)	(0.174)
Panel B: Heavy industry				
Unionization	0.125	0.124	0.018	−0.477*
	(0.123)	(0.130)	(0.297)	(0.267)

Notes: This table presents the unionization effect on changes in waste releases and treatment up to three years post election. We split our sample in observations from non-heavy industries in panel A and heavy industries in panel B. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel function. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Overall, our results of decreasing waste ratios and simultaneously increasing release ratios are stronger for facilities in non-heavy industries. This finding suggests that workers from heavy industries have different risk expectations and interests regarding toxic waste management. Moreover, regulations and higher marginal costs of changing waste management practices might limit the wiggle room for unions to influence the ecology-safety tradeoff in heavy industries.

4.6 Further Analyses

In our last results section, we aim to examine alternative explications and further disentangle the drivers of our main effects, increasing on-site release and decreasing on-site waste treatment. To this end, we first investigate whether changes in production output mechanically affect our results. Second, we explore whether our main effects might be driven by motivations to save costs. Finally, we test our hypothesis of more pollution prevention activities due to their multi-win character.

4.6.1 Production Output

Production output is highly positively correlated to waste releases and waste treatment. Hence, quantitative changes in these waste management procedures could be purely mechanical and result from changing production output after unionization, e.g. because of lower productivity and shirking due to misaligned incentives (Bradley et al., 2017). To examine the role of production output, we use the production ratio as presented in Section 4.3.2, i.e. output related to chemical use in one year divided by output in the previous year.

Table 4.9: Production Output

	Production	Changes in waste releases		Changes in waste treatment	
	ratio	Total	On-site	Total	On-site
	(1)	(2)	(3)	(4)	(5)
Unionization	0.100	0.108	0.131*	−0.281*	−0.599**
	(0.098)	(0.093)	(0.077)	(0.166)	(0.234)
Production ratio		0.265***	0.272***	0.206**	0.274*
		(0.059)	(0.069)	(0.084)	(0.144)

Notes: This table presents the unionization effect on the production ratio in column (1). We report the unionization effect on changes in waste releases and treatment up to three years post election when controlling for the production ratio in columns (2)-(5). We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth of our main analysis and triangular kernel function. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

In Table 4.9, we first test whether unionization has a significant effect on this production ratio. Column (1) shows that unionization does not significantly affect the production ratio up to three years after the election takes place. This finding is consistent with DiNardo and Lee (2004) and does not point to the presence of shirking on job duties by unionized workers.

Next, we report unionization and production effects on waste management strategies in columns (2) to (5). We find no relevant changes in coefficients and significance levels when including the production ratio as a control variable, compared to our main results in Tables 4.2 and 4.3. Hence, we rule out that the increase in on-site waste releases and strong decrease in treated waste after unionization is a purely mechanic consequence of changing production levels.[50] Furthermore, these findings address concerns with respect to the observed pre-election unbalance of the production ratio between treatment and control group.

4.6.2 Financial Constraints

Next, we consider financial constraints, approximated by the minimum Paydex credit score, as a possible mechanism of our results. The unionization effect on financing decisions, such as debt-to-equity ratios, is well documented in the literature (Bronars and Deere, 1991, Klasa et al., 2009,

[50] In untabulated robustness checks, we use the log of sales and the log of employees from NETS instead of TRI's production ratio to proxy for production output. Our results remain virtually unchanged.

Matsa, 2010). Moreover, other studies present evidence that more financially constrained firms release more toxic chemicals (Xu and Kim, 2022), potentially because the costs associated with end-of-pipe treatment procedures require sufficient funding (Frondel et al., 2007, Dutt and King, 2014). Our sample reflects these findings as the Paydex score and changes in waste treatment are positively correlated.

Table 4.10: Financial Constraints

	Paydex	Changes in waste releases		Changes in waste treatment	
	score	Total	On-site	Total	On-site
	(1)	(2)	(3)	(4)	(5)
Unionization	6.099	0.183**	0.163**	−0.265	−0.700***
	(3.817)	(0.071)	(0.074)	(0.226)	(0.260)
Paydex score		−0.000	−0.001	0.005	0.009**
		(0.002)	(0.002)	(0.003)	(0.004)

Notes: This table presents the unionization effect on the minimum Paydex credit score in column (1). We report the unionization effect on changes in waste releases and treatment up to three years post election when controlling for the Paydex score in columns (2)-(5). We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth of our main analysis and triangular kernel function. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

We examine whether unionization directly impacts financial constraints and thereby indirectly impacts waste releases and treatment. As shown in column (1) of Table 4.10, we find a positive but insignificant local unionization effect on the Paydex score. We show that financial constraints do not significantly mediate the relationship between unionization and changes in waste releases and total waste treatment (columns (2) to (4)). In column (5), we show that, ceteris paribus, an increase in the Paydex score increases on-site treatment. However, the mediating effect is relatively small. These results suggest that financial constraints, and possibly cost savings, are not the main motivation of our EOP waste treatment effect. Thus, workplace safety concerns appear to be more relevant for the observed decrease in waste treatment.

4.6.3 Prevention Activities

Our empirical results indicate that unions care about workplace safety, leading to reduced on-site waste treatment but increased on-site releases. However, the magnitude and significance of the effect on waste releases is generally weaker. Subsequently, we investigate potential channels mitigating the increase in waste releases.

First, employee training should be a primary concern for labor unions to achieve higher workplace safety. We proxy training by the binary variable "Cata" which is equal to one if a facility reports catastrophic releases and zero otherwise. These releases occur rarely and unplanned due to human or technical failure and might decrease with better training possibilities. As shown in column (1) of Table 4.11, we find a significant negative local effect of unionization on Cata, i.e. catastrophic releases. Hence, unions might bargain for higher safety and training standards facilitating this decrease in catastrophic releases.

Table 4.11: Prevention Activities

	Cata	Inno	Changes in waste releases		Changes in waste treatment	
			Total	On-site	Total	On-site
	(1)	(2)	(3)	(4)	(5)	(6)
Unionization	-0.067^{***}	0.045^{**}	0.122	0.166^{**}	-0.222	-0.589^{**}
	(0.026)	(0.019)	(0.086)	(0.072)	(0.181)	(0.244)
Cata			0.195	0.164	0.059	0.001
			(0.163)	(0.174)	(0.203)	(0.141)
Inno			-0.154^{*}	-0.073	-0.170^{*}	-0.175^{**}
			(0.084)	(0.124)	(0.097)	(0.087)

Notes: This table presents the unionization effect on catastrophic releases (Cata) and innovative pollution prevention (Inno) in columns (1) and (2). In columns, 3 to 6, we present unionization effects on changes in waste releases and treatment up to three years post election when controlling for the alternative pollution prevention mechanisms, catastrophic releases and innovative prevention. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth of our main analysis and triangular kernel function. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Next, we analyse a potential channel through which facilities and unions can generate a multi-win outcome: pollution prevention through innovative product and process modifications. Specifically, by eco-designing products or by inventing new production processes and technologies, facilities can manufacture the same level of output with a lower chemical waste intensity. Consequently, such innovation also reduces pressure on the ecology-safety tradeoff, as there is less necessity for treatment for the same level of releases. We operationalize innovative prevention by means of a binary variable ("Inno") equal to one if facilities report a pollution prevention activity related to innovation and zero otherwise. We report the positive unionization effect on Inno, i.e. the adoption of innovative pollution prevention activities, in column (2) of Table 4.11.[51]

[51] Our results are robust to using a more narrow definition of innovation, EPA's category of product innovation. We also investigate other source reduction activities such as the adoption of good operating practices, but do not find a significant effect of unionization on these indicators. Since Cata and Inno are both binary variables, we rerun the RDD in columns (1) and (2) of Table 4.11 using logit and poisson estimation. Again, results remain robust (untabulated).

Finally, we examine whether catastrophic releases and innovative prevention activities relate to changes in waste management practices. To this end, we add corresponding indicator variables as controls and repeat the discontinuity estimations for the release and treatment effects in columns (3) to (6).[52] As predicted, facilities that report innovative prevention activities are associated with less waste releases (columns (3) and (4)) and less treatment (columns (5) and (6)), ceteris paribus. Nevertheless, our unionization effects stay large even after controlling for both potential channels, catastrophic releases and innovative prevention.

4.7 Discussion and Conclusion

This paper investigates changes in waste management practices by facilities following a union election. Based on prior literature, we argue that unions essentially face a tradeoff between protecting their members' safety at the workplace and supporting ecology by protecting members, neighboring communities, and the environment from pollution. In the context of waste management, the tradeoff exists because curing waste is costly and relatively dangerous for its workers whereas releases negatively affect the environment and the health of workers and community members.

Exploiting a quasi-experimental setting with close-call union elections, we document that facilities increase on-site waste releases and decrease on-site EOP waste treatment after unionization. The discontinuity estimates of our local RDD are economically large and hold across several contextual and econometric robustness checks. Moreover, we test and show the generalizability of our results to all union elections using a global RDD. In cross-sectional analyses, we find that our results are not statistically significant in states with lower union bargaining power as indicated by effective RTW laws. Chemical toxicity and industry affiliation also play a role, with more toxic chemicals and heavy industries attenuating our main effects.

Taken together, these results add to previous evidence of a negative effect of unionization on globally relevant externalities (Ertugrul and Marciukaityte, 2021, Heitz et al., 2021). The locality of toxic waste tightens the tradeoff workers face as they are also exposed to negative pollution externalities on the local facility level. Although workers derive disutility from both releases and EOP treatment, the distaste for treatment dominates. Moreover, we rule out changes

[52]The similarity of the unionization discontinuity estimates when controlling and when not controlling for our mechanisms ease concerns about measurement error due to unionization-induced changes in mechanisms that confound with changes in waste management practices (Angrist and Pischke, 2009, Heckman et al., 2013).

in production output as a mechanical driver of our results. Similarly, we show that financial constraints do not mediate our main effects. Our results call upon managers and policymakers to reconsider current waste treatment practices with a focus on increasing safety and workers' trust.

Furthermore, we find that unions decrease catastrophic releases and support the adoption of innovative prevention activities like modifying the design or composition of a product in order to prevent pollution. These activities relax the ecology-safety tradeoff. Given their multi-win character, managers, governmental institutions, and policymakers should focus on supporting pollution prevention activities with financial resources and expert knowledge. Efforts to increase pollution prevention induce positive external effects across facilities, e.g. because knowledgeable workers change employers and environmental externalities decline. The public good character of such efforts justifies policy support like EPA's Pollution Prevention program.

Finally, our paper highlights the role and importance of blue-collar workers on facilities' environmental performance. We investigate unions' perspective on the ecology-safety (i.e., release-treatment) tradeoff in manufacturing and demonstrate novel channels, through which unions provide benefits for their members. As such, we shed light on potential environmental consequences from increasing union power relative to other stakeholders. i.e. through new legislation currently discussed by the US Senate, the Protecting-the-Right-to-Organize Act. What is good for (unionized) workers is not necessarily good for other stakeholders, such as neighboring communities and the planet. Future research could investigate whether loosening procedural standards through Advanced Recycling legislations will lead to fewer waste releases, in light of workers' distaste for waste treatment.

5 Discussion and Conclusion

5.1 Research Overview and Policy Implications

In order to achieve environmental targets from international policy treaties like the Sustainable Development Goals and the climate-oriented Paris Agreement, innovation and technological change is necessary across the global economy. This thesis quantifies technological change toward more sustainability and investigates a range of underlying drivers in two crucial sectors, energy and manufacturing. Among these drivers of technological change are learning and innovation channels, production factors, economies of scale, market characteristics, and strategic behavior of several actors like firms and labor unions.

The energy sector – and especially electricity generation – as the largest contributor of greenhouse gases likely has to reach net zero by 2050 for compliance with the 1.5 °C target of the Paris Agreement. Technological change in terms of declining costs and improving performance is already happening, in particular for solar (PV) and wind technologies. Nevertheless, capacity has to grow at unprecedented rates on a global scale while achieving further progress in multiple technologies to address intermittency, resource constraints, and affordability.

Chapter 2 examines technological change of onshore wind between 1998 and 2018 in Europe, a comparatively mature market with a long history of commercial onshore wind deployment. Using a multi-factor learning curve model with experience, knowledge, commodity prices, economies of scale, and country fixed effects, we estimate learning by doing rates of 2-3% and learning by searching rates of 7-9% in terms of the levelized cost of electricity. As expected, commodity prices are positively related to LCOE and economies of scale in manufacturing are negatively related to LCOE. We test the sensitivity of our results to depreciation rate assumptions. LBD does not change much and is still small. However, LBS rates estimated with an RD&D-based

knowledge stock vary by more than ten percentage points for depreciation rates between 0% and 10% whereas patent-based LBS rates remain virtually unaffected. When we disaggregate technological change from LCOE into upfront investment cost and capacity factor, we only find significant learning by searching effects for the capacity factor, whereas learning in investment costs is insignificant. Our main results are robust to an instrumental variable specification and further changes in the specification, e.g. with respect to the criteria determining a patent's inclusion in the knowledge stock.

Chapter 3 addresses the soaring need for battery energy storage to balance intermittent renewable energy generation, boost end-user self-consumption of decentrally generated electricity, and safeguard against power shutoffs. Using a one-factor experience curve and total system price as technological change measure, we find low experience rates of about 1.3%. Next, we investigate heterogeneity in experience rates and find that small, i.e. residential, systems show negative learning while larger, commercial systems above 10 kW show experience rates of up to 11%. We extend our model and find that system size – proxied by longer duration and more storage capacity in kWh – explain lower system prices. Moreover, less competition as indicated by a higher HHI is significantly associated with higher system prices. Substituting BOS prices for total system prices confirms the attenuating effect of non-battery pack prices on total system prices: experience rates are lower for BOS. Finally, we decompose experience into industry experience and installer firm experience. We find positive spillover effects from industry experience but negative learning effects from increasing firm experience.

A substantial amount of greenhouse gas and other emissions comes from industry and are generally perceived as more difficult to abate (Fan and Friedmann, 2021, Vogl et al., 2021, Yokoi et al., 2022). Moreover, sustainable development with rapid adoption of cleaner technologies requires multifaceted, system-level efforts that includes a range of stakeholders (Geels et al., 2017). Against this backdrop, chapter 4 investigates the role of unions toward sustainability, represented by toxic waste management practices in manufacturing. Specifically, we report causal evidence of more toxic releases and less toxic waste cure following facility-level unionization. This year-on-year average effect over three years after the election is large, and strongest in the year following the election. We find that the effects are moderated by union power, chemical toxicity, and industry affiliation. Furthermore, we rule out changes in production output and financial constraints as alternative explanations. These findings support our reasoning that after unionization, facilities care for workplace safety in particular as waste cure operations are more dangerous, even if this comes at the expense of the environment. However, additional analyses indicate that unionization leads to less catastrophic release incidents and more innovative product and process activity to prevent pollution, suggesting that union bargaining can also bring multi-win sustainable outcomes.

5.2 Implications for Research and Policy

The findings of this thesis have several implications for research and energy or power system modeling in particular. We provide onshore wind learning rates and battery storage experience rates for use in energy or power system models. Moreover, our findings call for more detailed system modeling along four dimensions. First, breaking down a technology into its components – e.g. main component such as modules, turbines, battery packs versus BOS components – or according to size segments – e.g. residential versus commercial versus utility-scale – could increase modeling accuracy by allowing for separate learning curves. Second, due to our finding of LCOE and capacity factor learning, modelers should consider whether their endogeneous technological change variables are sufficient. Specifically, modeling learning in quality, i.e. capacity factors, has been a crucial driver of declining LCOE for onshore wind as opposed to typically modeled investment costs. As such, models that do not account for these quality improvements likely overestimate technology costs and thus underestimate optimal capacity investment. Third, endogeneous technological change within a model should also occur through learning by doing from experience alone. In light of significant and sizeable learning by searching effects, two-factor endogeneous technological change from experience *and* knowledge would allow for more targeted policy recommendations: support adoption and capacity investments or research and development. Lastly, our findings illustrate that learning and experience rates can be sensitive to modeling assumptions, specifically depreciation rates.

Implementing all these recommendations arguably increases complexity and computing time considerably. Nevertheless, some recent work exemplifies that more detailed modeling along the formulated implications is feasible, at least in parts (e.g. Straus et al., 2021, Mier et al., 2022). In sum, such modeling should lead to higher-quality policy recommendations derived from system models.

Our findings also have direct implications for policy and practitioners. First, we show strongly increasing shares of non-battery pack costs in distributed battery storage. Put differently, prices paid by end-users do not match the pace of technological change in battery cells which we attribute to limited competition and mark-ups for more experienced installers. Consequently, fostering competition, increasing price transparency, and streamlining operations and installations both on part of installers and authorities are among the priorities to make end-user prices reflect strongly falling technology costs.

Second, our results highlight the importance of manufacturing-level and project-level scale effects. While scaling up markets and avoiding political uncertainty should support the former, additional tools are necessary for the latter. Generally, a more inclusive energy transition seems desirable. End-users should have access to peer-to-peer trading or electricity markets in order to get compensated for flexibility provision of their decentral storage capacity. Through these additional revenues combined with the observed economies of scale, larger systems and storage capacities should become financially viable.

Third, our findings point to some justifications for using subsidies. For distributed battery storage, subsidies appear reasonable in light of positive spillovers and the decarbonization potential. Yet, design and magnitude of the subsidies might be re-considered to spur competition and further price declines. For innovative activities preventing toxic waste pollution, subsidies, or other support like best practice sharing, also appear warranted to ease conflicts of interests between different stakeholder groups.

Lastly, policy and managers need to take tradeoffs into account when advocating for more sustainability. For instance, interests of unionized workers entail workplace safety and wage security that can counteract pursuits for environmental protection. Sustainable development is full of similar socio-economic tradeoffs. Further examples include the use of highly climate potent F-gases in onshore wind turbines or morbid effects due to the burning of wood even if this comes from a sustainable forestry. Anticipating such tradeoffs when making policy or strategy can be important to establish stakeholders' trust and maximize sustainability impact.

5.3 Closing Remarks

Taken together, the findings of this thesis can contribute to sustainable development in line with halting climate change and curbing pollution from manufacturing. New energy technologies, product innovations or chemical process innovations at ideation, lab, demonstration, or small-scale commercialization stage can further help to achieve these policy targets.

Candidates coming to mind are new solar technologies (perovskite-silicon tandem PV, space PV) or applications (agrivoltaics, floating PV, building-integrated PV), floating offshore wind, power-to-X, other new storage technologies (liquid metal, redox-flow, or sodium-ion batteries, compressed air energy storage, flywheel), carbon capture and storage, (e.g. direct air capture), biotechnology (e.g. algae as biofuel, plastic-eating bacteria), new processes to dissolve long-lasting chemicals like per- and polyfluoroalkyl substances (Trang et al., 2022), and the rather controversially discussed geoengineering like solar radiation management (Nordhaus, 2019, Sovacool, 2021).

Future research can build on insights of this thesis to model drivers of change for these technologies, project necessary capacity extensions and likely cost developments, assess affects on or relations to other stakeholders, and derive policy recommendations such as necessary support mechanisms. With speedy, strong innovation and adoption of clean energy and manufacturing, society can achieve conservation of a habitable planet with restored ecosystems and healthy air, land, and water.

Appendix

Mills of Progress Grind Slowly? Estimating Learning Rates for Onshore Wind Energy — Appendix

Table A.1: Robustness Checks – Alternative Patent Measures

Dependent variable: LCOE	(1) Triadic	(2) PCT	(3) Y > 1	(4) Y-PCT	(5) Cites
EXP	-0.035^{**}	-0.020	-0.013	-0.024	-0.028^{*}
	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)
KS^{PAT}	-0.082^{***}	-0.129^{***}	-0.094^{***}	-0.122^{***}	-0.087^{***}
	(0.018)	(0.018)	(0.014)	(0.018)	(0.017)
CI	0.212^{***}	0.202^{***}	0.196^{***}	0.202^{***}	0.192^{***}
	(0.044)	(0.040)	(0.041)	(0.041)	(0.044)
EOS	-0.120^{***}	-0.085^{***}	-0.094^{***}	-0.086^{***}	-0.102^{***}
	(0.028)	(0.023)	(0.024)	(0.024)	(0.026)
LA	0.521^{***}	0.427^{**}	0.470^{***}	0.386^{**}	0.602^{***}
	(0.184)	(0.171)	(0.174)	(0.176)	(0.181)
Constant	-4.167^{***}	-3.769^{***}	-4.109^{***}	-3.515^{***}	-4.443^{***}
	(0.860)	(0.795)	(0.809)	(0.818)	(0.849)
Country FE	Yes	Yes	Yes	Yes	Yes
LBD (in %)	2.40	1.36	0.93	1.68	1.90
LBS (in %)	5.51	8.58	6.28	8.08	5.83
Adjusted R^2	0.73	0.77	0.76	0.76	0.73
N	145	147	143	147	143

Notes: This table presents log-log scale regression results of alternative patent specifications. Column 1 uses triadic patent families, i.e. patents filed to the European, Japanese, and US patent office. Column 2 uses "international" patent applications filed under the Patent Cooperation Treaty (PCT). Column 3-5 measure patents with the Y-scheme classification Y02e 10/70 "Wind Energy", sourced from PATSTAT. We apply granted patents with a family size larger than 1 in column 3, citations to these patents in column 5, and PCT applications in column 4. The citation-based measure is truncation-adjusted. It thus allows us to weigh patents by quality (Popp et al., 2011). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

TABLE A.2: Robustness Checks – Generation, Lagged Experience, EOS

Dependent variable: LCOE	(1) Generation	(2) Generation	(3) EXP_{t-1}	(4) EXP_{t-1}	(5) EXP	(6) EXP
EXP	-0.046^{***}	-0.057^{***}	-0.035^{***}	-0.028^{*}	-0.038^{***}	-0.031^{*}
	(0.014)	(0.016)	(0.013)	(0.016)	(0.014)	(0.016)
KS^{PAT}	-0.090^{***}		-0.103^{***}		-0.100^{***}	
	(0.016)		(0.015)		(0.015)	
KS^{RDD}		-0.089^{**}		-0.131^{***}		-0.112^{***}
		(0.042)		(0.042)		(0.041)
CI	0.175^{***}	0.172^{***}	0.178^{***}	0.169^{***}	0.225^{***}	0.234^{***}
	(0.040)	(0.044)	(0.040)	(0.045)	(0.043)	(0.050)
EOS / EOS (Revenue)	-0.074^{***}	-0.125^{***}	-0.084^{***}	-0.157^{***}	-0.145^{***}	-0.252^{***}
	(0.024)	(0.024)	(0.024)	(0.023)	(0.035)	(0.034)
LA	0.491^{***}	0.627^{***}	0.471^{***}	0.621^{***}	0.479^{***}	0.664^{***}
	(0.168)	(0.184)	(0.171)	(0.190)	(0.168)	(0.187)
Constant	-3.835^{***}	-3.883^{***}	-3.825^{***}	-3.768^{***}	-3.584^{***}	-3.567^{***}
	(0.784)	(0.916)	(0.797)	(0.946)	(0.779)	(0.930)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
LBD (in %)	3.15	3.90	2.43	1.90	2.61	2.14
LBS (in %)	6.05	5.97	6.89	8.68	6.68	7.50
Adjusted R^2	0.78	0.73	0.77	0.71	0.78	0.72
N	147	147	147	147	147	147

Notes: This table presents log-log scale regression results of alternative variable specifications. We run each model specification twice, first for patents, then for RD&D as the knowledge stock. In columns 1 and 2, we measure experience with generation rather than capacity. Columns 3 and 4 assume a one-year lagged rather than immediate addition of new capacity to the experience stock. Columns 5 and 6 use average deflated revenues instead of total assets to approximate economies of scale. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

TABLE A.3: Sensitivity Analysis – Start and End Date

Dependent variable: LCOE	1999 – 2018 (1)	1999 – 2018 (2)	1998 – 2017 (3)	1998 – 2017 (4)	1999 – 2017 (5)	1999 – 2017 (6)
EXP	−0.037*	−0.028	−0.040**	−0.030	−0.038**	−0.031
	(0.015)	(0.017)	(0.013)	(0.016)	(0.014)	(0.016)
KS^{PAT}	−0.103***		−0.103***		−0.104***	
	(0.015)		(0.013)		(0.014)	
KS^{RDD}		−0.119**		−0.133**		−0.124**
		(0.042)		(0.040)		(0.041)
CI	0.228***	0.235***	0.150***	0.140**	0.182***	0.192***
	(0.043)	(0.049)	(0.036)	(0.042)	(0.039)	(0.046)
EOS	−0.119***	−0.207***	−0.062**	−0.136***	−0.085**	−0.172***
	(0.029)	(0.028)	(0.021)	(0.021)	(0.026)	(0.027)
LA	0.408*	0.589**	0.385*	0.556**	0.351*	0.546**
	(0.171)	(0.190)	(0.153)	(0.175)	(0.155)	(0.177)
Constant	−3.501***	−3.642***	−3.734***	−3.721***	−3.586***	−3.700***
	(0.798)	(0.943)	(0.707)	(0.852)	(0.711)	(0.857)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
LBD (in %)	2.55	1.91	2.77	2.05	2.63	2.10
LBS (in %)	6.86	7.89	6.86	8.78	6.92	8.23
Adjusted R^2	0.77	0.71	0.78	0.70	0.77	0.69
N	140	140	140	140	133	133

Notes: This table presents regression results when altering the sample period, as indicated in the respective column header. We run each model specification twice, first for patents, then for RD&D as the knowledge stock. All variables are logs. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

System Price Dynamics for Battery Storage — Appendix

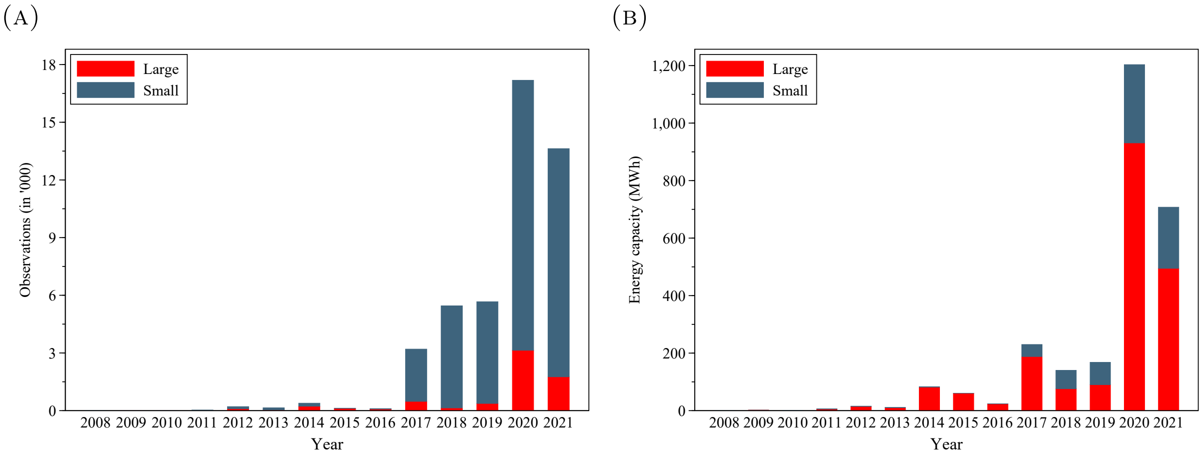


Figure A.1: Battery Systems and Installed Capacity by Application Year in California. (A), number of subsidized storage systems. (B), installed storage capacities.

Notes: We do not include systems marked as "cancelled" or "waitlist".

Table A.4: Descriptive Statistics - All Battery Projects

Variable	Mean	SD	Min.	P25	Median	P75	Max.
Price kWh	1121.47	482.35	253.33	893.60	1032.13	1176.90	5959.64
Price kW	2625.11	1080.18	497.51	1924.67	2594.14	2894.91	11919.29
BOS price kWh	918.42	448.75	6.39	690.90	854.49	1003.05	5662.51
Incentive kWh	419.42	313.78	34.72	230.12	279.15	433.38	2755.69
Size kWh	36.97	172.40	2.41	8.52	13.20	26.40	8400.00
Size kW	16.17	78.45	0.54	4.94	5.00	10.00	3000.00
Duration	2.38	0.47	1.00	1.91	2.64	2.64	7.92
EXP #	14871.33	8572.74	1.00	7439.00	14881.00	22348.00	29625.00
EXP Firm #	809.46	1049.75	1.00	69.00	345.00	1078.00	4178.00
EXP MWh	615.24	284.62	0.03	383.42	641.02	864.19	1095.03
HHI	0.18	0.12	0.05	0.11	0.15	0.21	1.00
Observations	28956						

Notes: This table reports summary statistics for all major regression variables and some additional variables for all SGIP-administered systems connected by the of December 2021. We include all projects with an interconnection date, so that the maximum of EXP exceeds the number of observations in our main sample. The Herfindahl-Hirschmann-index (HHI) is normalized between zero (perfect competition) and one (monopoly) by construction.

Table A.5: Descriptive Statistics - Large Segment

Variable	Mean	SD	Min.	P25	Median	P75	Max.
Price kWh	1288.94	602.84	382.16	952.73	1066.67	1404.99	5350.18
Price kW	3024.53	1164.04	723.93	2413.96	2755.69	3320.41	11396.12
BOS price kWh	1023.17	484.79	169.13	779.50	886.80	1147.86	4897.64
Incentive kWh	636.85	385.22	102.15	269.11	443.89	1039.25	2755.69
Size kWh	214.97	495.33	15.00	39.60	39.60	120.00	8400.00
Size kW	97.50	225.38	10.02	15.00	15.00	60.00	3000.00
Duration	2.44	0.49	1.00	2.00	2.64	2.64	7.67
EXP #	16333.38	10012.74	8.00	6338.00	19760.00	25022.00	29625.00
EXP Firm #	537.46	891.73	1.00	22.00	112.00	687.00	4176.00
EXP MWh	650.70	345.40	2.15	324.51	790.57	932.40	1095.03
HHI	0.19	0.14	0.05	0.11	0.14	0.24	1.00
Observations	3061						

Notes: This table reports summary statistics for all major regression variables and some additional variables for the subsample of larger systems, i.e. above 10 kW.

Table A.6: Descriptive Statistics - Small Segment

Variable	Mean	SD	Min.	P25	Median	P75	Max.
Price kWh	1101.70	462.09	253.33	893.42	1024.96	1157.35	5959.64
Price kW	2577.95	1059.99	497.51	1854.94	2561.11	2858.84	11919.29
BOS price kWh	906.06	442.67	6.39	687.99	848.25	991.22	5662.51
Incentive kWh	393.72	293.78	34.72	210.68	268.30	389.96	2755.69
Size kWh	15.93	7.39	2.41	8.39	13.20	26.40	79.20
Size kW	6.56	2.36	0.54	4.94	5.00	10.00	20.00
Duration	2.37	0.46	1.00	1.70	2.64	2.64	7.92
EXP #	14698.51	8369.56	1.00	7540.00	14500.00	21876.00	29625.00
EXP Firm #	841.61	1062.31	1.00	83.00	381.00	1148.00	4178.00
EXP MWh	611.05	276.27	0.03	384.97	628.18	851.55	1095.03
HHI	0.18	0.12	0.05	0.11	0.15	0.21	1.00
Observations	25895						

Notes: This table reports summary statistics for all major regression variables and some additional variables for the subsample of residential, i.e. small, systems with a power rating of 10 kW or less.

Table A.7: BOS Experience Curves

BOS prices in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	−0.115***	−0.087***	0.104***	0.084***
	(0.010)	(0.018)	(0.018)	(0.010)
HHI		0.084		0.660***
		(0.103)		(0.133)
Size kWh		−0.049**		−0.216***
		(0.023)		(0.016)
Duration		−0.176*		−0.518***
		(0.092)		(0.038)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate (%)	7.66	5.88	−7.48	−5.97
Adjusted R^2	0.16	0.52	0.06	0.68
N	2,956	2,956	25,331	25,331

Notes: This table shows regression results for balance-of-system (BOS) prices. We calculate BOS price as total system price from the SGIP minus adjusted battery pack price as obtained from Bloomberg. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.8: Experience Curves – Sample and Period Robustness

Price in 2021 USD/kWh	After 2013		Paid	
	(1)	(2)	(3)	(4)
EXP #	−0.011		−0.014	
	(0.010)		(0.012)	
EXP kWh		−0.039***		−0.047***
		(0.014)		(0.016)
Experience rate %	0.74	2.64	0.99	3.20
Adjusted R^2	0.00	0.01	0.00	0.01
N	28,258	28,258	25,701	25,701

Notes: This table shows robustness tests for one factor experience curves using all connected systems. In columns (1) and (2), we exclude systems connected in 2013 or before. In columns (3) and (4), we only include systems which the SGIP administrator marks as “paid”. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Table A.9: Experience Curves – Robustness to Excluding Installers

Price in 2021 USD/kWh	No SCTE		≥20 observations	
	(1)	(2)	(3)	(4)
EXP #	-0.034^{**}		-0.013	
	(0.014)		(0.011)	
EXP kWh		-0.055^{***}		-0.042^{***}
		(0.019)		(0.015)
Experience rate %	2.35	3.75	0.89	2.87
Adjusted R^2	0.01	0.01	0.00	0.01
N	25,564	25,564	27,102	27,102

Notes: This table shows robustness tests for one factor experience curves using all connected systems. In columns (1) and (2), we exclude systems installed by SolarCity/Tesla (SCTE) as the corresponding system prices might be appraised values. In columns (3) and (4), we only include systems by installers with at least 20 installations over the sample period. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Table A.10: Segment Experience Curves – Cumulative Capacity

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP kWh	-0.224^{***}	-0.162^{***}	0.010	-0.006
	(0.010)	(0.026)	(0.021)	(0.012)
HHI		0.074		0.504^{***}
		(0.102)		(0.123)
Size kWh		-0.036^{*}		-0.165^{***}
		(0.019)		(0.013)
Duration		-0.149^{**}		-0.410^{***}
		(0.071)		(0.032)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	14.36	10.64	-0.72	0.44
Adjusted R^2	0.39	0.65	0.00	0.67
N	2,957	2,957	25,331	25,331

Notes: This table shows regression results by segment when changing the definition of the experience variable from projects to cumulative capacity in kWh. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.11: Segment Experience Curves – Starting with 2014 Installations

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.173^{***}	-0.126^{***}	0.039^{***}	0.022^{***}
	(0.008)	(0.018)	(0.011)	(0.007)
HHI		0.161^{*}		0.580^{***}
		(0.091)		(0.107)
Size kWh		-0.039^{**}		-0.173^{***}
		(0.019)		(0.013)
Duration		-0.121^{*}		-0.426^{***}
		(0.072)		(0.031)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	11.28	8.36	−2.75	−1.52
Adjusted R^2	0.39	0.65	0.01	0.66
N	2,949	2,949	25,298	25,298

Notes: This table shows regression results by segment when excluding systems installed before 2014. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.12: Segment Experience Curves – Systems Classified as Paid

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.185^{***}	-0.083^{***}	0.026^{*}	0.026^{***}
	(0.007)	(0.026)	(0.015)	(0.007)
HHI		0.326^{**}		0.623^{***}
		(0.125)		(0.123)
Size kWh		-0.038^{*}		-0.169^{***}
		(0.021)		(0.012)
Duration		-1.184^{***}		-0.441^{***}
		(0.204)		(0.037)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	12.06	5.62	−1.80	−1.84
Adjusted R^2	0.54	0.81	0.01	0.67
N	2,057	2,057	23,634	23,634

Notes: This table shows regression results by segment when including only those systems that the SGIP administrator marks as paid. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.13: Segment Experience Curves – Excluding SolarCity/Tesla

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.186^{***}	-0.110^{***}	0.028	0.033^{***}
	(0.005)	(0.028)	(0.022)	(0.003)
HHI		0.070		0.166^{***}
		(0.108)		(0.050)
Size kWh		-0.101^{***}		-0.168^{***}
		(0.015)		(0.017)
Duration		-0.444^{***}		-0.322^{***}
		(0.073)		(0.027)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	12.10	7.34	−1.99	−2.34
Adjusted R^2	0.45	0.70	0.01	0.66
N	2,684	2,684	22,869	22,869

Notes: This table shows regression results for the large and small segment when excluding systems installed by SolarCity/Tesla. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.14: Segment Experience Curves – Firms with At Least 20 Observations

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.169^{***}	-0.132^{***}	0.032^{**}	0.023^{***}
	(0.008)	(0.017)	(0.014)	(0.008)
HHI		0.162^{*}		0.586^{***}
		(0.083)		(0.107)
Size kWh		−0.029		-0.171^{***}
		(0.022)		(0.013)
Duration		−0.119		-0.448^{***}
		(0.075)		(0.034)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	11.08	8.76	−2.24	−1.58
Adjusted R^2	0.42	0.64	0.01	0.64
N	2,683	2,683	24,408	24,408

Notes: This table shows regression results for the large and small segment when excluding very small installer firms, i.e. those with less than 20 installations over the sample period. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

TABLE A.15: Segment Experience Curves – New Segment Definition

Price in 2021 USD/kWh	Large (> 50 kWh)		Small (≤ 50 kWh)	
	(1)	(2)	(3)	(4)
EXP #	-0.163^{***}	-0.156^{***}	0.006	0.020^{***}
	(0.008)	(0.019)	(0.012)	(0.007)
HHI		-0.025		0.557^{***}
		(0.106)		(0.103)
Size kWh		-0.061^{***}		-0.146^{***}
		(0.022)		(0.012)
Duration		0.050		-0.472^{***}
		(0.063)		(0.031)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	10.71	10.27	-0.43	-1.42
Adjusted R^2	0.34	0.63	0.00	0.67
N	1,344	1,344	26,944	26,944

Notes: This table shows regression results by segment when deviating from the 10 kW size threshold applied by the California Public Utilities Commission for budget purposes. In this robustness check, smaller systems have a storage capacity of 50 kWh or less. Large systems have a capacity of more than 50 kWh. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

TABLE A.16: BOS Experience Curves – Cumulative Capacity

BOS prices in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP kWh	-0.151^{***}	-0.098^{***}	0.109^{***}	0.075^{***}
	(0.012)	(0.030)	(0.026)	(0.017)
HHI		0.072		0.609^{***}
		(0.117)		(0.158)
Size kWh		-0.047^{*}		-0.207^{***}
		(0.024)		(0.016)
Duration		-0.204^{**}		-0.505^{***}
		(0.090)		(0.040)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate (%)	9.96	6.58	-7.88	-5.37
Adjusted R^2	0.16	0.52	0.03	0.67
N	2,956	2,956	25,331	25,331

Notes: This table shows regression results for balance-of-system (BOS) prices when using cumulative capacity as a proxy for experience. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.17: BOS Experience Curves – Excluding SolarCity/Tesla

BOS prices in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.133^{***}	-0.058^{*}	0.089^{***}	0.093^{***}
	(0.006)	(0.029)	(0.026)	(0.006)
HHI		-0.007		0.130^{**}
		(0.104)		(0.059)
Size kWh		-0.133^{***}		-0.206^{***}
		(0.016)		(0.021)
Duration		-0.522^{***}		-0.388^{***}
		(0.085)		(0.033)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate (%)	8.83	3.93	−6.35	−6.67
Adjusted R^2	0.22	0.59	0.04	0.67
N	2,683	2,683	22,869	22,869

Notes: This table shows regression results BOS prices when excluding SolarCity/Tesla systems. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.18: BOS Experience Curves – Unadjusted Battery Pack Price

BOS prices in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.125^{***}	-0.094^{***}	0.090^{***}	0.072^{***}
	(0.009)	(0.018)	(0.017)	(0.010)
HHI		0.097		0.651^{***}
		(0.100)		(0.127)
Size kWh		-0.047^{**}		-0.208^{***}
		(0.023)		(0.015)
Duration		-0.166^{*}		-0.501^{***}
		(0.089)		(0.037)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate (%)	8.27	6.33	−6.47	−5.11
Adjusted R^2	0.20	0.54	0.05	0.68
N	2,956	2,956	25,331	25,331

Notes: This table shows regression results for BOS prices, using average battery pack prices reported by Bloomberg to calculate BOS. In other words, we do not adjust battery pack prices according to their application in stationary storage. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.19: Spillover – Cumulative Capacity

Price in 2021 USD/kWh	Price		BOS	
	(Large) (1)	(Small) (2)	(Large) (3)	(Small) (4)
SPILL kWh	-0.259^{***}	-0.152^{***}	-0.207^{***}	-0.109^{***}
	(0.029)	(0.021)	(0.033)	(0.029)
EXP Firm kWh	0.066^{***}	0.073^{***}	0.067^{***}	0.083^{***}
	(0.012)	(0.007)	(0.016)	(0.009)
HHI	0.009	0.342^{***}	0.009	0.409^{***}
	(0.099)	(0.097)	(0.108)	(0.124)
Size kWh	-0.045^{**}	-0.181^{***}	-0.054^{**}	-0.217^{***}
	(0.019)	(0.013)	(0.024)	(0.015)
Duration	-0.110	-0.404^{***}	-0.155^{*}	-0.480^{***}
	(0.077)	(0.032)	(0.092)	(0.038)
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry experience rate (%)	16.45	10.03	13.39	7.26
Firm experience rate (%)	−4.69	−5.16	−4.75	−5.96
Adjusted R^2	0.66	0.69	0.54	0.69
N	2,957	25,331	2,957	25,331

Notes: This table shows robustness tests for the spillover analysis. All variables except HHI are on log scale. The variable SPILL captures learning from industry-wide experience, i.e. spillover learning. The variable EXP Firm captures learning from firm-specific experience. For each observation, we compute SPILL as the industry-wide cumulative capacity excluding the cumulative capacity of the firm that installs the system. For each observation, we compute EXP Firm as the cumulative capacity of the firm that installs the system. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table A.20: Spillover – Excluding SolarCity/Tesla

Price in 2021 USD/kWh	Price		BOS	
	(Large) (1)	(Small) (2)	(Large) (3)	(Small) (4)
SPILL #	-0.166^{***}	-0.018^{**}	-0.131^{***}	0.029^{**}
	(0.033)	(0.007)	(0.031)	(0.012)
EXP Firm #	0.061^{***}	0.033^{***}	0.070^{***}	0.035^{***}
	(0.012)	(0.005)	(0.013)	(0.007)
HHI	0.096	0.148^{***}	0.036	0.131^{**}
	(0.111)	(0.044)	(0.108)	(0.050)
Size kWh	-0.100^{***}	-0.174^{***}	-0.127^{***}	-0.206^{***}
	(0.016)	(0.016)	(0.016)	(0.019)
Duration	-0.460^{***}	-0.318^{***}	-0.528^{***}	-0.372^{***}
	(0.073)	(0.027)	(0.084)	(0.032)
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry experience rate (%)	10.89	1.21	8.68	−2.06
Firm experience rate (%)	−4.34	−2.32	−4.95	−2.44
Adjusted R^2	0.71	0.67	0.61	0.67
N	2,684	22,869	2,683	22,869

Notes: This table shows robustness tests for the spillover analysis. Specifically, we exclude observations from SolarCity/Tesla as they might represent appraised values. All variables except HHI are on log scale, SPILL and EXP Firm are defined as in Table 3. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Better Safe than Sorry? Toxic Waste Management after Unionization — Appendix

Table A.21: List of Variables

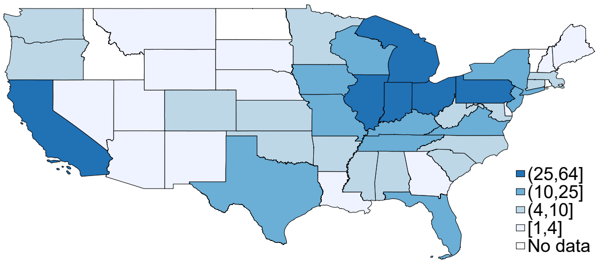
Variable Name	Description	Source
Adjusted vote share	Number of valid votes for joining the union divided by total votes. For even total votes, $^{0.5}/_{\text{number of votes cast}}$ is subtracted from the vote share (DiNardo and Lee, 2004).	NLRB
Catastrophic releases	Dummy variable equal to 1 if a facility reported releases not associated with routine production processes of a specific chemical and zero otherwise.	TRI file 2a
Innovative prevention	Dummy variable equal to 1 if a facility, for a given chemical, reports prevention activity related to innovative product and process modifications (W-codes W50, W51, W59, W80, W82, W83, W84, W89).	TRI file 2a
Paydex score	Facility-level minimum business credit score based on trade credit performance.	NETS
Production ratio	Output changes in the manufactured product or supporting operation related to the use of chemical i at facility j from last $t-1$ to current year t ($PR_{i,j,t}/PR_{i,j,t-1}$).	TRI file 2a
Waste treatment ratio	Changes in waste that is recycled, used for energy recovery, or otherwise treated for chemical i at facility j (total, on-site, and off-site) from last $t-1$ to current year t ($WC_{i,j,t}/WC_{i,j,t-1}$).	TRI file 1a
Waste release ratio	Changes in waste that is released to air, land, and water for chemical i at facility j (total, on-site, and off-site) from last $t-1$ to current year t ($WR_{i,j,t}/WR_{i,j,t-1}$).	TRI file 1a
Unionization	Dummy variable equal to 1 if the adjusted vote share is greater or equal to 50.	NLRB
Voters	Number of eligible voters at facility union elections.	NLRB

Table A.22: Descriptive Statistics

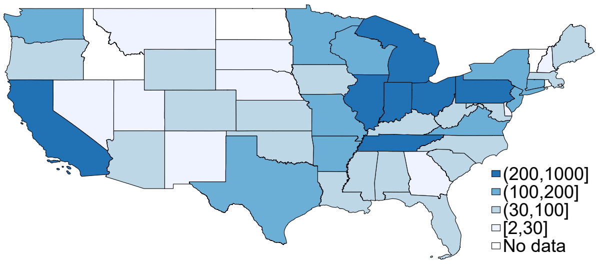
	Mean	SD	Min	p25	Median	p75	Max
Vote share	44.44	20.34	7.89	30.32	40.71	54.87	100.00
Voters	265.51	481.85	50	80	135.50	290	7000
Total waste release ratio	0.93	0.53	0.00	0.65	0.99	1.11	3.00
On-site release ratio	0.93	0.49	0.00	0.70	1.00	1.07	3.00
Off-site release ratio	0.91	0.66	0.00	0.33	0.96	1.21	3.00
Total waste treatment ratio	0.97	0.51	0.00	0.72	0.99	1.19	3.00
On-site treatment ratio	0.97	0.48	0.00	0.76	1.00	1.18	2.97
Off-site treatment ratio	0.94	0.58	0.00	0.59	0.93	1.19	3.00
Total waste ratio	0.99	0.47	0.00	0.76	0.99	1.17	3.00
Production ratio	1.00	0.37	0.00	0.88	1.00	1.12	3.00
Paydex score	67.95	8.43	21.00	64.00	70.00	74.00	83.00
Innovative prevention	0.02	0.12	0.00	0.00	0.00	0.00	1.00
Catastrophic releases	0.02	0.15	0.00	0.00	0.00	0.00	1.00

Notes: This table presents summary statistics for our main variables. All variables are defined in Appendix Table A.21.

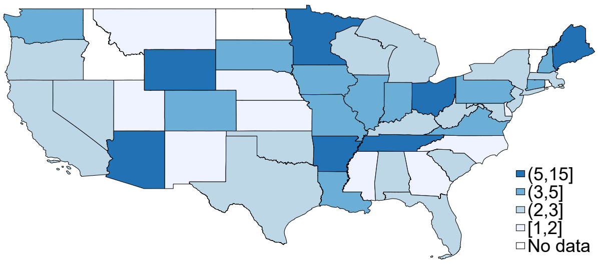
(A) Elections



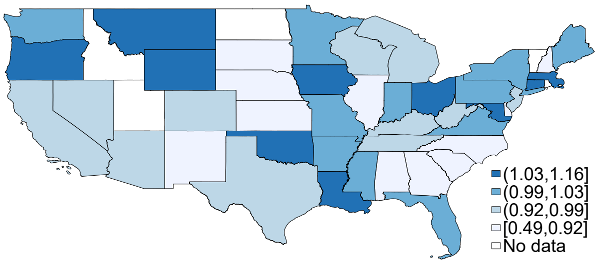
(B) Observations



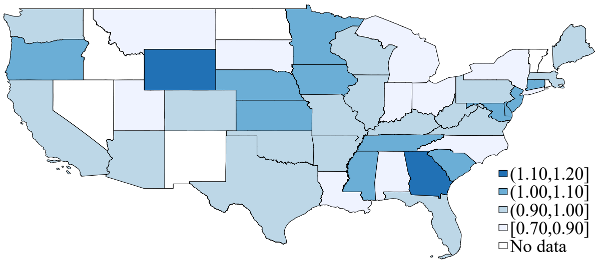
(C) Average chemicals reported by year



(D) Changes in production activity



(E) Changes in waste releases



(F) Changes in waste treatment

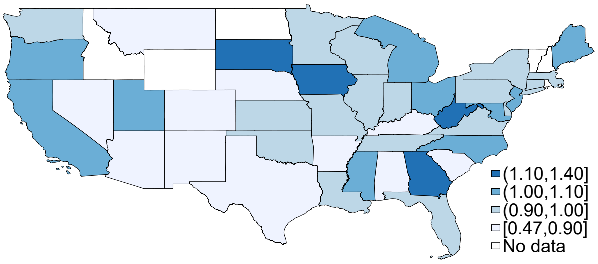


FIGURE A.2: Cross-State Characterization of Sample.

Notes: This figure presents the sample distribution of our observations and main variables of interest over the United States.

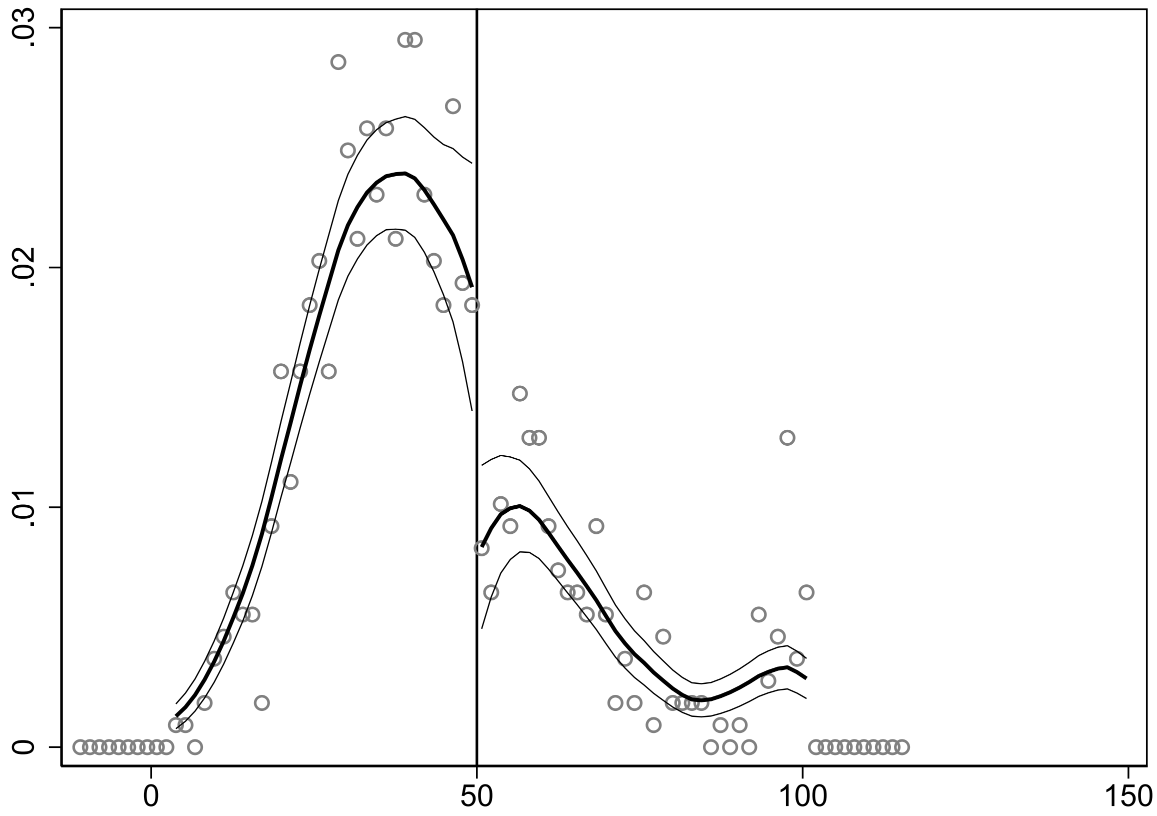


FIGURE A.3: McCrary (2008) Discontinuity Test.

Notes: This figure plots the McCrary (2008) discontinuity test for the density of the adjusted vote share variable. Dots represent bins of vote share data. For estimation of the density function and corresponding confidence intervals, the raw data rather than the bins are used. .

TABLE A.23: Estimation Results for Contextual Robustness Tests

	Changes in waste releases		Changes in waste treatment	
	Total	On-site	Total	On-site
	(1)	(2)	(3)	(4)
Panel A: Ratio threshold at 2				
Unionization	0.164*	0.216***	−0.219	−0.497**
	(0.085)	(0.078)	(0.149)	(0.223)
Panel B: Ratio threshold at 4				
Unionization	0.187*	0.226***	−0.300*	−0.625**
	(0.100)	(0.085)	(0.175)	(0.282)
Panel C: Ln(ratios)				
Unionization	0.192	0.259**	−0.172	−1.094**
	(0.275)	(0.132)	(0.203)	(0.525)
Panel D: Cumulative ratios				
Unionization	0.372	0.500**	−0.286	−1.189*
	(0.268)	(0.251)	(0.616)	(0.704)
Panel E: Year + chemical FE				
Unionization	0.052	0.139**	−0.477***	−0.988***
	(0.069)	(0.066)	(0.157)	(0.159)
Panel F: At least 25 voters				
Unionization	0.080	0.112**	−0.107	−0.068
	(0.067)	(0.056)	(0.150)	(0.250)
Panel G: At least 75 voters				
Unionization	0.047	0.116*	−0.407***	−0.999***
	(0.093)	(0.069)	(0.150)	(0.185)
Panel H: Always mandated				
Unionization	0.087	0.128*	−0.184	−0.598**
	(0.084)	(0.066)	(0.147)	(0.249)

Notes: This table presents contextual robustness checks to our main analysis. In panels A and B, we change the threshold value of our waste treatment and release ratios to two and four, respectively. In panel C, we estimate our effect with the natural logarithm of these ratios. Panel D shows results for cumulative ratios, estimating compound unionization effects of three years following the election. In panel E, we include year and chemical fixed effects (FE) as covariates. In panels F and G, we restrict our sample to elections with at least 25 and 75 eligible voters, respectively. In panel H, we restrict our sample to chemicals that were mandatory to report in every year of our sample period. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Table A.24: Estimation Results for Econometric Robustness Tests

	Changes in waste releases		Changes in waste treatment	
	Total (1)	On-site (2)	Total (3)	On-site (4)
Panel A: Second-order polynomial				
Unionization	0.057	0.147^{*}	-0.381^{**}	-0.883^{***}
	(0.112)	(0.089)	(0.185)	(0.322)
Panel B: Epanechnikov kernel				
Unionization	0.097	0.149^{**}	-0.223	-0.596^{**}
	(0.084)	(0.072)	(0.185)	(0.253)
Panel C: Donut RDD				
Unionization	0.143	0.229^{***}	-0.201	-0.588^{**}
	(0.106)	(0.087)	(0.175)	(0.251)

Notes: This table presents econometric, local RDD-specific robustness checks of our main results. Specifically, we estimate the discontinuity around the cutoff using a local second-order polynomial in panel A. In panel B, we use an epanechnikov kernel function that, compared to the default triangular kernel, gives relatively more weight to observations further from the cutoff. Finally, we exclude observations directly at the cutoff, i.e. those with an (adjusted) vote share of 50 percent, to estimate a "Donut" RDD in panel C (Barreca et al., 2011). Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Table A.25: Union Power – Robustness

	Changes in waste releases		Changes in waste treatment	
	Total (1)	On-site (2)	Total (3)	On-site (4)
Panel A: Eventually RTW				
Unionization	0.042	0.091	0.037	-0.421
	(0.107)	(0.115)	(0.180)	(0.303)
Panel B: Non-RTW				
Unionization	0.206	0.358^{***}	-0.380^{***}	-0.978^{***}
	(0.150)	(0.115)	(0.108)	(0.166)

Notes: This table presents the unionization effect on changes in waste releases and treatment up to three years post election. We split our sample in observations from US states that eventually become RTW states in panel A and those that do not become RTW states in panel B. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel function. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Table A.26: Chemical Toxicity – Human Toxicity Potential

	Changes in waste releases		Changes in waste treatment	
	Total	On-site	Total	On-site
	(1)	(2)	(3)	(4)
Panel A: High Air-HTP				
Unionization	−0.045	0.001	−0.323*	−0.700**
	(0.104)	(0.082)	(0.188)	(0.333)
Panel B: Low Air-HTP				
Unionization	0.372***	0.350***	−0.178	−0.724**
	(0.112)	(0.124)	(0.286)	(0.352)
Panel C: High Water-HTP				
Unionization	0.092	0.151	−0.124	−0.631*
	(0.114)	(0.093)	(0.196)	(0.351)
Panel D: Low Water-HTP				
Unionization	0.201**	0.182*	−0.695***	−1.134***
	(0.102)	(0.107)	(0.184)	(0.187)

Notes: This table presents the unionization effect on changes in waste releases and treatment up to three years post election. We split our sample in chemicals that are above the human toxicity potential median of all chemicals in our sample and those below. We distinguish between air- and water human toxicity potential. We report bias-corrected local regression discontinuity estimates using the MSE-optimal bandwidth and triangular kernel function. Robust standard errors clustered at the facility are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

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