One- versus two-factor experience curves

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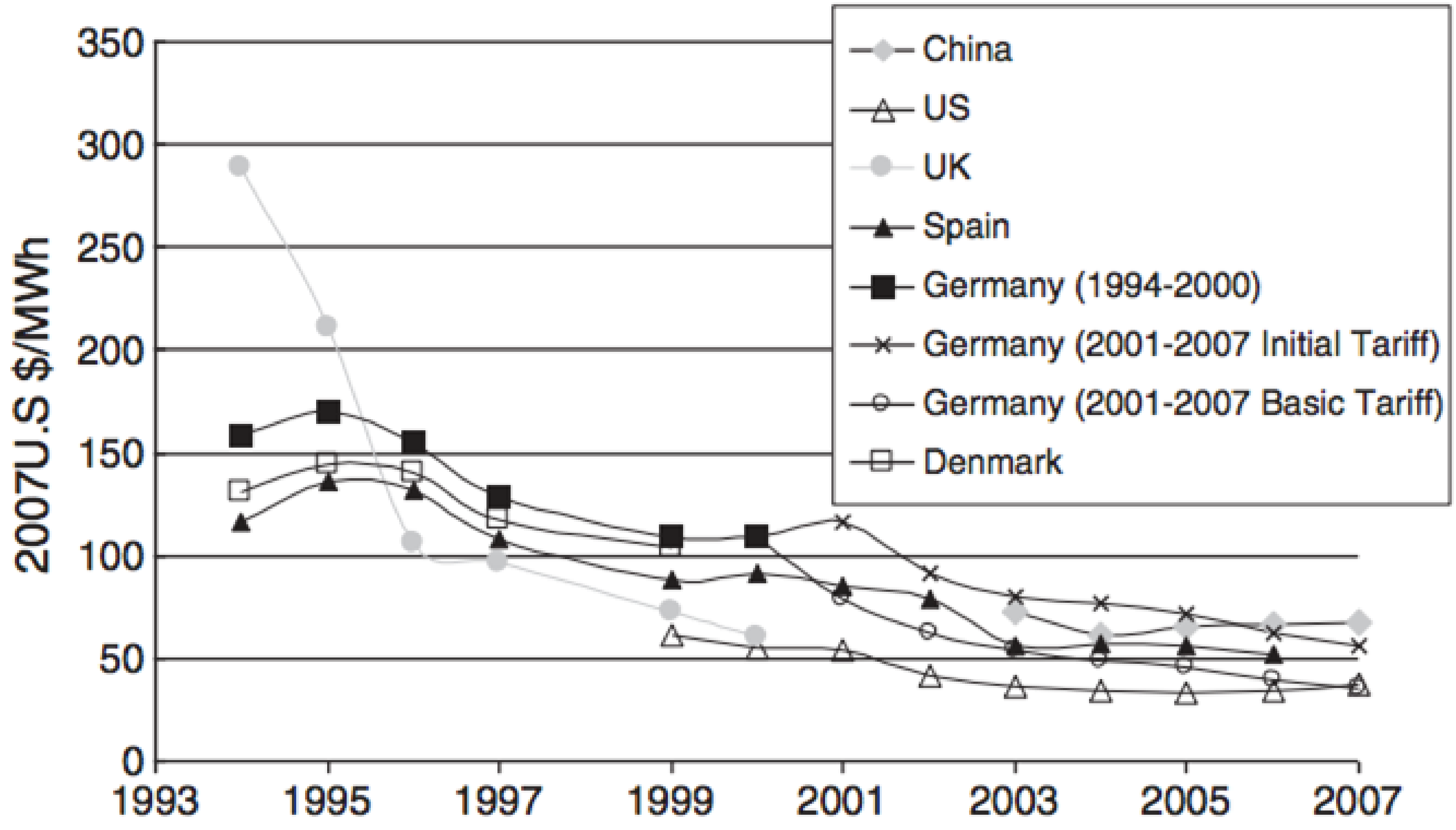
Experience curves

- Learning rates typically relate cost reduction of new technology to key factors
  i.e. cumulative installed capacity, units of output produced
- Typical experience curves use one-factor
- However, new multi-factor models are emerging

Toward multi-factor experience curves

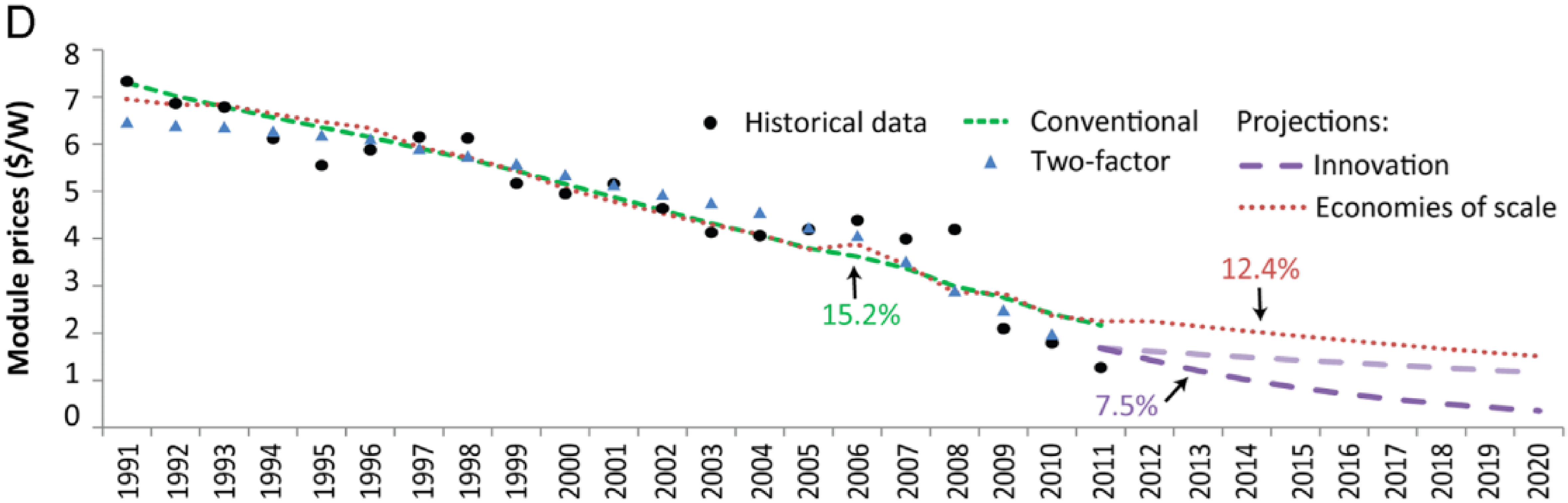
- One-factor experience curves usually explain decreased costs with increases in production volume (e.g. economies of scale)
- May underestimate surges of innovation or breakthrough discoveries (especially for high-tech products)
- Simultaneously, could overestimate the cost of deployment measures
- Challenge: data (e.g. for innovation) is lacking and proxy information often necessary

Two-factor learning for wind



Qiu, Y., & Anadon, L. D. (2012). The price of wind power in China during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization. Energy Economics 34(3), 772-785

Two-factor learning for solar



Zheng, C., & Kammen, D. M. (2014). An innovation-focused roadmap for a sustainable global photovoltaic industry. Energy Policy, 67, 159-169.

One- and two-factor learning curves

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Range of reported one-factor and two-factor learning rates for electric power generation technologies.

Technology and energy source	No. of studies with one factor[a]	No. of studies with two factors	One-factor models[b]		Two-factor models[c]				Years covered across all studies
			Range of learning rates	Mean LR	Range of rates for LBD	Mean LBD rate	Range of rates for LBR	Mean LBR rate	
Coal									
PC	4	0	5.6–12%	8.3%	–	–	–	–	1902–2006
PC+CCS[d]	*2*	*0*	*1.1–9.9%*[d]		–	–	–	–	*Projections*
IGCC[d]	*2*	*0*	*2.5–16%*[d]		–	–	–	–	*Projections*
IGCC+CCS[d]	*2*	*0*	*2.5–20%*[d]		–	–	–	–	*Projections*
Natural gas									
NGCC	5	1	−11 to 34%	14%	0.7–2.2%	1.4%	2.4–17.7%	10%	1980–1998
Gas turbine	11	0	10–22%	15%	–	–	–	–	1958–1990
NGCC+CCS[d]	*1*	*0*	*2–7%*[d]		–	–	–	–	*Projections*
Nuclear	4	0	Negative to 6%	–	–	–	–	–	1972–1996
Wind									
Onshore	12	6	−11 to 32%	12%	3.1–13.1%	9.6%	10–26.8%	16.5%	1979–2010
Offshore	2	1	5–19%	12%	1%	1%	4.9%	4.9%	1985–2001
Solar PV	13	3	10–47%	23%	14–32%	18%	10–14.3%	12%	1959–2011
Biomass									
Power generation[e]	2	0	0–24%	11%	–	–	–	–	1976–2005
Biomass production	3	0	20–45%	32%					1971–2006
Geothermal[f]	0	0	–	–	–	–	–	–	
Hydroelectric	1	1	1.4%	1.4%	0.5–11.4%	6%	2.6–20.6%	11.6%	1980–2001

[a] Some studies report multiple values based on different datasets, regions, or assumptions.
[b] LR=learning rate. Values in italics reflect model estimates, not empirical data.
[c] LBD=learning by doing; LBR=learning by researching.
[d] No historical data for this technology. Values are projected learning rates based on different assumptions.
[e] Includes combined heat and power (CHP) systems and biodigesters.
[f] Several studies reviewed presented data on cost reductions but did not report learning rates.

LRs for power generation

	one-f	two-f
Coal:	8.3%	-
Natural gas:	14%	10%
Wind onshore:	12%	16.5%
Solar PV:	23%	12%
Biomass:	11%	-
Hydroelectric:	1.4%	11.6%

Rubin, E. S., Azevedo, I. M., Jaramillo, P., & Yeh, S. (2015). A review of learning rates for electricity supply technologies. *Energy Policy*, *86*, 198-218.

Two-factor curves: case of storage

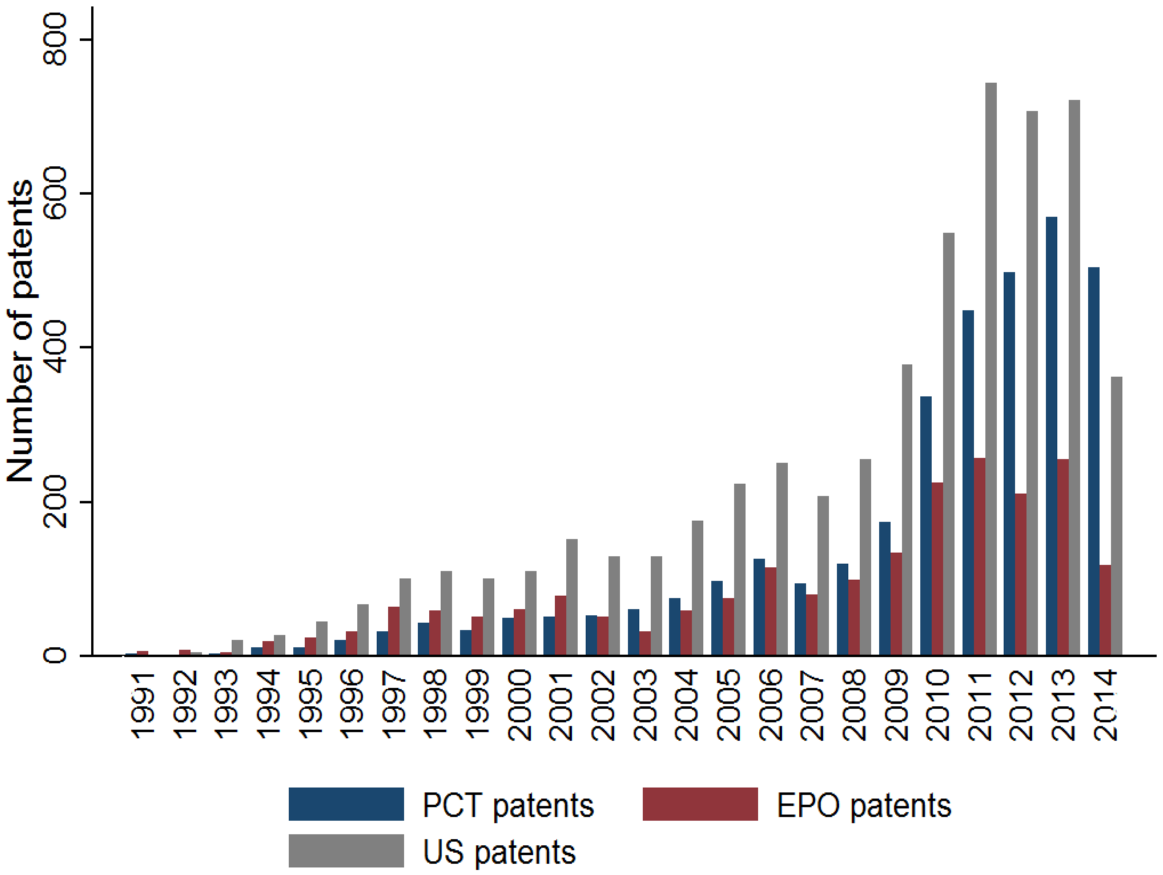
- Use one-factor and two-factor models to understand value of economies of scale and innovation (time frame: 1991 - 2015)
- Develop multi-factor model to go beyond "economies-of-scale" only
- Build off work for wind turbines and solar PV (Qiu & Anadon, 2012; Zheng & Kammen, 2014)
- Patents as a representation of innovation for technological cost reduction (Griliches, 1987)

Global patent activity for LiB

Queries were conducted using the Patentscope database, part of the World Intellectual Property Organization (WIPO)

Searched for terms including "lithium and ion and (battery or batteries or accumulator or accumulators or cell or cells)"

We include patents in the manufacturing process and were inclusive of any patent that contained the search terms we determined that we found in Patentscope.



Kittner, N., Lill, F., Kammen, D.M. (2017). "Energy storage deployment and innovation for the clean energy transition." *Nature Energy* 2 17125.

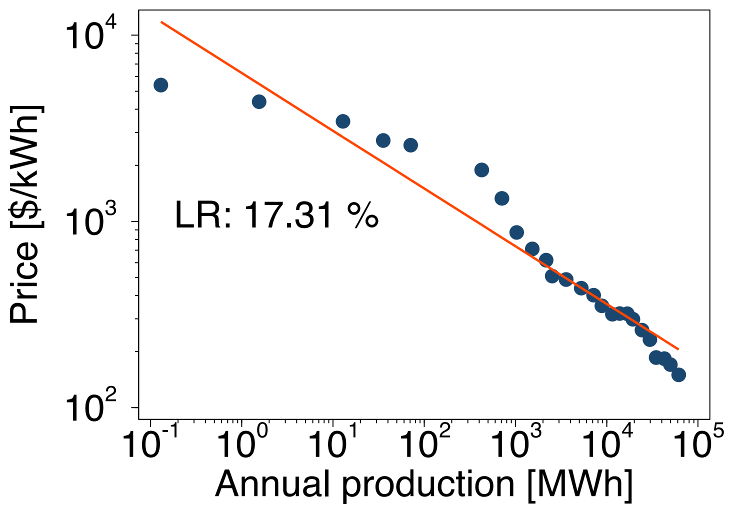
One-factor experience curve (LiB)

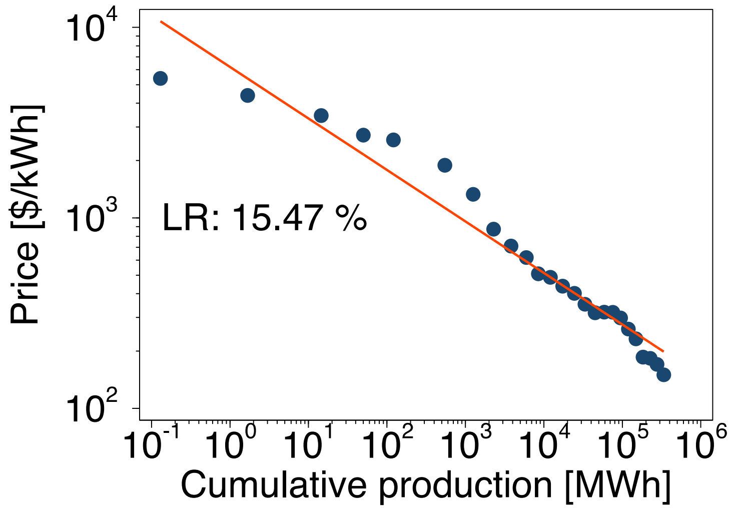
(1) $P_t = \delta_0 + \delta_1 Q_t + \epsilon_t$

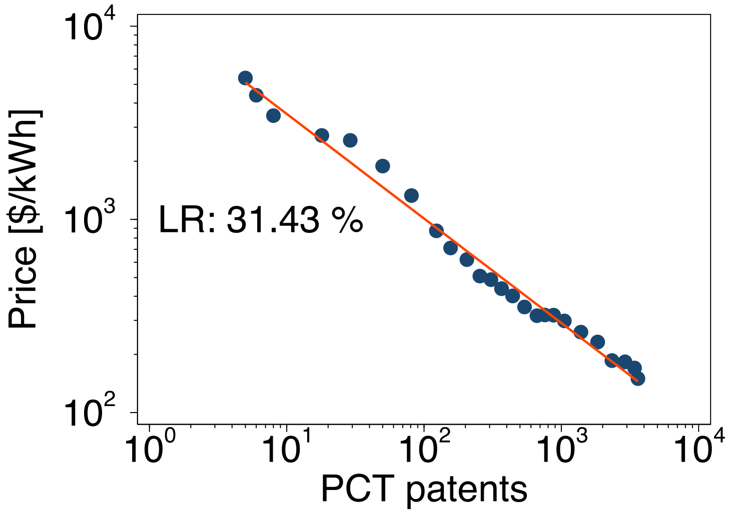
(2) $P_t = \zeta_0 + \zeta_1 CQ_t + \epsilon_t$

(3) $P_t = \vartheta_0 + \vartheta_1 I_t + \epsilon_t$

P_t = log price
Q_t = log production volumes
CQ_t = log cumulative production volumes
I_t = innovation activity (cumulative patents)







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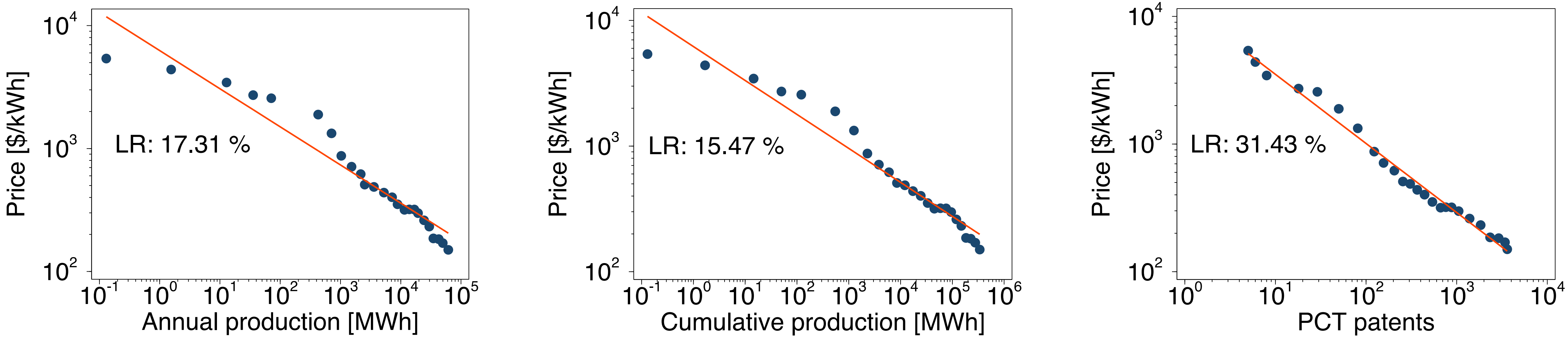
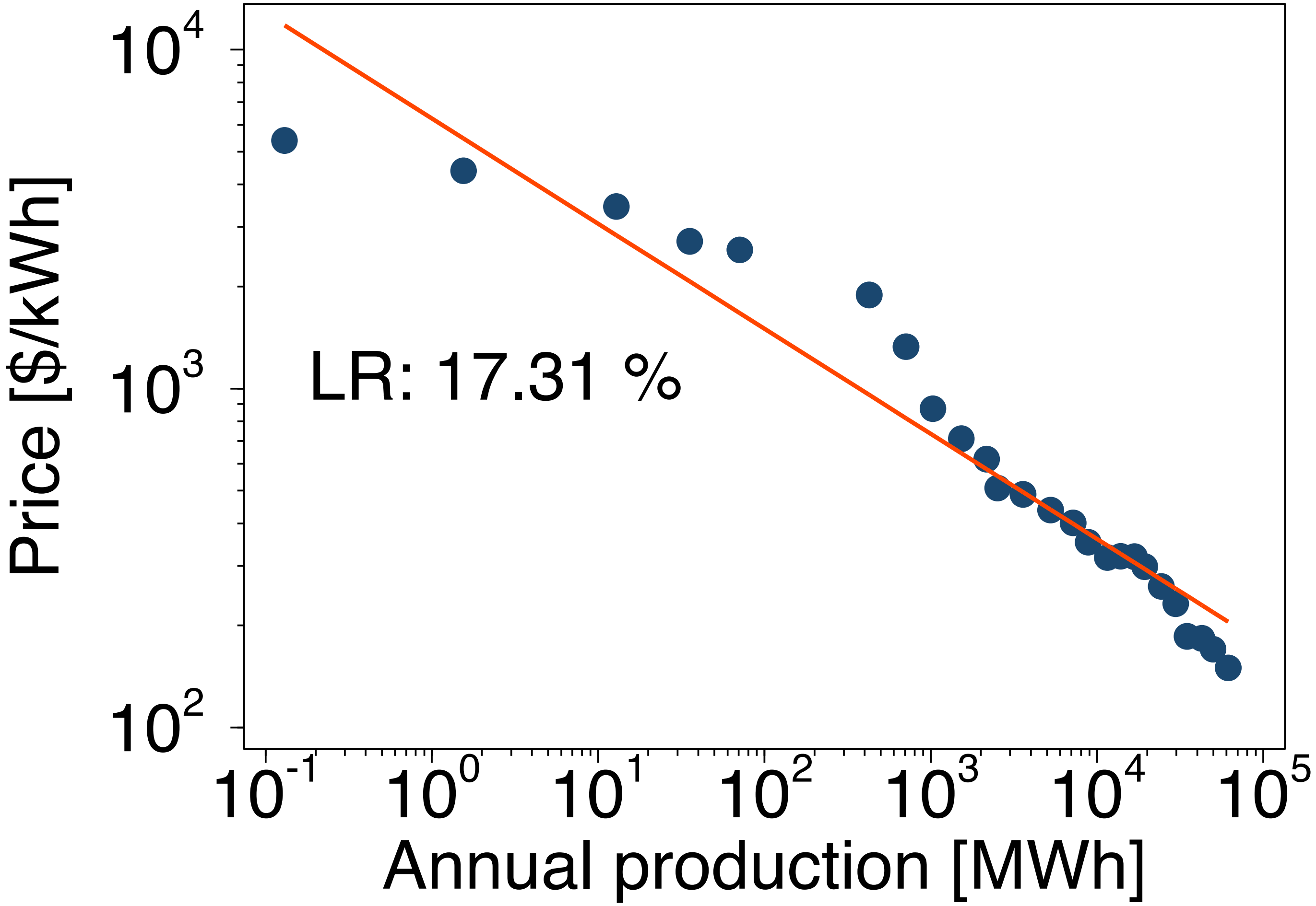
One-factor experience curve (LiB)

- Lithium-ion storage is developing at faster "learning rates" than solar PV or wind
- Further investment is needed to reach $100/kWh target by DOE



One-factor for LiB: annual production



Annual production

- LR: 17.31%
- Overestimation of the last years
- Adj. R^2: 0.9228
- BIC: -26.17094

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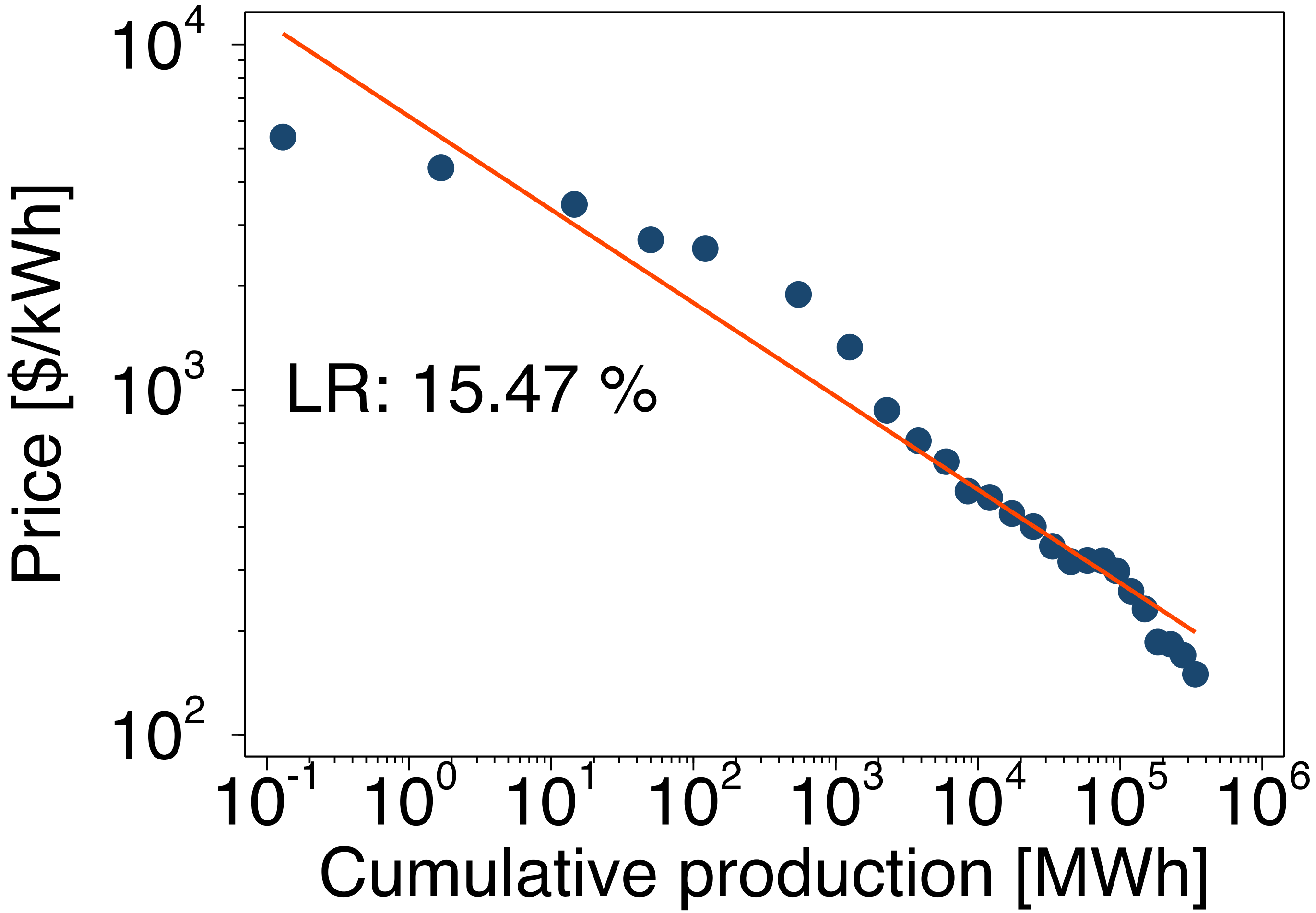
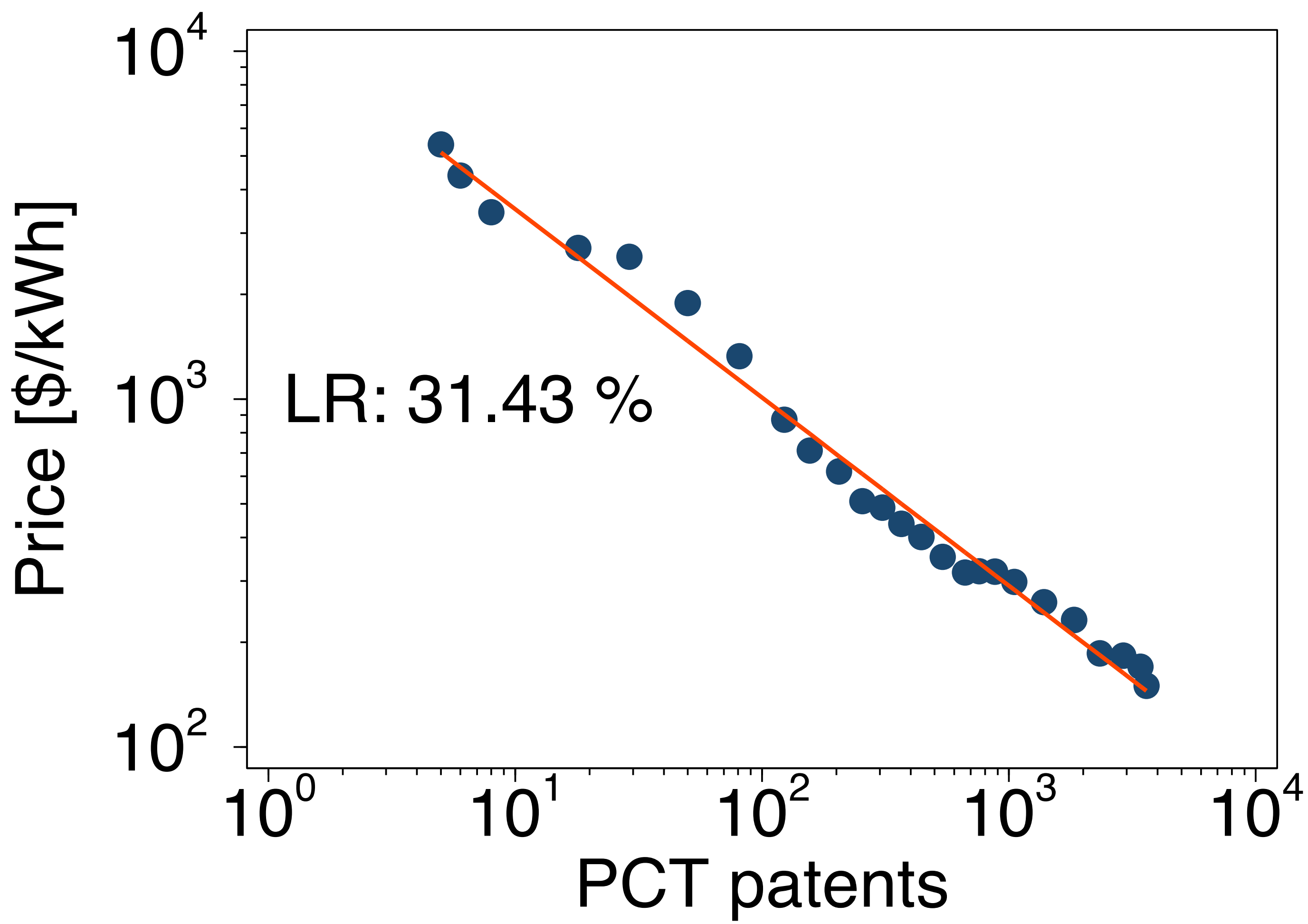
One-factor for LiB: cum. production



Cummulative production

- LR: 15.47%
- Overestimation of the last years
- Adj. R^2: 0.9471
- BIC: -35.62775

One-factor for LiB: PCT patents



Innovation / PCT patents

- LR: 31.43%
- Good fitting of the recent years
- Adj. R^2: 0.9861
- BIC: -69.0026

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From one-factor to two-factors

Developing the two-factor learning curve model follows the subsequent rationale:

(1) $I_i = \alpha_0 + \alpha_1 Q_i + \eta_i$

(1') $\eta_i = I_i - \alpha_0 - \alpha_1 Q_i$

After introducing the residual variable to remove the correlation, the reformed Eq. 1' is inserted in Eq. 2. Further transformation gives the new coefficients γ_0, γ_2 and γ_3. Information on the correlation and variance inflation factor after introducing the residual variable is displayed in A3 - 4.

(2) $P_i = \beta_0 + \beta_1 Q_i + \beta_2 \eta_i + \epsilon_i$

(1') in (2) $P_i = \beta_0 + \beta_1 Q_i + \beta_2 I_i - \beta_2 \alpha_0 - \beta_2 \alpha_1 Q_i + \epsilon_i$

(2') $P_i = [\beta_0 - \beta_2 \alpha_0] + [\beta_1 - \beta_2 \alpha_1] Q_i + \beta_2 I_i + \epsilon_i$

$\gamma_0 = \beta_0 - \beta_2 \alpha_0$

$\gamma_1 = \beta_1 - \beta_2 \alpha_1$

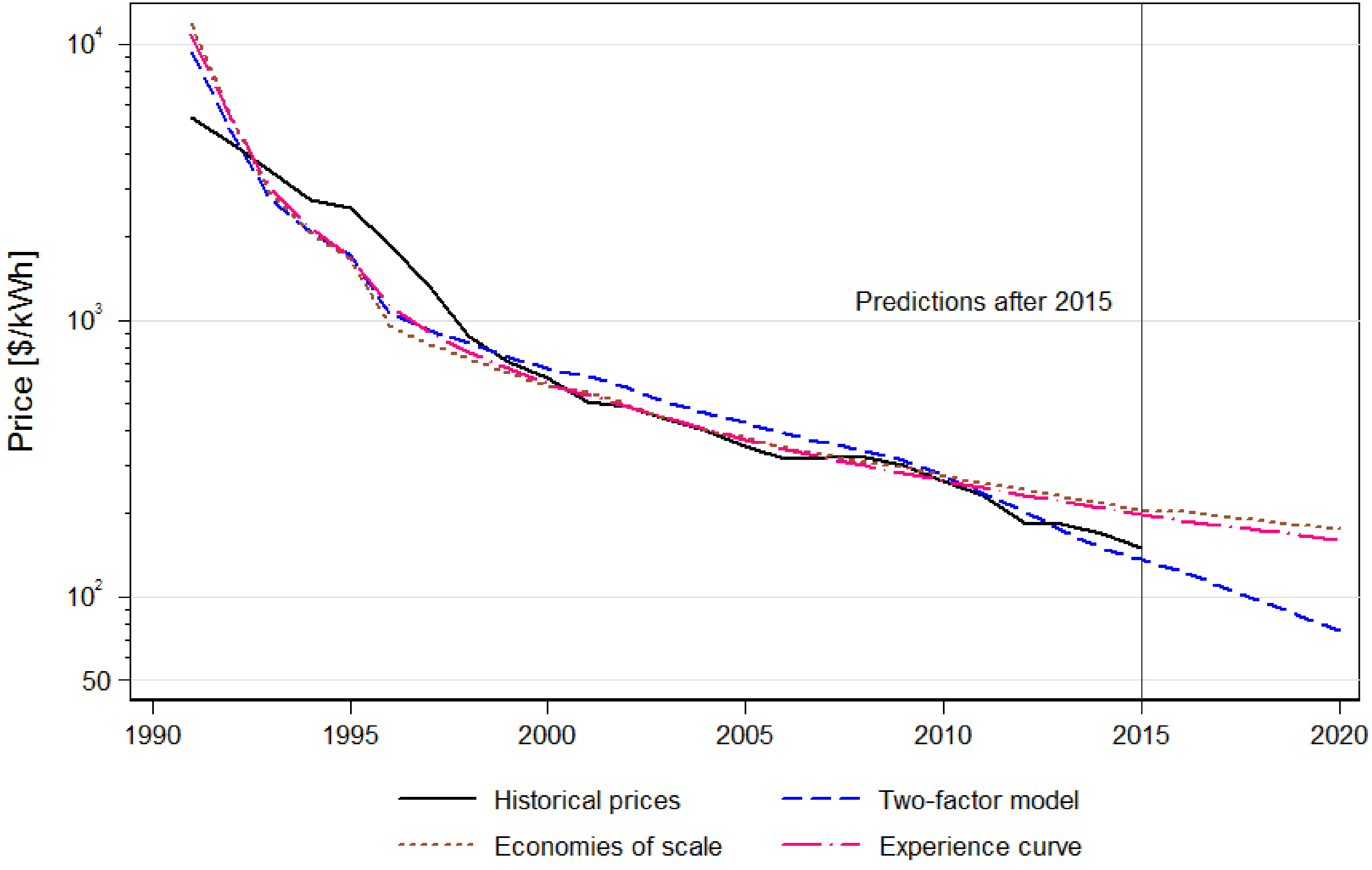
$\gamma_2 = \beta_2$

The final model and be found in Eq. 3 and 4.

(3) $P_i = \gamma_0 + \gamma_1 Q_i + \gamma_2 I_i + \epsilon_i$

(4) $Forecasted\ price = \left(\frac{10^{\gamma_0}}{Q_i^{-\gamma_1}}\right)(10^{\gamma_2})^{I_i}$

One- vs. two-factor learning curves



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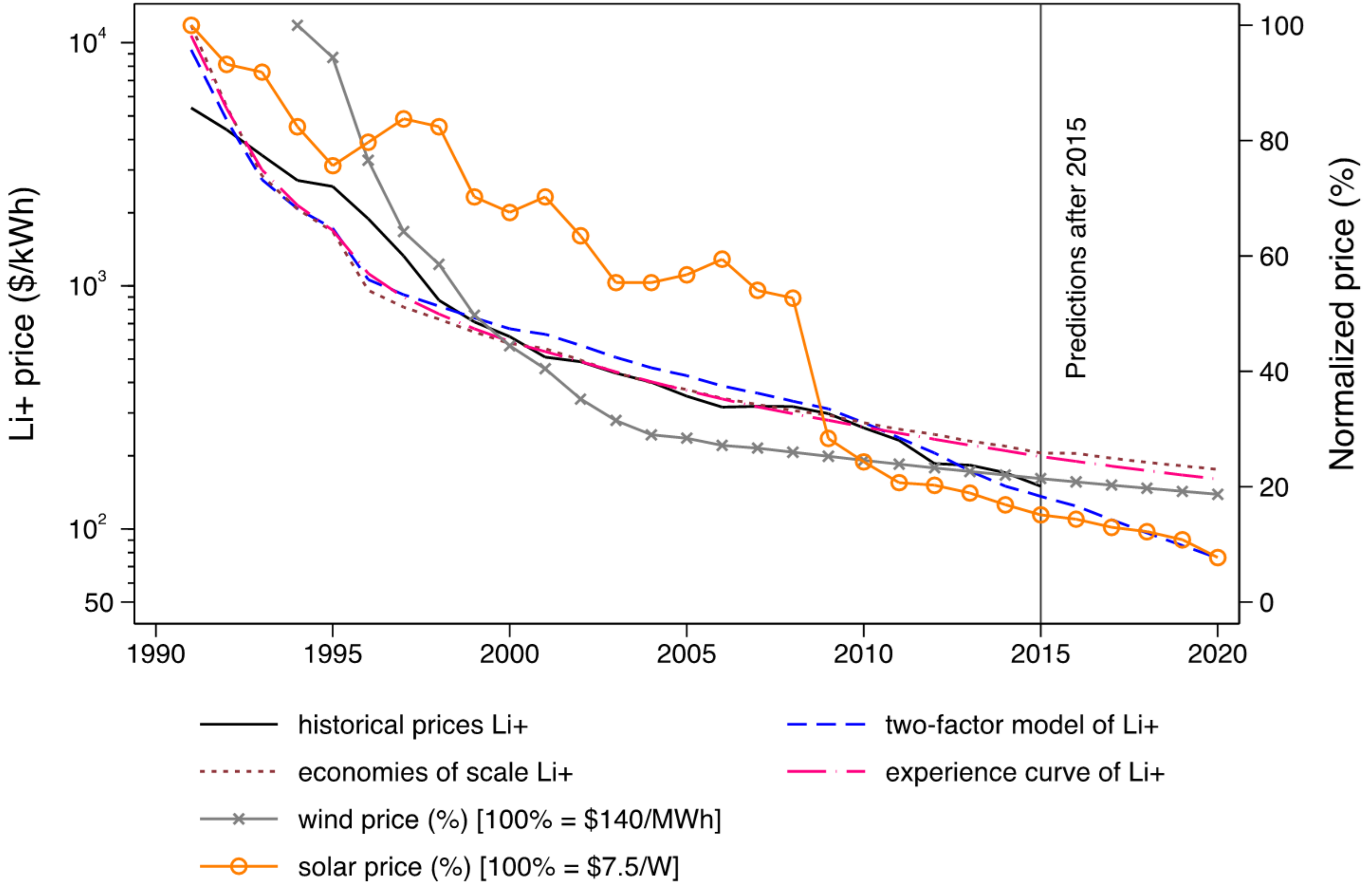
Two-factor approach: LiB, wind & solar



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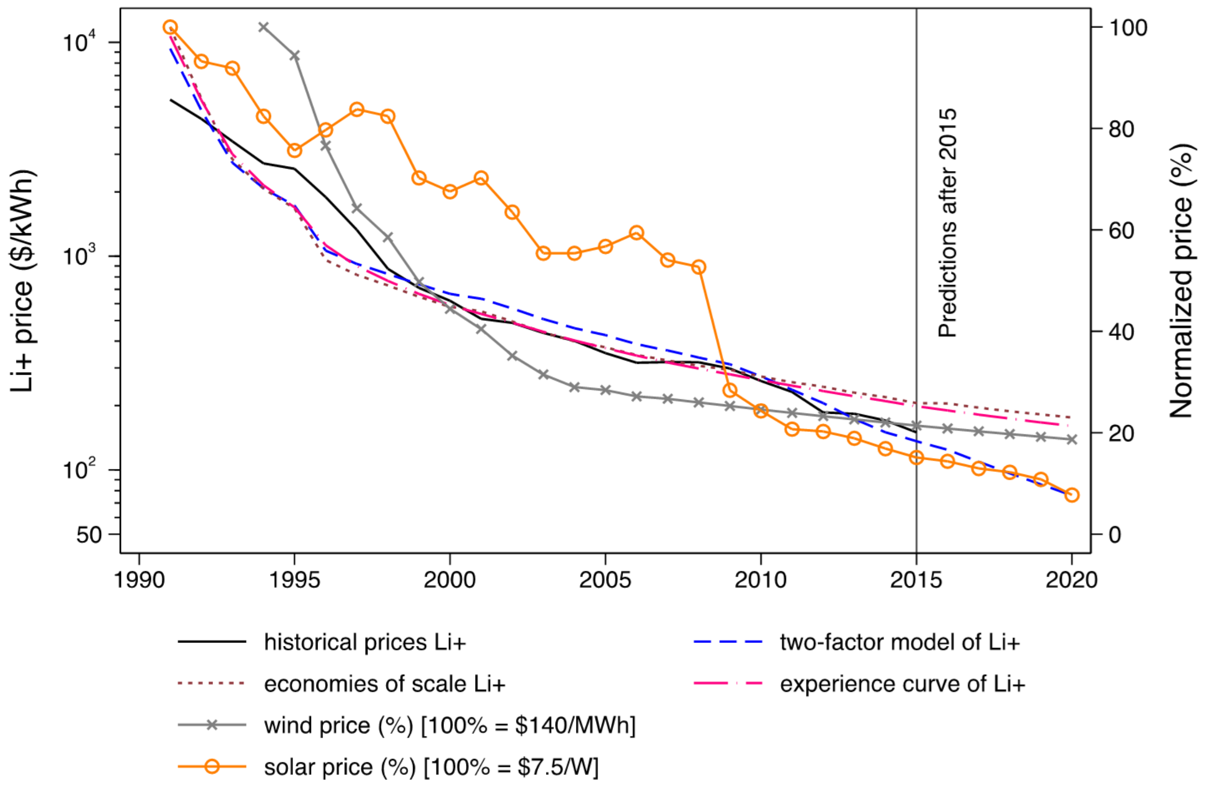


Significance:
Investment in R&D and innovation are critical for battery storage to become cost-competitive with fossil fuel plants-- we could get to $100/kWh with modest investment

Model assessment and selection

	one-factor models			two-factor model	four-factor model
	A	B	C	Eq. 2 (leading to D)	Eq. 5
Coef 0	-3.797221*** (0.0651777)	3.79099*** (0.0531146)	4.085781*** (0.0334454)	3.797658*** (0.0542746)	1.1723533* (0.6300552)
Coef 1	-0.3100554*** (0.0182732)	-0.270016*** (0.0130085)	-0.5407248*** (0.0131083)	-0.3101608*** (0.0152164)	-0.2875361*** (0.0162777)
Coef 2				-0.0000881*** (0.0000263)	-0.0001167*** (0.000038)
Coef 3					0.2129343 (0.146463)
Coef 4					0.2606368 (0.1684335)
# obs	25	25	25	25	23
F	287.91	430.85.18	1701.61	213.18	137.14
Prob > F	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
R^2	0.9260	0.9493	0.9867	0.9509	0.9682
Adj. R^2	0.9228	0.9471	0.9861	0.9465	0.9612
BIC	-26.17094	-35.62775	-69.0026	-33.21648	-35.22165
|ΔBIC|	0	9.4568	42.8317	7.0455	9.0507

A: Annual production

- Adj. R^2: 0.9228
- BIC: -26.17094

B: Cumulative production

- Adj. R^2: 0.9471
- BIC: -35.62775

C: Innovation / PCT patents

- Adj. R^2: 0.9861
- BIC: -69.0026

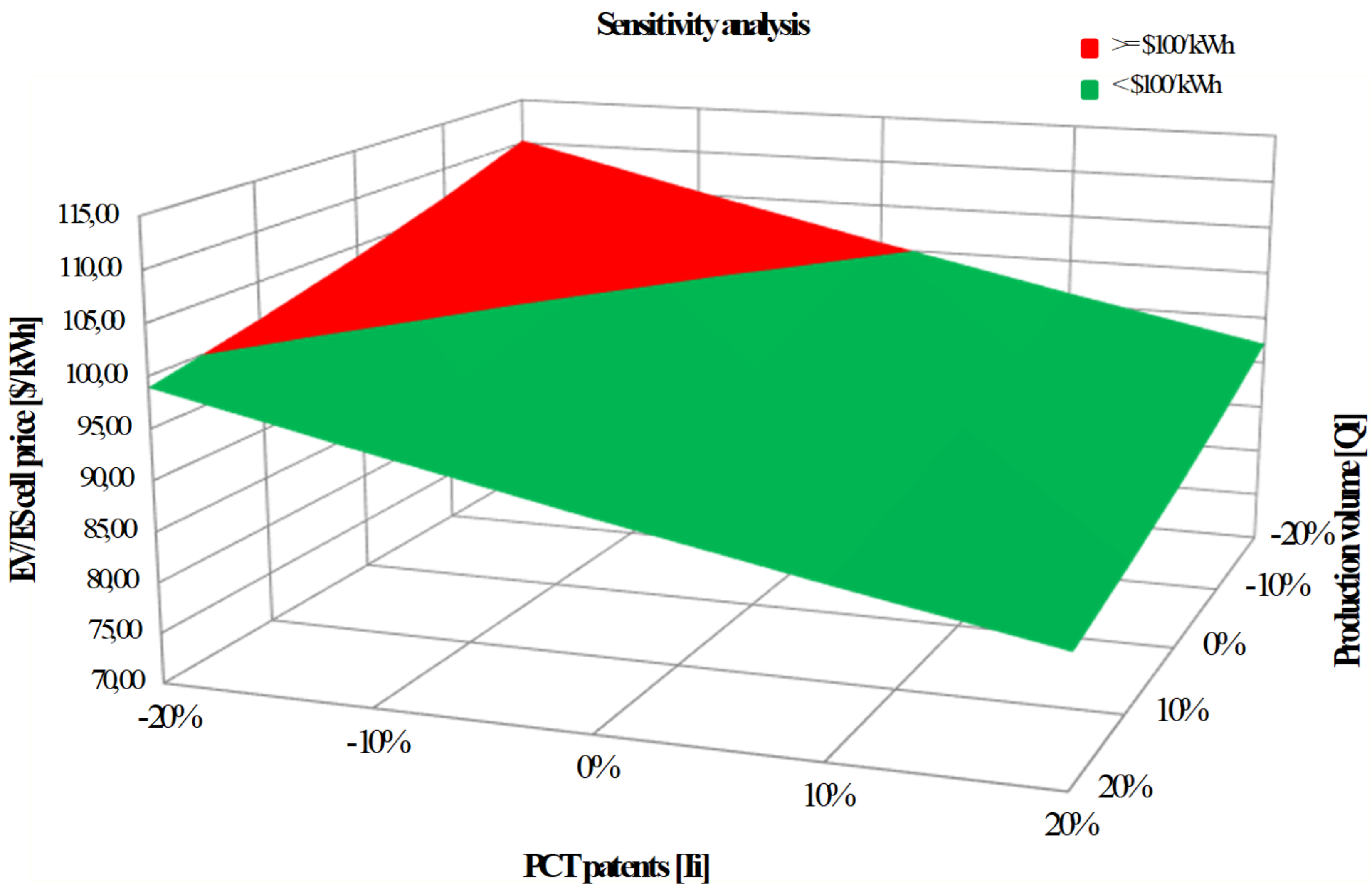
D: two-factor

- Adj. R^2: 0.9465
- BIC: -33.21648

Forecasted prices: two-factor model

Year	Forecast: consumer cells	EV/ES cells	EV/ES battery pac
2016	124.15	155.00	202.8
2017	109.18	136.31	178.4
2018	96.38	120.33	157.5
2019	85.55	106.81	139.8
2020	76.03	94.92	124.2
sensitivity range	(66.17-88.32)	(82.61-110.27)	(108.13-144.33

Sensitivity analysis



Conclusion

- Intermittency is large-scale problem holding back solar and wind power from replacing coal
- Battery storage may provide innovative technology to "unlock" baseload renewable electricity
- Multi-factor experience curve models can incorporate more and new information as a way to improve forecasting
- Caution: dangers of over-fitting, correlation versus causation, and challenges of data access
- Outcome: Multi-factor experience curves shed new light on value of R&D investment and innovation activity on renewable energy
- Highlights "co-evolutionary" aspect of innovation and deployment strategies

Kittner, N., Lill, F., Kammen, D.M. (2017). "Energy storage deployment and innovation for the clean energy transition." ***Nature Energy*** **2 17125.**

Research team

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Backup slides

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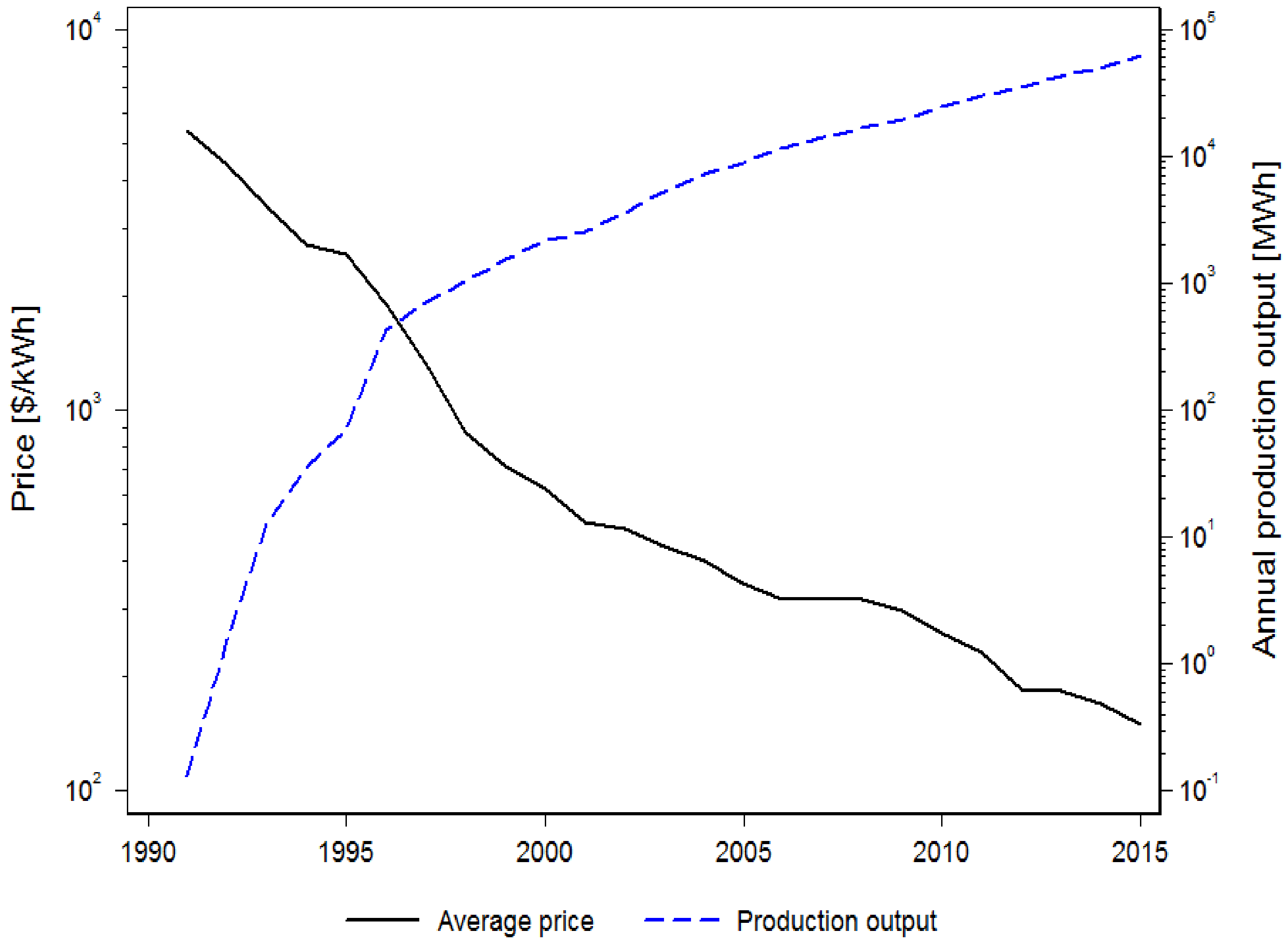
Relationship: average price and output



Raw materials: price and production

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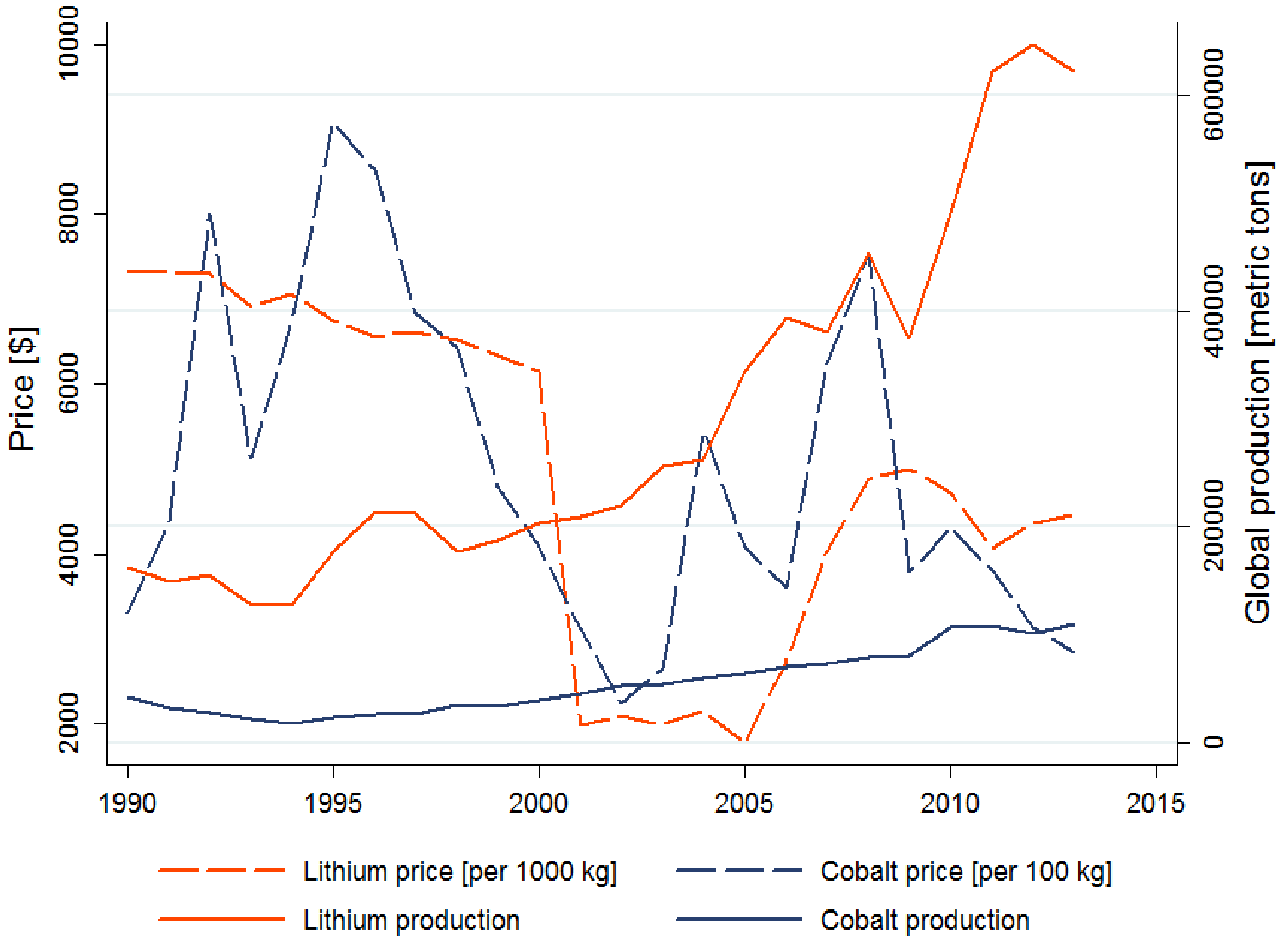
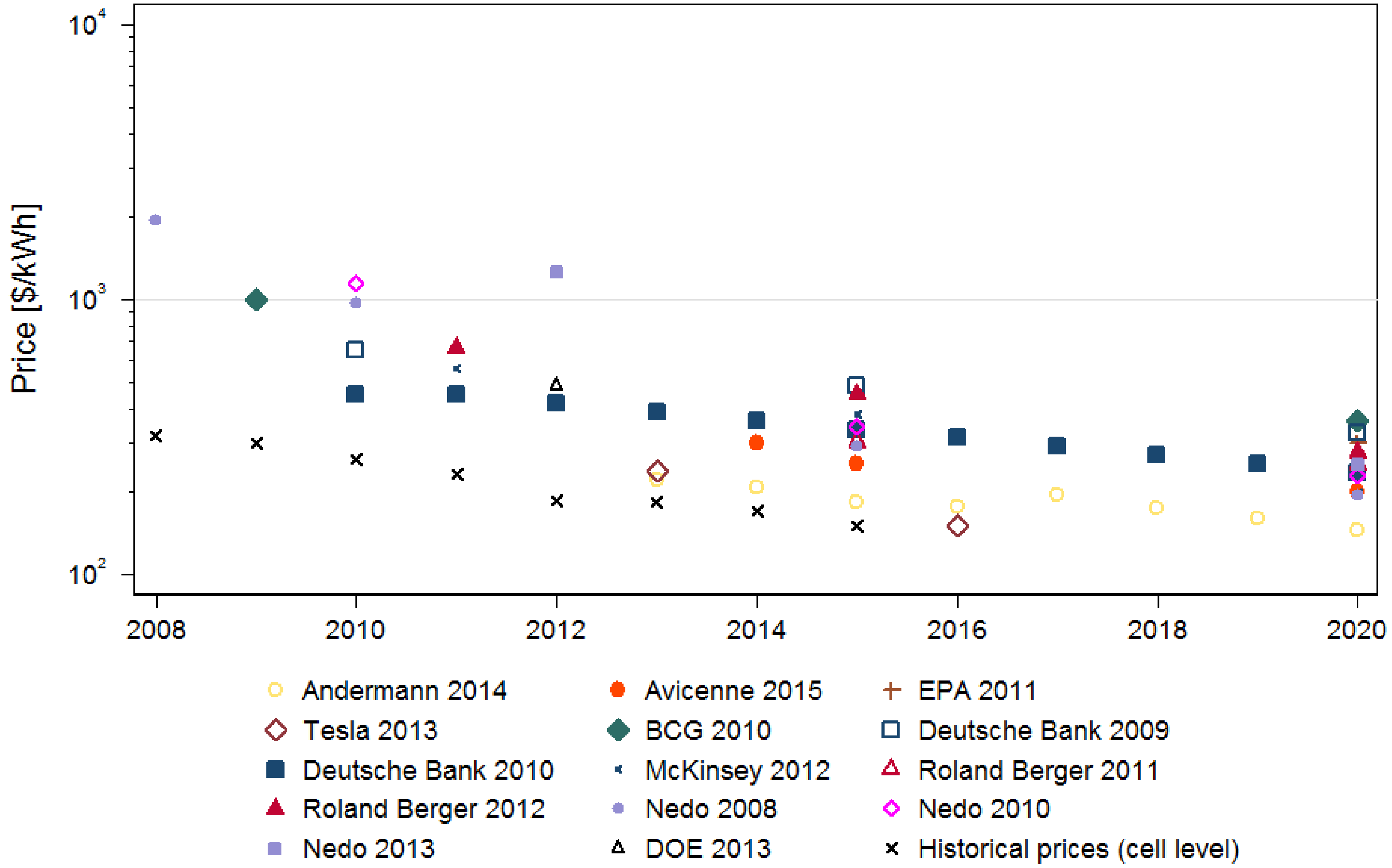
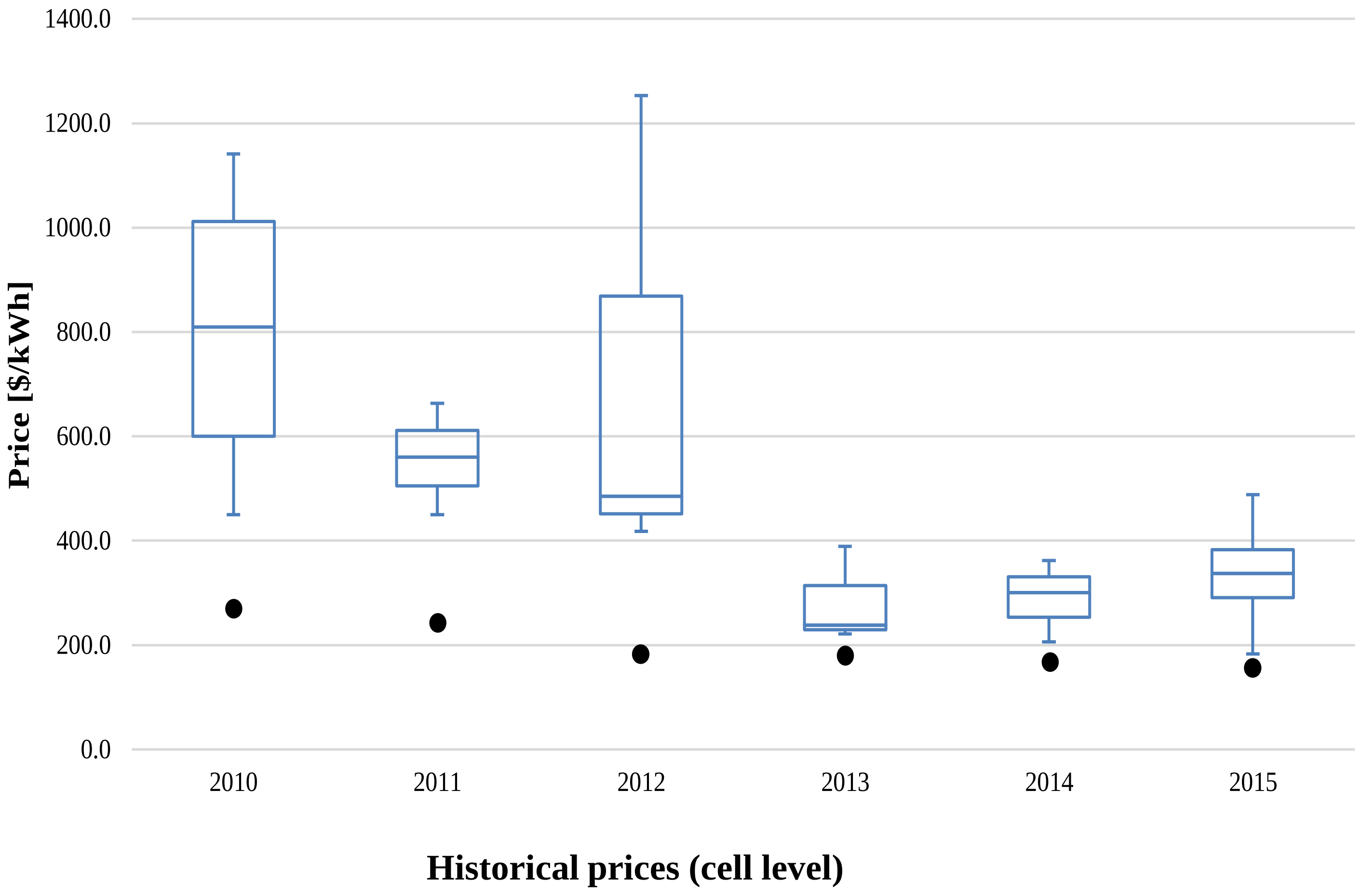


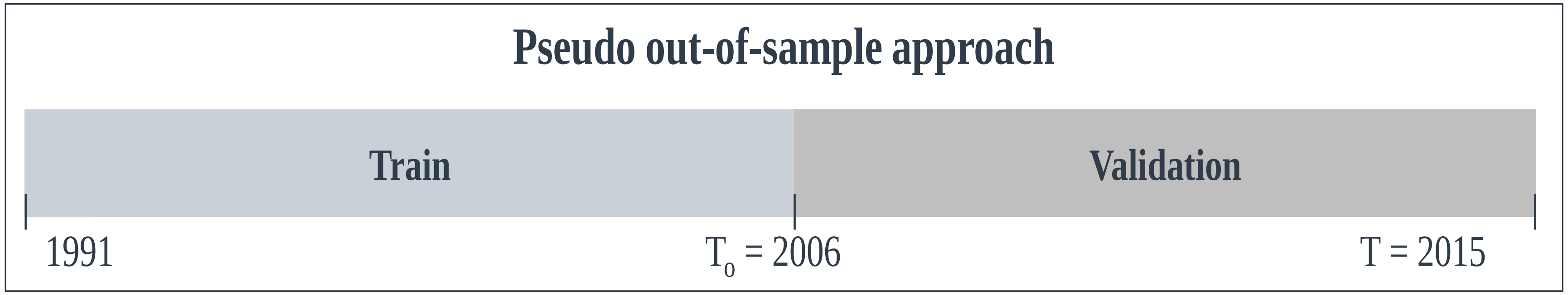
LiB price forecasts



LiB price forecasts



Pseudo out-of-sample approach



Results: Pseudo out-of-sample test

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Year	Average price [$]	Forecasted price [$]	Deviation
2007	320.1	245.3	|-23.0%|
2008	319.3	396.9	24.3%
2009	298.3	363.0	21.7%
2010	260.9	294.7	13.0%
2011	231.8	251.7	8.6%
2012	185.8	229.8	23.7%
2013	183.1	203.0	10.9%
2014	170.2	204.7	20.3%
2015	150.0	248.2	65.4%
Mean			23.4%

Kittner, N., Lill, F., Kammen, D.M. (2017). "Energy storage deployment and innovation for the clean energy transition." ***Nature Energy*** **2 17125.**

Summary of key statistics

	Mean	Standard deviation	Minimum	Maximum
y_aprice	1142.466	1446.228	150	5394.66
logy_aprice (P_t)	2.7852	0.4729792	2.18	3.73
y_output	13514.85	17534.07	0.1	61487
logy_output (Q_t)	3.264	1.467958	-0.9	4.8
cum_output	67087.28	96196.25	0.1	337871.1
logcum_output	3.724926	1.706709	-0.8860567	5.528751
y_pctpatents	144.28	178.1686	1	570
logy_pctpatents	1.73479	0.757657	0	2.755875
cum_ pctpatents (I_t)	857.2	1104.121	5	3610
logcum_ pctpatents	2.405254	0.8688611	0.69897	3.557507
residual variable (η_t)	1.052853	847.7372	-709.7451	2019.939

Kittner, N., Lill, F., Kammen, D.M. (2017). "Energy storage deployment and innovation for the clean energy transition." ***Nature Energy*** **2 17125.**

Correlation matrix of the main variables

	logy_aprice (P_t)	logy_output (Q_t)	cum_pctpatents (I_t)
logy_aprice (P_t)	1.0000		
logy_output (Q_t)	-0.9623	1.0000	
cum_pctpatents (I_t)	-0.9933	0.9644	1.0000

Variance inflation factor

	logy_aprice (P_t)	logy_output (Q_t)	cum_pctpatents (I_t)
logy_aprice (P_t)	1.0000		
logy_output (Q_t)	-0.9623	1.0000	
cum_pctpatents (I_t)	-0.9933	0.9644	1.0000

Correlation matrix incl. residual variable

	logy_aprice (P_t)	logy_output (Q_t)	residual variable (n_t)
logy_aprice (P_t)	1.0000		
logy_output (Q_t)	-0.9623	1.0000	
residual variable (n_t)	-0.1558	-0.0021	1.0000

Overview of key regression results

	Equation 1	Equation 2
Coef 0	α_0 =-711.5858*** (430.2888)	β_0 = 3.797658*** (0.0542746)
Coef 1	α_1 = 480.6329	β_1 = -0.3101608**
	(120.6356)	(0.0152164)
Coef 2		β_2 = -0.0000881***
		(0.0000263)
# obs	25	25
F	15.87	213.18
Prob > F	0.0006***	0.0000***
R^2	0.4083	0.9509
Adj. R^2	0.3826	0.9465

Kittner, N., Lill, F., Kammen, D.M. (2017). "Energy storage deployment and innovation for the clean energy transition." *Nature Energy* 2 17125.

Statistical results for all four models

	one-factor models			two-factor model
	A	B	C	Eq. 2 (leading to D)
Coef 0	-3.797221*** (0.0651777)	3.79099*** (0.0531146)	4.085781*** (0.0334454)	3.797658*** (0.0542746)
Coef 1	-0.3100554*** (0.0182732)	-0.270016*** (0.0130085)	-0.5407248*** (0.0131083)	-0.3101608** (0.0152164)
Coef 2				-0.0000881*** (0.0000263)
# obs	25	25	25	25
F	287.91	430.85.18	1701.61	213.18
Prob > F	0.0000***	0.0000***	0.0000***	0.0000***
R^2	0.9260	0.9493	0.9867	0.9509
Adj. R^2	0.9228	0.9471	0.9861	0.9465
BIC	-26.17094	-35.62775	-69.0026	-33.21648
$\lvert\Delta BIC\rvert$	0	9.4568	42.8317	7.0455