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Quantifying the cost savings of global solar photovoltaic supply chains*

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Abstract

Achieving carbon neutrality requires deploying renewable energy at unprecedented speed and scale, yet countries sometimes implement policies that increase costs by restricting the free flow of capital, talent, and innovation in favor of localizing benefits such as economic growth, employment, and trade surpluses. Here we assess the cost savings from a globalized solar photovoltaic (PV) module supply chain. We develop a two-factor learning model using historical capacity, component, and input material price data of solar PV deployment in the U.S., Germany, and China. We estimate that the globalized PV module market has saved PV installers in the U.S. $24 ($19–$31) billion, Germany $7 ($5–$9) billion, and China $36 ($26–$45) billion from 2008 to 2020 compared to a counterfactual scenario where domestic manufacturers supply an increasing proportion of installed capacities over a 10-year period. Projecting the same scenario forward from 2020 results in estimated solar module prices that are approximately 20% – 25% higher in 2030 compared to a future with globalized supply chains. International climate policy benefits from a globalized low-carbon value chain, and these results point to the need for complementary policies to mitigate welfare distribution effects and potential impacts on technological crowding-out.

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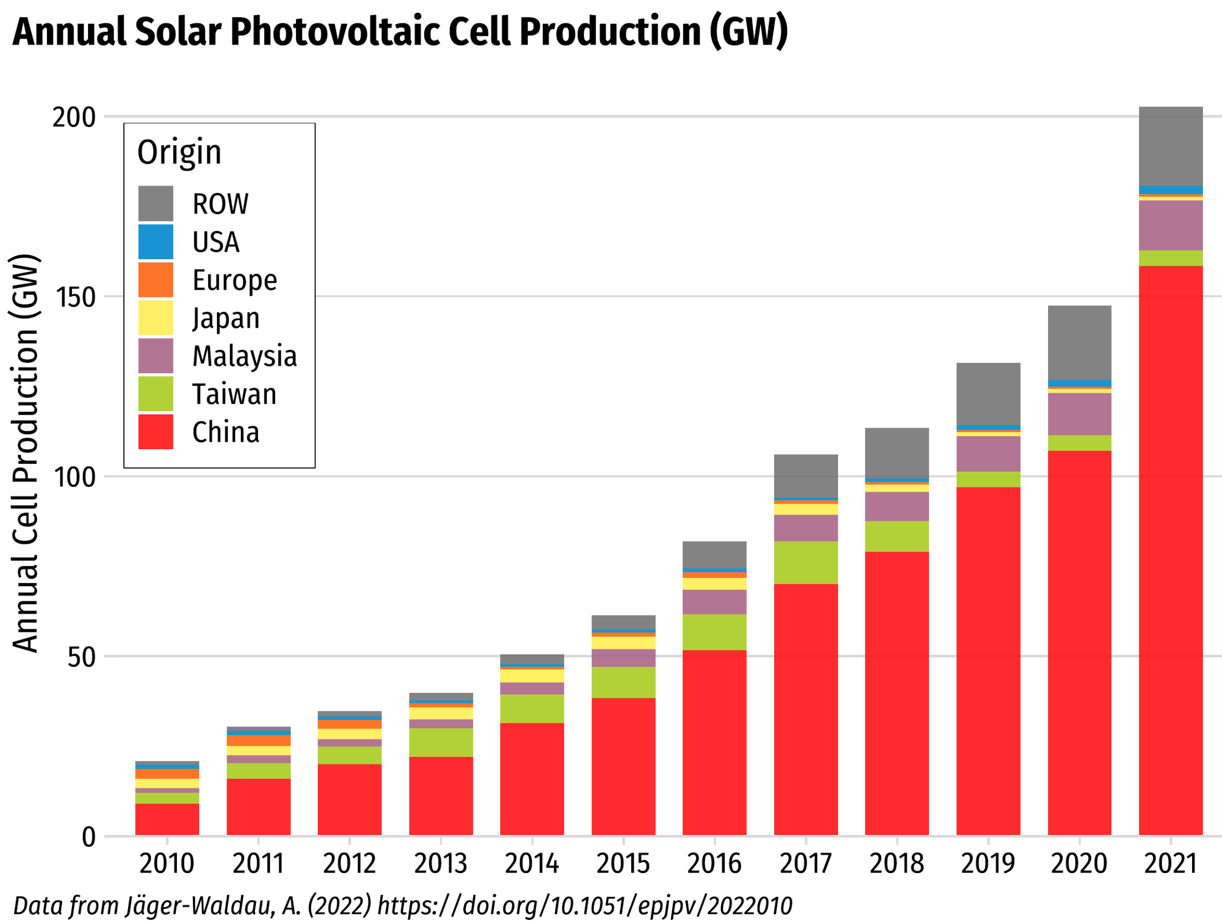
Main

Solar energy is promised to play a crucial role in achieving a sustainable, low-carbon energy future and avoiding the worst impacts of climate change [1]. Over the past 40 years, solar photovoltaic (PV) prices have fallen by over two orders of magnitude, and in the most recent decade (2010-2020), the global weighted-average levelized cost of energy (LCOE) of newly commissioned utility-scale solar PV fell by 85% [2], making solar PV cheaper than fossil fuel power in some parts of the world. Installed costs (excluding cost of capital) fell by 81% over this period. While these dramatic price declines have been a boon for accelerating low-carbon energy deployment [3], further declines will be necessary to deploy renewables at the speed and scale that is needed to achieve climate targets, especially in the remaining parts of the world where fossil fuel power is still cheaper [4]. Recent research suggests that the rates of solar and wind energy deployment in even the fastest-deploying nations are not high enough to meet targets necessary to avoid the worst consequences of climate change [5].

Nonetheless, rapid price declines in solar PV have not been without controversy. China, for example, has played an outsized role in scaling up the mass production of solar PV cells and modules, comprising 78% of global production in 2021 [6, 7] (see Figure 1). Greg Nemet went as far as to call this outcome China's "gift to the world" [8] referring to the dramatic manufacturing cost reductions achieved by Chinese firms in the last decade [2]. Yet other nations view the concentration of PV manufacturing in China as a competitive threat, and some have attributed this outcome to unfair trade practices and industrial policies implemented by China's government [9]. Countries seeking to capitalize on the growing clean energy sector are looking to protect and grow domestic manufacturers [10].

In response to these concerns, the U.S. and the European Union have imposed steep solar tariffs on imports from China and other countries. In June 2022, the Biden administration invoked the Defense Production Act to accelerate the onshoring of solar PV manufacturing [11]. These efforts could lead to less efficient national learning processes replacing the learning processes associated with global supply chains that have led to drastic price declines [12].



Note: Over the past decade, solar PV cell and module production has increasingly been concentrated in China.

Figure 1: Annual solar PV cell production by origin, 2010 - 2021 [6]

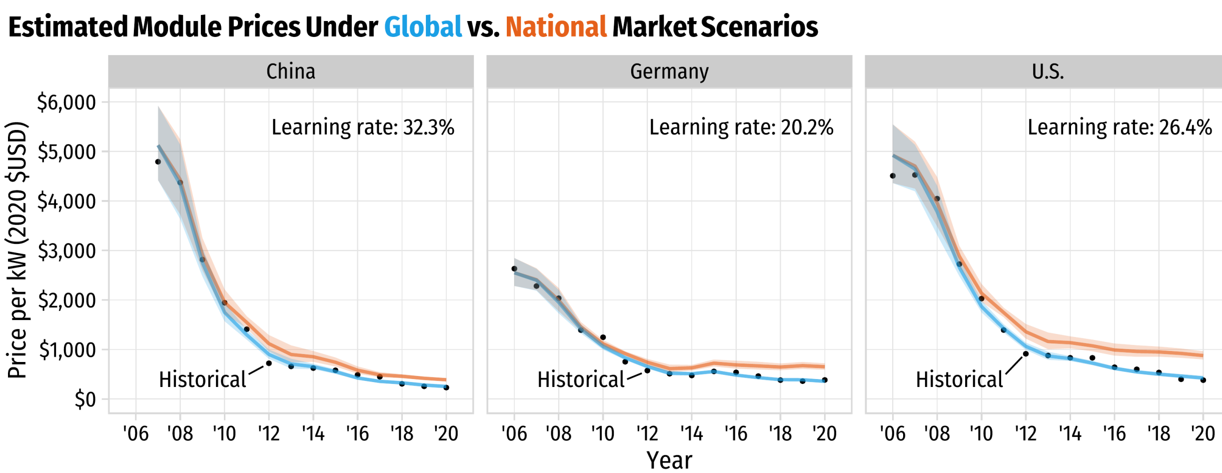
The free flow of capital (e.g., foreign finance-backed startups), talent (e.g., international collaborations with Chinese researchers), and innovations (e.g., technologies pioneered in labs overseas and licensed and mass-produced in China) were essential to the rise of China's competitive solar PV industry [13]. Each of these activities is increasingly under scrutiny by the U.S. and other governments [14]. In the event of strict nationalization policies (including, inter alia, trade barriers in final or intermediate solar goods, restrictions on cross-national R&D, and barriers to cross-border investment), subsequent cost and performance improvements could derive primarily from activities, knowledge, and capital within national borders, potentially slowing the rate of price declines in globally-traded solar PV components and, consequently, the rate of solar PV deployment.

International climate policy and renewable energy deployment policy now face a crossroads: continue relying on global supply chains, or pivot towards nationalization of technology development and production. This study attempts to quantify the difference between these two paths in terms of the costs of deploying solar PV to achieve ambitious low-carbon goals. We collect detailed historical capacity, component, and input material cost data of solar PV deployment in the U.S., Germany, and China and develop a two-factor learning model to estimate a learning curve associated with the historical (globalized) solar PV supply chain. We then use these learning models to compare counterfactual historical prices and potential future prices of solar PV modules under "global" versus "national" market conditions. The global market scenarios reflect learning under historical market conditions while the national market scenarios reflect a gradual transition to fully domestically-supplied markets over a 10-year period in each country.

We focus our scope on PV modules for two reasons. First, modules are a globally-traded component and comprise between 20% to 40% of the installed system cost for most PV installations [15]; combined with inverters, modules comprised 61% of the global weighted-average total installed price decline between 2010 and 2020 [2]. Second, other "soft costs" (such as permitting, installation, and marketing) vary widely by country and have geographically limited learning and spillover effects [16]; as a result, we expect these cost components to remain relatively similar regardless of where modules are manufactured. Our analysis is limited to installed prices, not LCOE as reflected in power purchase prices for solar energy, which also vary by country and project according to the cost of capital and other factors.

Modeling historical prices and savings

Using nation-specific, component-level price data and global PV installation and silicon price data, we estimate learning rates for solar PV modules in the three largest solar deploying countries (China, Germany, and the U.S.) between 2006 and 2020 using a two-factor learning model. Combined, these three markets comprised 54% of all global installed PV capacity during this period [2]. Estimated learning rates during this period are 20% in Germany, 26% in the U.S., and 33% in China. We then compute the counterfactual "national markets" scenario by assuming that starting in 2006 countries began implementing nationalistic policies that gradually restrict learning to installations within their country borders over a ten year period (for China, the starting year is 2007 due to data availability). Annual installed capacities are assumed unchanged in the counterfactual "national markets" scenario to provide the most policy-relevant results (see Methods Limitations). Figure 2 shows the resulting price curves between the "global market" and "national market" scenarios in each country as well as the true historical prices.

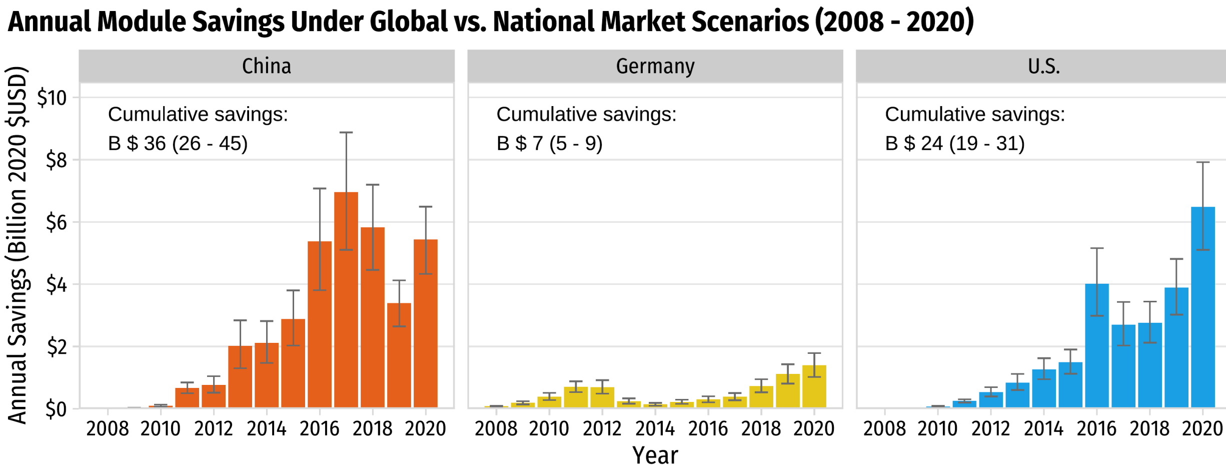


Note: Points are historical module prices, and the two solid lines reflect the modeled prices using global (blue) versus national (orange) markets scenarios. In each modeled curve, the learning rates are held constant by country and silicon prices follow historical global trends (Appendix Figure A6). The global market scenario uses global capacities and the national market scenario uses a weighted sum of national and global capacities that reflects a gradual transition to fully domestically-supplied markets over a 10-year period. Uncertainty bands represent 95% confidence intervals from the estimated learning models, which were computed via simulation.

Figure 2: Comparison of estimated solar PV module prices under global versus national market scenarios in China (2007 - 2020) and Germany and the U.S. (2006 - 2020)

Comparing the two scenarios, if each country had pursued a gradual transition to strict nationalistic policies while installing at the same rate over a ten year period, our results imply that solar PV module prices in 2020 would have been significantly higher than their actual historical prices: 54% higher in China ($387 versus $250 per kW), 83% in higher Germany

(\$652 versus \$357 per kW), and 107% higher in the U.S. (\$877 versus \$424 per kW). Early learning, boosted in part by Germany's generous solar feed-in-tariffs, led to compounded improvements over time for the U.S. and China, which led to steep increases in installations in the second half of the period. The combined estimated cumulative savings across all three countries during this period from global versus national markets is \$67 billion (2020 \$USD), with a 95% confidence interval of \$50 - \$84 billion (see Figure 3).



Note: Savings are calculated by multiplying the installed national capacity in each year with the difference between the modeled prices from the national and global markets scenarios. Error bars represent 95% confidence intervals computed via simulation.

Figure 3: Estimated annual savings from deployed annual solar PV modules using global versus national market scenarios in China, Germany, and the U.S. (2008 - 2020)

Future trajectories

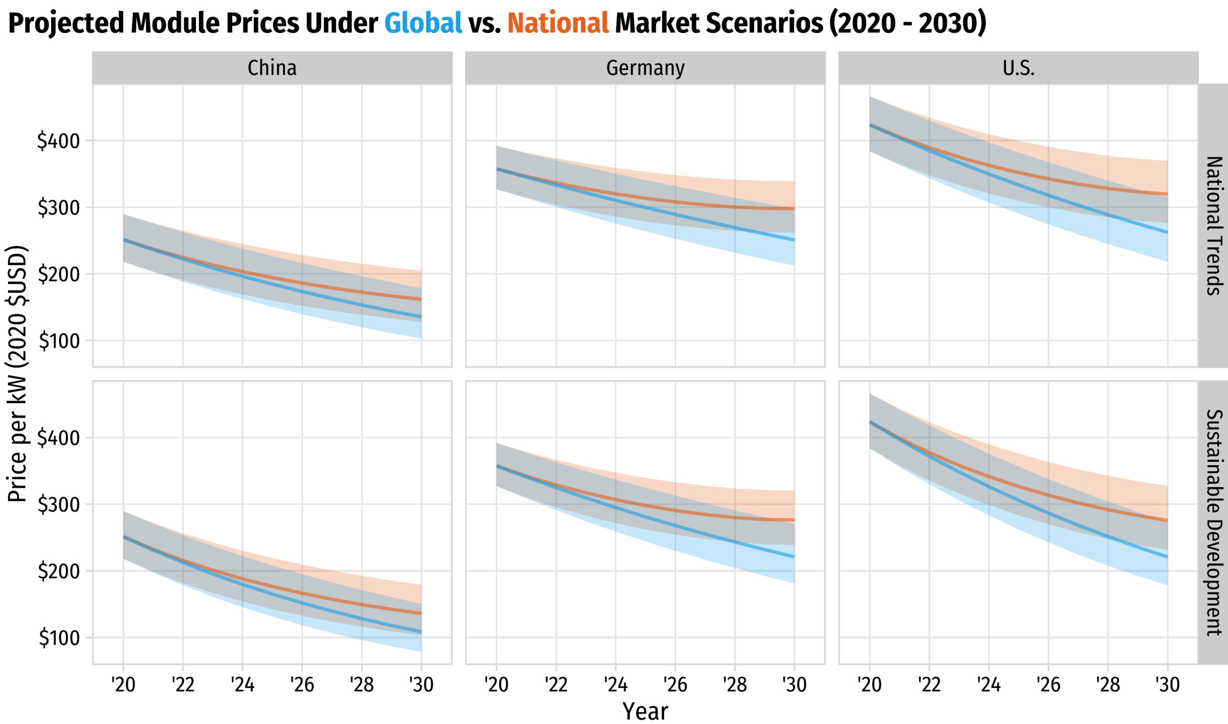
As more countries introduce policies aimed at protecting local manufacturers, such as import tariffs on PV modules, continued learning-based reductions in module prices may be delayed. To assess this effect, we project solar PV module prices out to 2030 based on continued global versus national market scenarios starting from historical 2020 PV prices. These projections assume capacity grows at a constant annual growth rate (CAGR) from 2020 installed capacity levels out to 2030 targets for each country. We consider two different future scenarios: National Trends (NT), which projects recent deployment trends out to 2030, and Sustainable

Development (SD), which reflects more aggressive installation growth to meet climate targets based on the Sustainable Development Scenario in the IEA World Energy Outlook 2020 [4]. Table 1 summarizes the specific 2030 targets for each country in each scenario, and Figure 4 shows the results of these projections.

Table 1: Solar PV 2030 Installation Targets for Projection Scenarios

Country	**National Trends(NT)**		**Sustainable Development(SD)**	
	2030 Target(GW)	**Implied CAGR**	**2030 Target(GW)**	**Implied CAGR**
U.S.	295	12%	628	21%
China	750	12%	1,106	17%
Germany	103	7%	147	11%
World	2,115	11%	3,125	16%

These projections imply that prices would be significantly higher in 2030 if strict nationalistic policies were gradually implemented in each country from 2020 to 2030. Under the National Trends scenario, 2030 prices would be approximately 20% higher in each country: \$162 versus \$135 per kW in China, \$298 versus \$251 per kW in Germany, and \$320 versus \$262 per kW in the U.S. Under the Sustainable Development scenario, the differences in prices would be approximately 25% higher in each country: \$136 versus \$108 per kW in China, \$276 versus \$221 per kW in Germany, and \$276 versus \$221 per kW in the U.S. For comparison, the U.S. National Renewable Energy Laboratory's (NREL) 2021 Annual Technology Baseline report predicts that solar PV modules will reach \$170 and \$320 / kW by 2030 in advanced and conservative improvement scenarios, respectively [17]. Based on the projected installed capacities, the estimated cumulative future savings from 2020 to 2030 across all three countries from global versus national markets is \$15 billion (2020 \$USD) with a 95% confidence interval of \$13 - \$16 billion under the National Trends scenario, and \$36 (\$33, \$39) billion under the Sustainable Development scenario (Appendix Figure A1).



Note: Projections assume constant annual growth rates in PV installations to achieve national and global 2030 installation targets. Each curve starts at historical 2020 module prices and follows a nation-specific learning rate. In the global market scenarios, global projected installed capacities are used to project prices whereas in the national market scenarios a weighted sum of national and global capacities is used that reflects a gradual transition to fully domestically-supplied markets over a 10-year period. Uncertainty bands represent 95% confidence intervals from the estimated learning models, which were computed via simulation.

Figure 4: Comparison of projected solar PV module prices (2020 - 2030) using global versus national market scenarios in China, Germany, and the U.S.

Discussions

The manufacturing of solar PV modules – a globally-traded commodity crucial to addressing climate change – is increasingly contested by governments seeking to localize benefits of the current and future scale of the industry. Yet achieving the rapid rates of solar PV deployment required to address climate change will necessarily require continued price declines at the same or greater rates as those experienced during the past decade, a period during which the free flow of global talent, capital, and innovations were instrumental to cost reductions. In this paper, we contribute to understanding the implications of strict nationalistic policies by assembling component-specific solar PV price data across major markets, establishing national-level estimates of learning rates that incorporate silicon prices, and quantifying the potential impact of restricted national learning on historical and projected prices and savings from solar PV deployment. The results may extend to other low-carbon technology sectors, such as wind generating systems and electric vehicles, with caveats related to the supply chain integration and complexity of technological components. Wind generating systems, for example, have a very globally-integrated and specialized trade in intermediate components [18]; as a result, achieving "national markets" for the entire wind supply chain could lead to even larger disruptions in terms of costs and reduced learning.

We identify three dilemmas facing policy-makers in preserving established globalized supply chains: trade disputes and domestic employment, "crowding-out" of alternative technology pathways, and additional benefits and drivers of domestic sourcing. Resolving these through complementary policies that mitigate impacts on global learning are difficult but important tasks moving forward.

Trade disputes and domestic employment. Some have attributed the concentration of PV manufacturing in China to unfair trade practices and industrial policies implemented by China's government [9]. While constant cost multipliers would be absorbed in the national learning rates, we do not attempt to disaggregate the contributions to these rates nor do we account for changes in national-level producer subsidies or tariffs faced by importers. The "learning curve" is a synthetic indicator that captures the cumulative effect of impacting factors on the cost evolution of a technology. Data limitations of time-varying government subsidies, industrial policies, tariffs, and firm relocations prevent us from disaggregating these precise effects on price and are beyond the scope of this study.

The loss of potential manufacturing jobs in importing countries coupled with trade disputes is prompting much of the impetus for nationalistic policies. NREL estimates that there are ten times more annual jobs in system installation compared to those in the entire manufacturing supply chain (though within manufacturing, solar module production is the most labor intensive per GW)[19]. Hence, if higher prices associated with nationalistic policies result in less deployment, total employment may decline, though there may be other redistributive concerns and political realities shaping preferences for certain types of jobs [20]. Our national markets counterfactual scenario is an illustrative example of more extreme decoupling, though because of the difficulty of onshoring, countries may instead opt to "near-shore" production to a subset of countries or onshore only select parts of the supply chain. Even the three countries studied could not costlessly onshore entire supply chains, hence our results likely represent an underestimate of the future costs of strict onshoring policies. Reciprocity in trade policies is another barrier limiting the extent to which nations can fulfill onshoring policy goals: for example, the U.S. polysilicon industry was once a dominant global supplier to solar PV manufacturers but became the first casualty of the solar trade war between China and the U.S. when China retaliated for tariffs on imported Chinese modules.

Technological "crowding-out". Some have argued that the rapid price declines of monocrystalline silicon (c-Si) PV cells, driven in part by Chinese industrial policies to ramp up production in China, might have "crowded out" other emerging solar technologies, such as "thin film" solar cells for which the U.S. has a sizable global market share and that could have achieved even lower prices without fierce competition from c-Si [21, 22]. Such an argument is not without precedent. For example, Fuchs and Kirchain (2010) found that offshoring manufacturing in the optoelectronics industry to developing East Asia led to such significant price reductions in the incumbent technology that emerging and potentially groundbreaking technologies could not compete and were largely abandoned [23].

While these concerns are not without merit, they are not necessarily the only forces at play in the global PV industry. Indeed, PV cell and module manufacturing has followed a developmental path common to many industries in which initial, intense experimentation is followed by the emergence of a "dominant design" [24] and a shift in productive activity away from product innovations and towards production improvements to increase scale and reduce costs [25–28]. This shift in focus towards production tends to precipitate two related phenomena: 1) unit costs drop dramatically as firms identify successful production innovations, and 2) many competing firms fail as production tends to concentrate around the handful of firms that are able to compete on lower costs. In some industries, this also coincides with offshoring production in search of lower cost production environments, though this is not always the case [10]. Thus, it remains unclear whether the concentration of PV cell and module production in China was purely a result of government intervention or perhaps a combination of factors, such as the natural evolution of a maturing industry [29]. Chinese policies may have accelerated cost declines in c-Si cells and modules, but whether they alone led to the crowding out of other potential technologies remains debatable. Additional domestic sourcing drivers. A domestic manufacturing base in solar PV may provide other benefits besides direct employment worthy of future study. Our model does not incorporate any spill-over benefits to adjacent industries, such as semiconductors and electronics. For example, polysilicon production is part of both advanced chip and solar supply chains, though solar-grade polysilicon has purity requirements several orders of magnitude lower [30]. Establishing a stronger link between public funding of R&D and the private sector has been identified as important to achieving climate technology innovation goals, both by reducing risks of scale-up and providing access to markets [31]. Foreign manufacturers may be undesirable or infeasible partners with public money. On the other hand, private sector-led efforts can be effective internationally: Chinese solar firms largely innovated through improved manufacturing processes and strategic international partnerships, including with U.S.-based startups unable to scale domestically [32].

Finally, maintaining adequate environmental, health and labor standards in the production of traded goods is important for ethical reasons and is increasingly raised in the context of maintaining a level-playing field in trade agreements. The Xinjiang region of China, where much of the world's solar-grade polysilicon is produced, has come under increased scrutiny due to allegations of forced labor. The solar industry has responded with proposed traceability protocols, which if effective could obviate the need to onshore production for ethical reasons [33]. Further work is needed on the feasibility of such protocols.

This study presents the first quantitative estimation of the historical and future cost savings from a globalized solar PV supply chain. The results provide evidence of the benefits of global learning processes in terms of achieving lower prices to accelerate low-carbon technology deployment, which could potentially be delayed by emerging nationalistic policy efforts. When negotiators meet to discuss accelerating action towards the goals of the Paris Agreement, and when policy-makers plan for pathways to achieve mid-century carbon neutrality, they should recognize that these aspirations may be difficult or impossible to achieve without globalized low-carbon supply chains. Complementary policies are necessary to address dilemmas and debates with respect to localizing manufacturing and to ensure continued price declines.

Methods

Learning models and simulations. The learning curve model is widely used to describe the evolution of production costs for technologies as they scale up [34–38]. In its simplest form, the learning curve defines a relationship in log-log space between cost (or price) and cumulative capacity [39]. The model can be expanded to incorporate not only the processes of "learning-by-doing," but "learning-by-researching" and changes in material input prices as well [40, 41]. Here, we adopt a two-factor learning model relating the unit price in year t and country i of solar PV modules, p_{it}, to the cumulative installed PV capacity in year t, q_t, and globally-averaged polysilicon prices in year t, s_t, (the primary input material to PV modules):

$$\ln p_{it} = \ln \alpha_i + \beta_i \ln q_t + \gamma_i \ln s_t \tag{1}$$

Here, α_i is a constant related to the starting year conditions in country i, γ_i measures the sensitivity to polysilicon prices, and β_i is the learning coefficient in country i, which is related to the learning rate (L_i) via:

$$L_i = 1 - 2^{\beta_i} \tag{2}$$

For each country, i, we estimate learning coefficients (Appendix Table A1), β_i, under historical "global market" conditions using linear least-squares regression on Equation 1. These learning models set a baseline for learning rates under historical market conditions and assume that variations in country-level module pricing were due to transportation, administrative, and other non-learning costs.

We then construct counterfactual "national market" scenarios by assuming that the learning-related price decreases in country i from the starting year, t_0, are derived from incrementally more nationally-installed PV capacity:

$$q_t - q_{(t-1)} = (q_{it} - q_{i(t-1)}) + (1 - \lambda_i)(q_{jt} - q_{j(t-1)}) \tag{3}$$

where q_{it} is the cumulative installed capacity in country i in year t, q_{jt} is the cumulative installed capacity in all other countries in year t, and λ_t is a value ranging from 0 to 1. This defines a scenario whereby incremental capacity installed in each year increasingly comes from national as opposed to global installations as λ_t shifts from 0 to 1. In our baseline simulations, λ_t ranges from 0.1 to 1.0 in increments of 0.1 as t goes from 1 to 10, simulating a gradual transition to a scenario where all new national PV capacity is domestically-supplied. At the starting year of both the historical and projection scenarios, $\lambda_t = 0$ and the cumulative capacity is set to the globally installed capacity in that year. Unit price declines under national market conditions thus evolve more slowly according to how rapidly λ_t approaches 1. The national market scenarios propose that national-specific learning is proportionally derived from national versus global cumulative installed capacities, and by definition $q_{it} < q_t$. Extended Data Figure 5 illustrates the relationship between λ_{it} and the proportion of national to global cumulative installed capacity over all years for each country. Note that the same value of λ_i does not translate to the same proportion of national learning for each country. For example, if $\lambda_i = 0.4$, then the proportion of national learning is 15% in the U.S., 44% in China, and 40% in Germany.

Uncertainty in parameter estimates is propagated throughout all of our analyses using multivariate normal draws from the full covariance matrix of model parameters. Lower and upper bounds on results reflect a 95% confidence interval taken from the 2.5% and 97.5% percentiles from these draws.

Limitations. Learning rate analyses, while widely used, are subject to critiques in terms of under-specifying learning mechanisms [36, 42, 43]. In our application of these models, we include exogenous factors that could influence module prices but are not directly linked to learning (e.g., polysilicon prices). Otherwise, we estimate a single learning coefficient for each country that captures the average learning due to a variety of nation-specific factors that contribute to learning, such as learning by doing (average plant size), and learning by searching (research, and development), etc. While other studies have estimated learning models that attempt to disaggregate learning into constituent components [44], our research focuses on the nation-specific price implications of trade barriers. Data gaps and insufficient observations preclude explaining the contributing factors to learning in each country. This introduces potential biases if learning mechanisms are differentially affected by globalization. Given the concentration of PV panel manufacturing in China, it is possible that a portion of the learning in China was due to achieving higher economies of scale than manufacturers in the U.S. and Germany. If so, then the savings reported from the differences in the global versus national market scenarios may be overestimated, assuming that U.S. and German manufacturers would have achieved similar economies of scale in a counterfactual scenario where national producers meet domestic demand. Three alternative models were estimated to disaggregate module production, installation capacity, and average plant size. Those results are shown in Appendix Tables A2, A3, and A4. Improving ease of access to credit for solar projects, as reflected in declining trends in weighted-average cost of capital (WACC), has and will continue to have a large impact on reducing power purchase prices for solar [45]. Therefore, restrictions in capital flows following from nationalistic policies could lead to even larger costs on developers. Finally, the specific outcomes in terms of estimating savings from global versus national market scenarios are sensitive to simulation parameters, such as the number of years until all national capacity is domestically supplied. These parameters can be varied and the outcomes compared using an open source application available at `https://jhelvy.shinyapps.io/solar-learning-2021/`.

Data availability

We compile a comprehensive dataset of historical solar capacity and component price globally and in the U.S., China, and Germany. All code and data are publicly available on Github at `https://github.com/jhelvy/solar-learning-2021`. Global installed PV capacity and price data are from the open database of the International Renewable Energy Agency (IRENA)[2] (`https://www.irena.org/statistics`). In the U.S, solar capacity data are from the Solar Energy Industries Association (SEIA) [46], and module prices are assembled from two sources: the Lawrence Berkeley National Laboratory (LBNL) [47] and the National Renewable Energy Laboratory (NREL)[15]. The LBNL data are used for the 2006 - 2018 period since this series ends in 2018, and the NREL data are used for 2019 - 2020 to extend the series to 2020. This was chosen because the NREL data only start in 2010, and thus the LBNL series covers a broader range (Appendix Figures A2, A3, A4). For China, both the installed capacity and module price data (2007 - 2018) were extracted from reports and presentations by the Energy Research Institute (ERI) [48], and the 2019-2020 data were extracted from China Photovoltaic Industry Association where the historical data are identical to that of ERI [49]. For Germany, capacity data are from IRENA, and module price data were extracted from Fraunhofer ISE [50]. All prices are in $2020 USD, and we adopt inflation adjustments using IMF (`https://data.imf.org/`) and exchange rates from the Federal Reserve Bank (`https://www.federalreserve.gov/releases/h10/hist/`).

Code availability

All of the raw data as well as the code used to process the data and produce all analyses and figures are publicly available on Github at `https://github.com/jhelvy/solar-learning-2021`.

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Author contributions

G.H. initiated the research idea. J.P.H. led data curation. M.R.D. wrote the initial analysis code, and J.P.H. wrote the final analysis and visualization code. All authors contributed equally to conceptualization and writing.

Competing interests

The authors declare no competing interests.

Materials & Correspondence

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Appendix

Table A1: Estimated learning model coefficients

	United States	China	Germany
(Intercept)	15 (1.04)***	18 (1.58)***	12 (0.96)***
log(cum_capacity_kw)	-0.44 (0.045)***	-0.57 (0.070)***	-0.33 (0.042)***
log(price_si)	0.15 (0.058)*	0.23 (0.079)	0.21 (0.054)
*p<0.05; **p<0.01; ***p<0.001			

Table A2: Estimated learning model coefficients from alternative model 1, which includes an additional covariate for cumulative national module production capacity

	United States	China	Germany
(Intercept)	16 (2.47)***	15 (4.89)*	18 (2.28)***
log(cum_installed_kw)	-0.23 (0.347)	0.04 (0.906)	-0.14 (0.103)
log(cum_production_kw)	-0.35 (0.505))	-0.42 (0.686)	-0.52 (0.203)*
log(price_si)	0.05 (0.146)	0.21 (0.216)	0.02 (0.105)
*p<0.05; **p<0.01; ***p<0.001			

Table A3: Estimated learning model coefficients from alternative model 2, which includes an additional covariate for cumulative national installed capacity

	United States	China	Germany
(Intercept)	15 (1.08)***	19 (2.09)***	15 (2.14)***
log(cum_installed_kw)	-0.41 (0.073)***	-0.60 (0.166)**	-0.26 (0.063)**
log(cum_installed_kw_i)	-0.04 (0.077)	0.03 (0.103)	-0.21 (0.157)
log(price_si)	0.16 (0.064)*	0.18 (0.117)	0.16 (0.063)*
*p<0.05; **p<0.01; ***p<0.001			

Table A4: Estimated learning model coefficients from alternative model 3, which includes an additional covariate for global average plant size

	United States	China	Germany
(Intercept)	15 (1.57)***	17 (2.25)***	13 (1.60)******
log(cum_installed_kw)	-0.32 (0.150)	-0.37 (0.216)	-0.49 (0.153)*
log(ave_plant_size_kw)	-0.22 (0.166)	-0.22 (0.239)	0.19 (0.170)
log(price_si)	0.20 (0.140)	0.38 (0.201)	0.09 (0.143)
*p<0.05; **p<0.01; ***p<0.001			

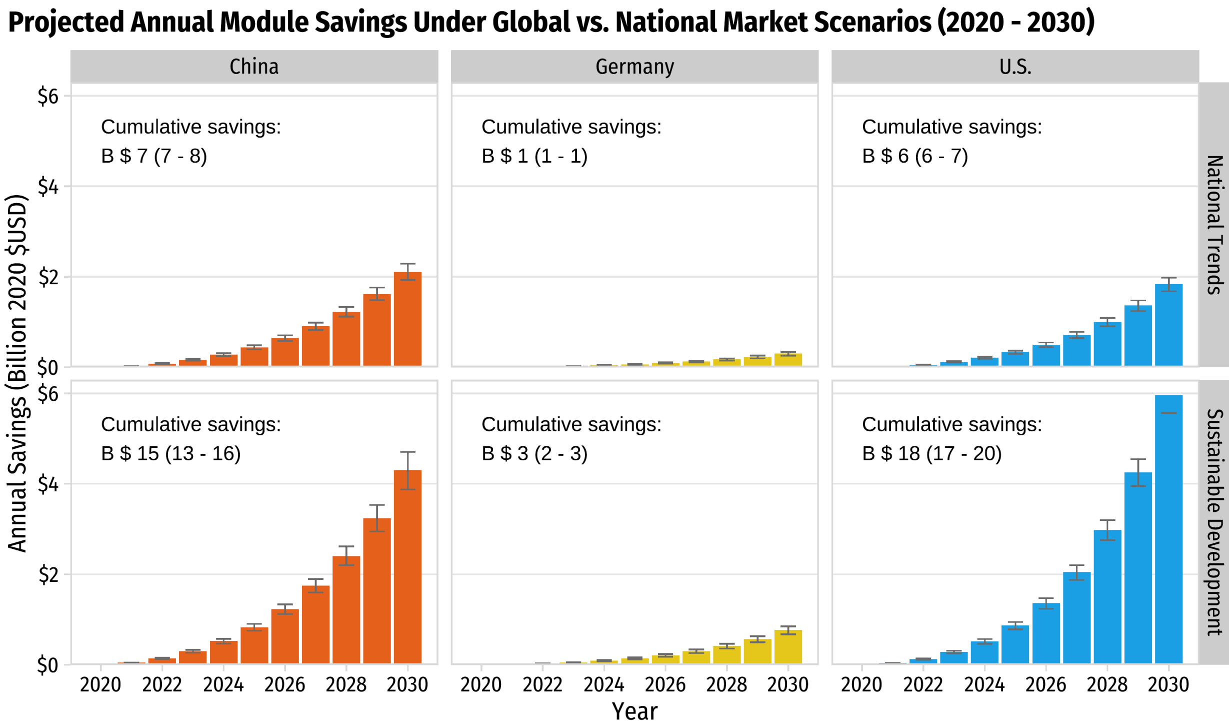

Figure A1: Comparison of projected annual savings (2020 - 2030) using global versus national market scenarios in China, Germany, and the U.S.

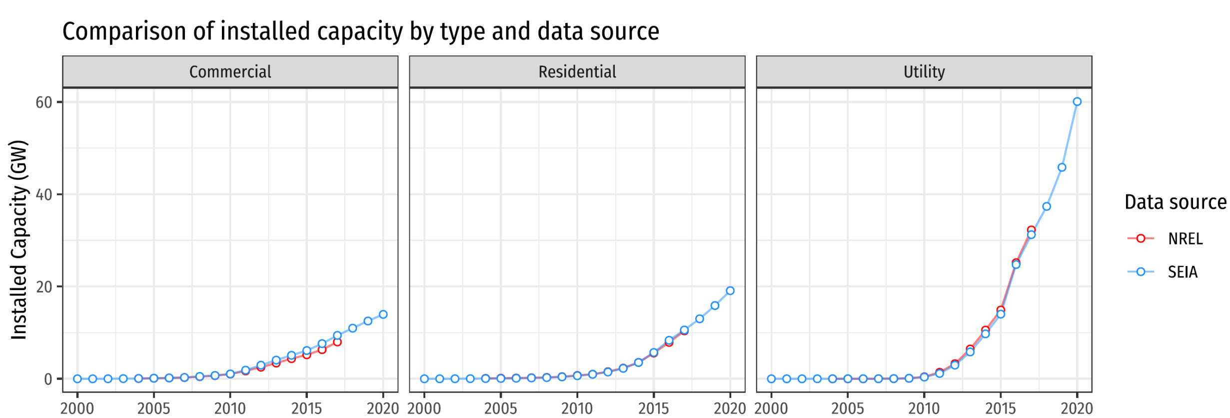

Figure A2: Comparison of the U.S. installed solar PV capacity by type and data source

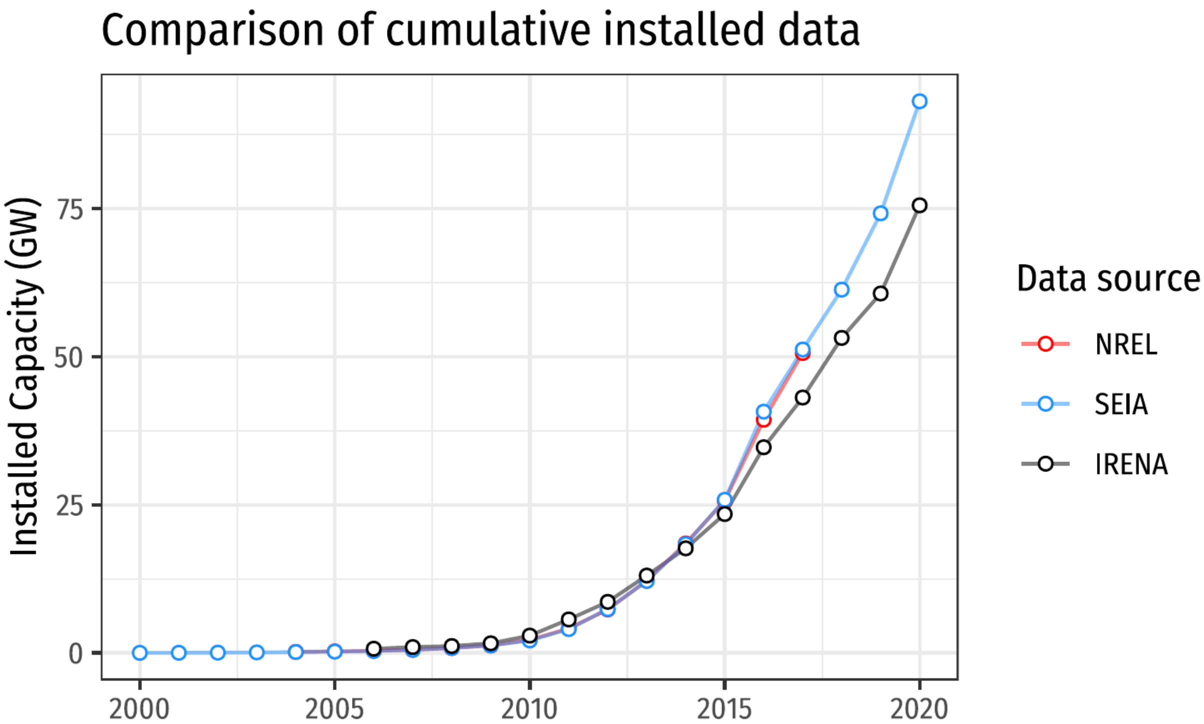

Figure A3: Comparison of the U.S. cumulative installed solar PV capacity by data source

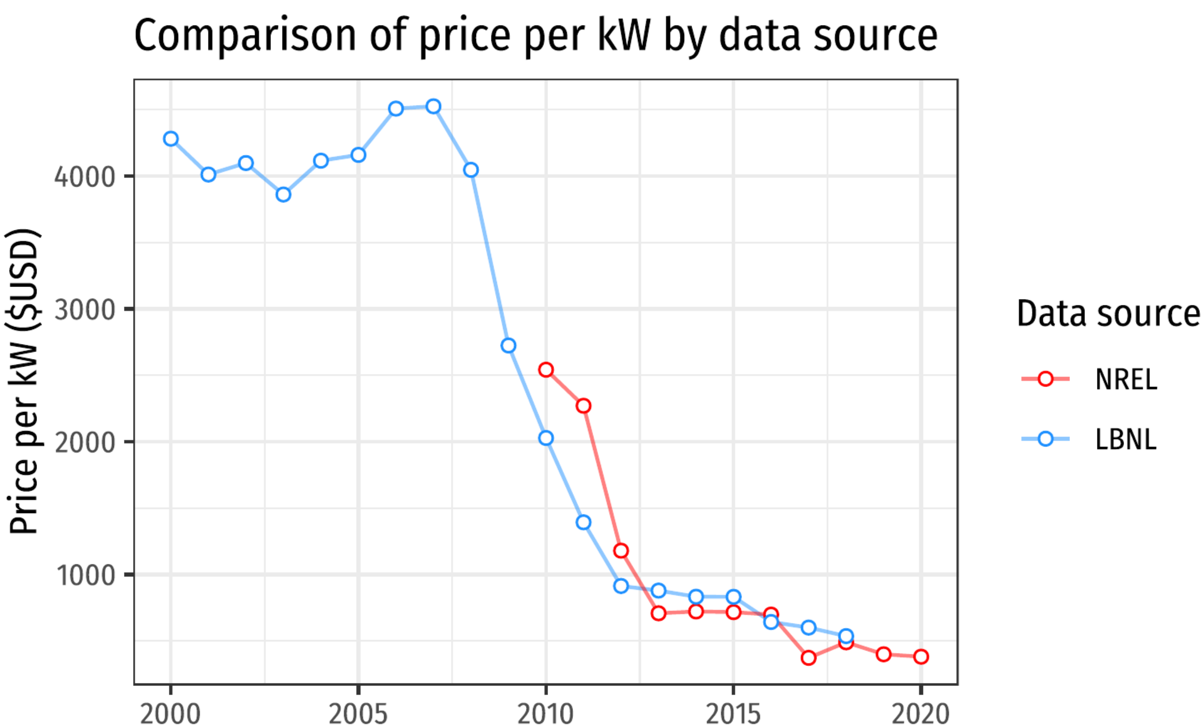

Figure A4: Comparison of the U.S. solar PV module prices by data source

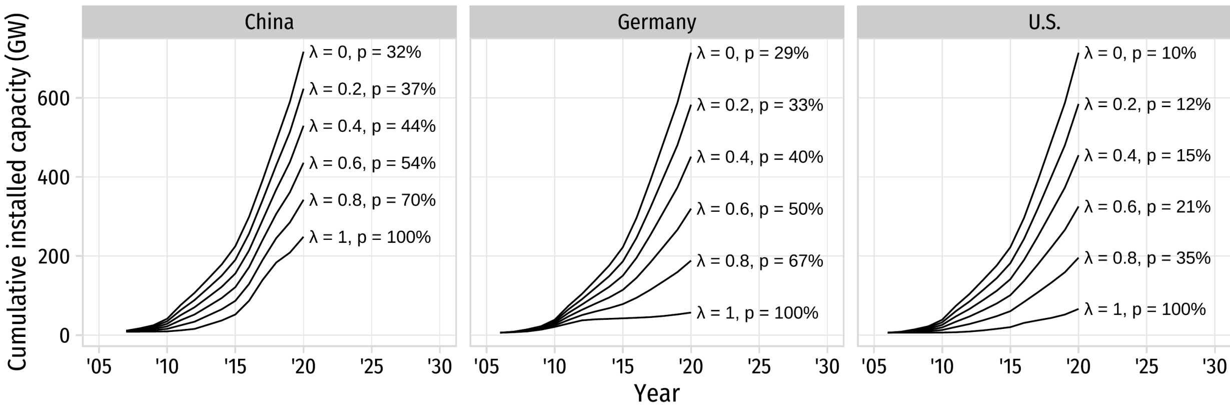

Figure A5: Relationship between λ and the proportion of national to global cumulative installed capacity (2006 - 2020)

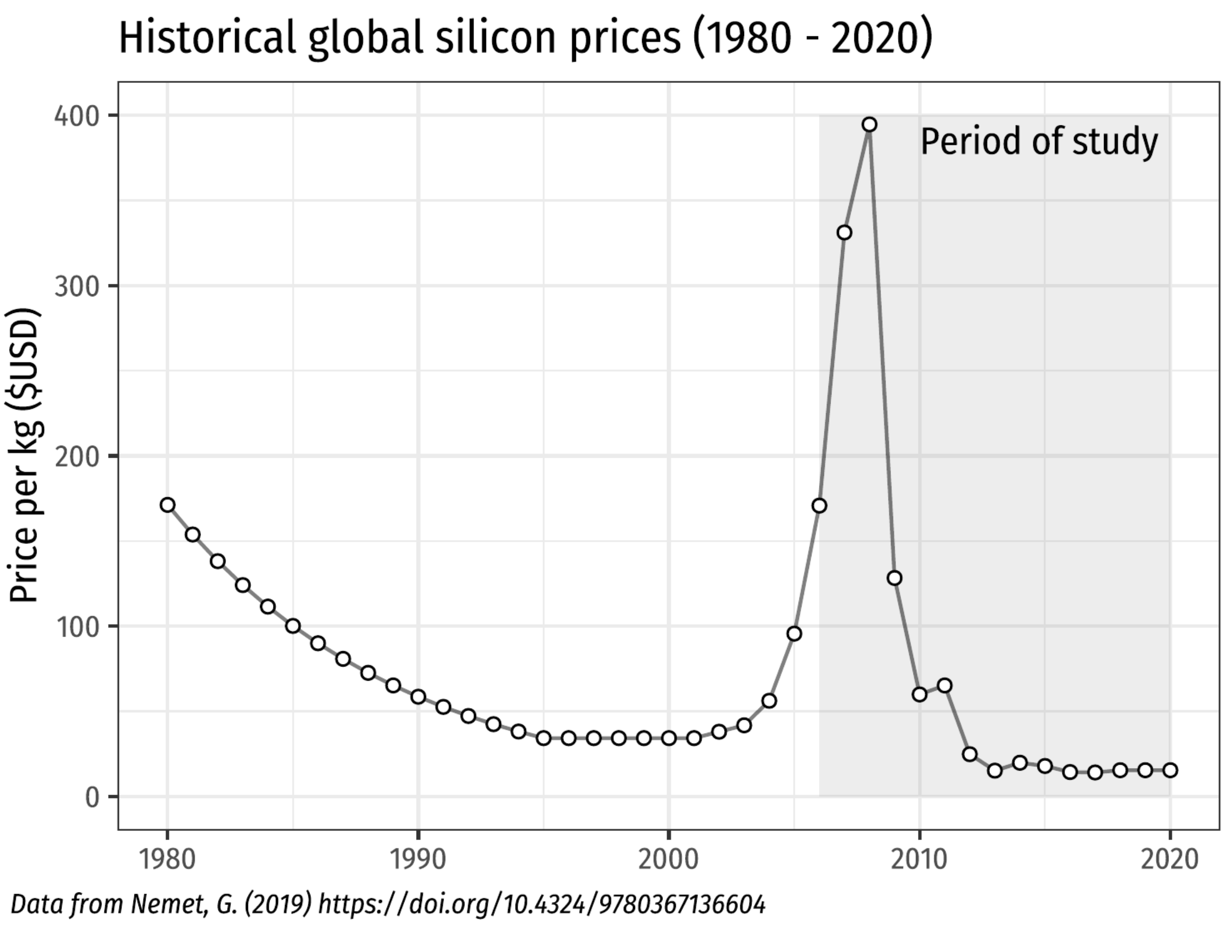

Figure A6: Historical global silicon prices (1980 - 2020)