Drivers of photovoltaics cost evolution

by

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Abstract

Photovoltaics (PV) have experienced notable development over the last forty years. PV module costs have declined 20% on average with every doubling of cumulative capacity, while global PV installations have increased at an average rate of 30% per year. However, costs must fall even further if PV is to achieve cost-competitiveness at high penetration levels and in a wide range of locations. Understanding the mechanisms that underlie the past cost evolution of PV can help sustain its pace of improvement in the future.

This thesis explores the drivers of and constraints to cost reduction and large-scale deployment of PV. By developing novel conceptual and mathematical models, we address the following questions: (1) What caused PV's cost to fall with time? (2) How may materials constraints influence PV cost and deployment? These questions are addressed in the analyses presented in Chapters 2-4.

Chapter 2 assesses the causes of cost reduction observed in PV modules since 1980. We develop a new model that identifies the causes of improvement at the engineering level and links these to higher-level mechanisms such as economies of scale. The methodology advanced can be used to evaluate the causes of improvements in any technology. By developing a model of PV modules, we find that in the early stages of the technology (1980-2001), improvements in the material usage and module conversion efficiency played an important role in reducing module cost. These improvements were mainly driven by research and development (R&D) efforts. As the PV technology matured (2001-2012), economies of scale from larger manufacturing plants resulted in significant gains. Both market-expansion policies and public R&D stimulated cost reduction, with the former contributing the majority of the cost decline from 1980 to 2012.

Chapter 3 turns to assessing the materials constraints to PV cost reduction. We ask how fast metals production should be scaled up to match the increasing demand by the PV sector, if installations grow to meet a significant portion of energy demand. Unlike previous studies, which primarily used inherently uncertain factors such as reserves to estimate limits to technology scalability, we use past growth rates of a large set of metals as a benchmark for future growth rates. This analysis shows that thin-film PV technologies such as CIGS and CdTe that employ rare metals would require unprecedented growth rates in metals production even for the most conservative PV growth scenarios. On the other hand, crystalline silicon PV can provide 100% of global electricity without silicon exceeding the historical growth rates observed by all metals in the periodic table.

Chapter 4 assesses the risks that material inputs bring to technologies today. This study develops cost-riskiness metrics based on the price behavior of metals along two dimensions: average price and price volatility. We first compare a large set of metals using these cost-

riskiness metrics. We observe that metals obtained as byproducts have higher risk than major metals. We then apply these metrics to different PV technologies by treating them as a portfolio of metals. We find that designs such as CIGS and CdTe, which use byproduct metals with high average prices and price volatilities, show signals of cost-riskiness. The approach advanced here can serve as an assessment of the cost-riskiness of technologies introduced by their materials inputs.

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Chapter 1

Introduction

1.1 Research motivation

Photovoltaics (PV) may be an attractive energy technology for mitigating climate change. Solar energy is the largest energy resource on Earth [1]. Using current PV technology in less than 1% of the land area of the United States for a year, one could meet the yearly energy consumption of the nation [2]. Despite some variability in its temporal and geographical availability, solar energy is well-distributed across the world, unlike fossil fuels and hydropower [3]. PV technologies have low emissions from operation, while emissions during manufacturing and decommissioning solar panels have the potential to go to zero as these processes are increasingly powered by low-carbon sources [4].

Besides the characteristics that make PV a good candidate for climate change mitigation, PV is an extraordinary energy technology from a technological change perspective. The costs of renewable energy technologies have fallen dramatically over the last 40 years [5], and PV in particular was one of the most rapid among electricity technologies due to ongoing research, production and installation experience, and scale economies [6, 7]. As of 2015, silicon-based PV modules were roughly 100 times cheaper than they were 40 years ago [6]. Global PV deployment has also been growing rapidly, at over 30% per year in this period [8, 9].

Continued PV deployment could reduce greenhouse gas emissions [4] and other pollutants from energy systems [10]. For PV deployment to experience continued growth in the future, however, particularly when considering the additional costs of addressing solar intermittency [11], further cost reductions are likely needed [12]. For this reason, it is important to identify what drove PV's past cost evolution to gain insight into maintaining the pace of improvement

in the future. In the process one may shed light on the drivers of technological progress in general.

Despite the rapid past decline in renewable energy technology costs, there may be constraints that could slow down or reverse these trends in the future. A relevant constraint for PV is materials [13, 14], which constitute a significant share of PV costs [15, 16, 17]. Increasing adoption of PV technologies at rates that would be relevant for climate change mitigation would require unprecedented growth in metals production [18, 19, 20]. Some current PV technologies use rare metals, e.g. tellurium and indium, which are obtained as byproducts of major metals such as copper and zinc [21, 22, 23]. Being byproducts, their price and production are dictated by the economics of the major metals that host them, giving rise to concerns about whether supply can meet demand increases [24, 25, 26, 27] with prices that remain stable enough for cost-effective PV production [28]. Assessing such materials constraints is critical for understanding the scalability of technologies, and sustaining high rates of deployment and cost improvement.

1.2   Background

Improvement trends in photovoltaics (PV) and other technologies have been studied by several research communities. One common approach, which we call 'correlational analysis', focuses on the relationship between a performance measure such as cost, and production or research investment levels [29]. One of the most widely-used correlational analysis models is the experience curve, which describes the relationship between a technology's cost and its cumulative production as a power law. Studies use the experience curve as an explanatory tool to measure the past improvement rates of technologies or as a predictive tool to estimate future rates [30, 31, 32, 29, 33]. For example, PV module costs fell by roughly 20% with every doubling of cumulative production since 1970s [34, 8]. Several mechanisms have been proposed to explain this cost reduction, such as research and development efforts, learning-by-doing, and economies of scale [7, 35, 36, 34, 37, 38]. While useful for comparing the improvement rates of different technologies, correlational analyses treat technologies as black boxes and do not model the determinants of cost within the technology. In addition, the definitions of these mechanisms in the literature are diverse and overlapping [38, 8, 39] making it difficult to separate their influence on technological improvement.

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Another group of studies models technology costs in a detailed manner [40, 41, 42, 43, 15]. These are mainly bottom-up engineering cost models that disaggregate the total cost of a technology into its cost components at a given snapshot in time, in order to understand how the components of a technology or a manufacturing process determine its cost. Only a few past studies decomposed technology costs into components over time (e.g. for coal-fired electricity [44]). In general what is missing from these studies is a method to disentangle the effects of simultaneous changes to multiple features of a technology.

In order to gain insight into the factors that led to the improvement of a technology over time, methods are needed that go beyond correlational analyses and static cost decompositions. In Chapter 2, we introduce the idea of a dynamic-yet-mechanistic model, which can be applied to PV or other technologies, and which captures engineering features.

As noted earlier, materials availability may limit the cost and deployment trends of PV [13, 18, 45, 21]. Previous research has highlighted that the availability of input materials at affordable prices would be essential for scaling up PV production in a cost-effective way [14, 13, 43, 42]. However, if the demand for materials grows rapidly while supply is constrained, materials prices can rise, limiting PV's potential for cost improvement. This can make an input a 'critical' material from the perspective of a technology or industry.

Previous studies generally described materials as 'critical' if they are essential to industry and difficult to substitute, but sourced from few and politically unstable regions [46, 47, 48, 49, 50, 51]. Studies have identified possible critical materials not only for PV but for many technologies, basing indicators of short-term and long-term risks on various political, economic and technological factors. Assessments of long-term risks have usually been made based on projections about future demand as well as future supply, the latter mainly determined by geology and technological capabilities to extract materials. On the other hand, short-term risks can be influenced more significantly by other factors such as the political situation in sourcing regions, or the effects of being a byproduct metal [28, 52].

In the case of PV, concerns about long-term materials risks have spurred research on materials availability for a rapidly growing PV industry [53, 21, 13, 54]. If PV deployment follows the growth trajectories outlined in several energy scenarios [55, 56, 57, 58, 59, 60, 61, 62], the demand for input materials will increase [18]. Studies have mainly focused on assessing the limits using data on reserves, together with expected annual production levels for long-term PV deployment. However, reserve estimates are uncertain and updated as

discoveries occur, limiting the usefulness of this approach. In Chapter 3 we introduce a new approach that characterizes the long-term risks while recognizing these sources of uncertainty.

We also analyze short-term materials risks that may already be evident in current data. Many metals have been deemed critical, including those used in low-carbon technologies such as PV, wind turbines and electric cars [63, 64, 65, 66, 67]. Across past studies, various definitions and indicators of criticality have been used, leading to different results in the comparison of metals [68]. However, these definitions have not focused on the risks to technology production costs. In Chapter 4, we propose a definition of criticality to evaluate the risks that may be posed by input materials in the short term from the perspective of technology costs.

1.3 Research contributions

This thesis is motivated by the dramatic reductions in PV costs over the past half century and by the potential material constraints that might limit further cost reductions. We aim to understand and evaluate the factors that enable and inhibit scaling up PV deployment: What are the mechanisms by which PV and other technologies improve, and what are the material constraints to further improvement and widespread deployment?

Addressing these research questions requires several new conceptual and mathematical models. One of the conceptual advancements of this thesis is that it views technology cost trends as processes that can be modeled starting from the components within the technology. This marks a departure from the correlational analyses used in previous studies that treat a technology as a black box when describing its cost trend over time. The conceptual advancement of this thesis allows one to identify the causes of improvement at the engineering level and to connect them to higher-level mechanisms such as learning-by-doing. The causes are identified by a novel dynamic and mechanistic model of technological change with two steps. The first step is to build a *cost model* that describes how several key variables determine the cost of a technology, and the second step is to develop a *cost change model* that computes the contributions of the key variables to the overall cost change, when the dependencies between variables are taken into account. By analyzing the mechanisms of improvement over time, this method bridges dynamic models of technology evolution and detailed engineering cost models.

By applying these models to PV module costs, we obtain critical lessons for technological improvement and policy. We find that multiple *low-level mechanisms*, such as increasing conversion efficiency, decreasing material usage, and increasing wafer area, played key roles in reducing PV costs. Technologies consisting of multiple features each with room for innovation, as in the case of PV, may be more likely to experience rapid cost declines. In the earlier stages of PV technology, public R&D was the main *high-level mechanism* that reduced costs by improving multiple low-level variables such as material usage and conversion efficiency. As the technology matured, economies of scale, which were achieved through building larger manufacturing plants, became a more significant high-level mechanism, approaching R&D in importance. Economies of scale will likely offer an avenue for further cost reductions.

This thesis also contributes insight to the ongoing debate on the effectiveness of market-expansion policies versus publicly-funded R&D [31, 69, 70], by estimating their relative contributions to cost reduction. We show that policies that stimulate market growth have played a key role in enabling PV's cost reduction, through privately-funded R&D and scale economies, and to a lesser extent learning-by-doing. These policies contribute around 70% of the cost decline in PV modules between 1980 and 2012. Going forward, complementing market-expansion policies by public R&D may help reduce the risks of exhausting the improvement potential of current silicon-based module technology. For example, exploring technologies based on other abundant semiconductor materials may unlock the potential for lower costs.

This thesis also advances the current understanding of materials constraints to technology cost and deployment trends. We evaluate materials-related risks over both the long term and the short term. In analyzing long-term risks, we project the material requirements of PV into the future. Unlike previous studies, which primarily used inherently uncertain factors such as reserves to estimate limits to technology scalability, we study constraints on long-term technological adoption by looking at historical metals production data. We quantify a range of past growth rates in the metals production sector by pooling historical annual production data on many metals. We use these historical growth rates to assess the degree to which future growth scenarios fall within the range of trends observed in the past. Our method of pooling data for many metals, instead of focusing on PV metals only, allows one to deal with the uncertainty about the path a given metal may follow in the future.

We apply our new method to quantify the possible materials constraints that might affect

costs of different PV technologies in the future. We observe that the median growth rate across all metals in the last 40 years was 2.3% per year. The maximum growth rate was 15% per year, while 95% of the past growth rates were below 9% per year. This information allows us to better observe differences between PV technologies in terms of long-term materials constraints. We find that the annual growth rates required for the production of byproduct metals (indium, gallium, tellurium, and selenium) employed in thin-film PV technologies to satisfy projected PV demand levels in 2030 are either unprecedented or fall on the higher end of the historical growth rates distribution. On the other hand, silicon supply restrictions do not appear to pose a binding scalability constraint, due to the abundance of this metal.

In analyzing the short-term materials risks of PV, we argue that metals price data contains information on material availability risks. If metals supply is constrained relative to demand, this can cause volatile prices. PV manufacturers or other users of metals may be adversely affected since increasing materials prices can increase production costs unexpectedly. To evaluate these effects, we propose a definition of metals criticality, namely the *cost-riskiness* that materials can bring to the technologies they are used in. This definition adds to the previous criticality literature and can be used to evaluate the materials risks of any technology.

To measure cost riskiness, we pool historical data on many metals as we do to analyze long-term materials risks. We measure the cost riskiness that a technology can face due to materials availability along two dimensions: Average price and price volatility of the metals. While average price provides information on the contribution of a unit mass of material to the overall technology cost, price volatility reflects the fluctuations in this impact. We observe that there are already signals of riskiness for certain metals, namely the byproduct metals such as tellurium and indium, since the prices of byproduct metals are higher and more volatile than other metals. PV technologies that use these materials, such as CdTe and CIGS, may be exposed to higher risks.

Our work on both the long-term and short-term materials risks can be used to assess whether a photovoltaic material that works well in a lab or a small commercial setting is a good candidate for reaching terawatt-scale PV adoption. We provide tools and insights that scientists and engineers who develop technologies can use to evaluate materials criticality. The methods and findings in this thesis can also be used to assess other low-carbon energy technologies, such as battery technologies.

1.4 Thesis overview

The following three chapters address the main research question of this thesis – how can we evaluate the enabling factors and constraints in scaling up PV deployment? The chapters are based on a journal paper that has been published [19], another paper that is in review [6], and a third paper that is in preparation.

Chapter 2. The second chapter assesses the causes for decreasing PV technology costs. Our method quantifies the low-level mechanisms that have reduced the costs at the engineering level and links these to high-level mechanisms. Applying this method to PV modules reveals that the key drivers of cost reduction have been changing over time. The most important low-level mechanism in 1980-2001 was the increased module efficiency that contributed almost 30% of the module cost decline in this period, and the main high-level mechanism that drove this change was research and development (R&D). After 2001, as the PV technology matured and manufacturing plant sizes grew, economies of scale became more significant, approaching R&D in importance. Overall, both market-expansion policies and public R&D have been important, with the former contributing around 70% of the cost decline in PV modules in 1980-2012.

Chapter 3. The third chapter turns to assessing the long-term materials risks that may slow down the cost decline and production growth in PV. We analyze long-term constraints by looking at historical metals production data. We first ask how fast metals production should be scaled up to match increasing PV deployment. We then compare the required growth rates in metals production to the past growth rates observed for a large set of metals over the last forty years, to see whether the required growth rates have a historical precedent. This analysis shows that thin-film PV technologies such as CIGS and CdTe that employ rare metals would require unprecedented growth rates in metals production to provide even low amounts of global electricity. On the other hand, crystalline silicon PV can provide 100% of global electricity without silicon exceeding the historical growth rates.

Chapter 4. The fourth chapter studies the materials risks that can affect PV technology costs and which may already be evident in price data. We ask what signals we get from the price behavior of metals that can indicate the risks in using these materials in PV production.

We first develop metrics to characterize the cost risk of a metal based on its average price and price volatility. We find that byproduct metals are in general riskier. We then develop a method for evaluating the cost-riskiness of a technology by treating it as a portfolio of metals. Demonstrating this approach on PV, we find that PV technologies such as CdTe and CIGS that rely on byproduct metals may face higher cost-riskiness, whereas other technologies such as perovskites perform better along our cost-riskiness metrics.

Chapter 2

Evaluating the causes of photovoltaics cost reduction

Photovoltaics (PV) module costs have declined rapidly over forty years but the reasons remain elusive. We advance a conceptual framework and quantitative method for quantifying the causes of cost changes in a technology, and apply it to PV modules. Our method begins with a cost model that breaks down cost into variables that changed over time. Cost change equations are then derived to quantify each variable's contribution. We distinguish between changes observed in variables of the cost model – which we term low-level mechanisms of cost reduction – and R&D, learning-by-doing, and scale economies, which we refer to as high-level mechanisms. Increased module efficiency was the leading low-level cause of cost reduction in 1980-2012, contributing over 25% of the decline. Government-funded and private R&D was the most important high-level mechanism over this period. After 2001, however, scale economies became a more significant cause of cost reduction, approaching R&D in importance. Policies that stimulate market growth have played a key role in enabling PV's cost reduction, through privately-funded R&D and scale economies, and to a lesser extent learning-by-doing. The method presented here can be adapted to retrospectively or prospectively study many technologies, and performance metrics besides cost.[1]

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[1]This chapter has been submitted for review with co-authors James McNerney and Jessika E. Trancik [6].

2.1 Introduction

Photovoltaics (PV) have exhibited the most rapid cost decline among energy technologies [4] (Fig. 2-1.) In parallel with cost declines and performance improvement, global PV deployment has grown rapidly [5]. Continued PV deployment could help reduce greenhouse gas emissions and other pollution from energy systems [10], and contribute to climate change mitigation [4]. For PV deployment to experience sustained growth in the future, however, particularly when considering the additional costs of addressing solar intermittency [11], further cost declines are likely needed [12]. This paper aims to identify the causes of PV's rapid cost declines in the past and gain insight into maintaining the pace of improvement in the future. More fundamentally, we aim to advance a model for understanding the mechanisms of technology improvement at multiple levels, from human efforts to devices, that can be applied to many technologies and measures of performance.

Improvement trends in PV and other technologies have been studied by various research communities. Correlational analysis is a common approach in these studies, often focusing on cost (or other measure of performance) and production or research investment levels [29]. One of the most widely-used models is the experience curve, which relates a technology's cost to cumulative production as a power law. Using this relationship as an explanatory or predictive tool, studies have estimated the rates of performance improvement for a range of technologies [30, 31, 32, 29, 33]. For example, PV module costs fell by about 20% with every doubling of cumulative capacity since the 1970s [34, 8]. Several explanations for this cost decline have been proposed, such as public research and development efforts and various consequences of market growth [7], including learning-by-doing, economies of scale, and private research and development efforts [35, 36, 34, 37, 38]. These studies share an approach to examining technology cost evolution where important high-level drivers of cost reduction are assumed and their influence on cost is inferred based on correlation. Technologies are treated as black boxes and the causes of cost reduction within technology are not modeled mechanistically.

Another group of studies uses detailed, device-level cost models, to understand how features of a technology or manufacturing process contribute to costs at one or more snapshots in time. Several such studies exist for PV, and they provide information on how individual cost components contribute to total costs, while taking into account the physics of PV
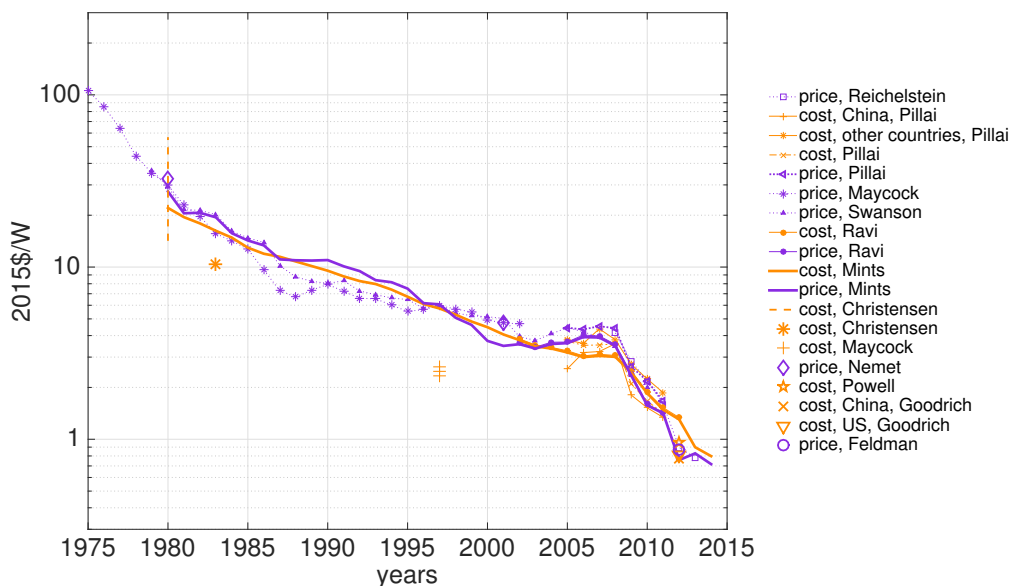
Figure 2-1: Costs are shown in orange, and prices are shown in purple. References: Reichelstein [71], Pillai [72], Maycock price data from [8] and cost data from [73], Swanson [74], Ravi [75], Mints [9], Christensen [76], Nemet [8], Powell [41], Goodrich [77], Feldman [78]. Values are averages across different PV technologies except for those in Powell [41] (multicrystalline silicon) and Goodrich [77] (monocrystalline silicon). Differences across datasets show the effect of sampling errors.

technologies [40, 41, 42, 43, 15]. They also propose avenues for future technical improvement at the device or manufacturing level, and estimate cost reductions that might be achieved in the future [79]. Missing from these studies, however, is a method of accurately quantifying how each change to a feature of the technology or manufacturing process contributes to cost reductions, when many changes occur simultaneously. This knowledge is needed to understand the mechanisms of cost reduction but requires further modeling advances.

Pursuing both dynamic and detailed, device-level models is critical for identifying the causes of improvement in PV and other technologies. This combined approach would address inherent limitations in using correlational analyses to identify causal effects, especially in the case where data is limited, as is often the case in technology evolution research. This approach would also address the lack of dynamics in device-level studies. A few past studies have begun to develop such a methodology by decomposing technology costs over time [8, 44]. A study of the drivers of PV module cost changes from the 1970s to the early 2000s [8] pioneered a bridge of this kind, and found that learning-by-doing had a limited effect on cost reductions.

In this paper we propose a new conceptual framework and dynamic-yet-detailed quantitative model for analyzing PV's (or any technology's) cost evolution. We start with a cost equation that computes costs from a set of explanatory variables, such as module efficiency, wafer area, and manufacturing plant size. From this we derive cost change equations that estimate the contribution of each variable to cost changes. Since multiple simultaneous changes to variables have different impacts on cost than individual changes summed together, attributing cost changes to individual variables is challenging. Our method of estimating variable contributions is based on adapting calculus derivative formulas to finite differences.

In attributing PV's cost decline to particular causes, we draw a distinction between *low-level* causes (or mechanisms) and *high-level* causes (or mechanisms). Low-level mechanisms explain cost reduction in terms of changes to particular variables of a cost model. High-level mechanisms explain cost reduction in terms of processes like public and private R&D, learning-by-doing, and scale economies that can influence technology costs in less specific ways. High-level mechanisms are discussed widely in studies of historical technology evolution.

By considering both the low-level and high-level causes of PV's improvement we uncover lessons that are useful for a variety of decision-makers. These may include engineers who design and manufacture PV modules, or firm managers and government policy-makers who develop strategy to support technological development. For example, our findings contribute to a long-standing debate concerning the effect of public investments in R&D versus market-expansion policies [31, 69, 70].

We focus on crystalline silicon PV modules because of their long history and dominant market share among PV technologies [80]. Since the 1950s, this technology has improved steadily due to R&D and manufacturing efforts [40]. We analyze the costs starting in 1980, when space applications of PV were overtaken by terrestrial applications, which did not require as high quality and reliability [81, 8, 82]. We look at typical costs globally, since PV modules are manufactured and traded globally. The method we develop can be adapted to study PV systems as a whole (including non-module cost components that show significant potential for cost reduction [83, 84]), and a wide range of other technologies and measures of performance other than cost [85, 10, 86]. The method might also prove a useful quantitative framework for eliciting high-quality input from experts on the prospects for future technological improvements [87].

This paper is organized as follows: Section 2.2 provides a detailed explanation of the cost

model. Section 2.3 explains the method of attributing cost changes to variables. Section 2.4 shows the results of our analysis and the connection between low-level and high-level mechanisms. In Section 2.5 we discuss the implications for future developments in PV and conclude.

2.2   Cost model

We first develop a cost model for PV modules. The cost components are calculated based on quantities (or usage ratios) ϕ and prices of inputs p used in manufacturing.

$$C_m \left(\frac{\$}{module} \right) = \underbrace{\frac{1}{y_m} \sum_{i \neq c,w} \phi_{mi} p_i}_{\text{non-cell module costs}} + \underbrace{\frac{n_{mc}}{y_m y_c} \sum_{i \neq w} \phi_{ci} p_i}_{\text{non-wafer cell costs}} + \underbrace{\frac{n_{mc} n_{cw}}{y_m y_c y_w} \sum_i \phi_{wi} p_i}_{\text{wafer costs}}, \qquad (2.1)$$

where

y_m yield at module manufacturing

y_c yield at cell manufacturing

y_w yield at wafer manufacturing

ϕ_{mi} quantity of input i per module

ϕ_{ci} quantity of input i per cell

ϕ_{wi} quantity of input i per wafer

p_i price of input i

n_{mc} number of cells per module

n_{cw} number of wafers per cell.

While this equation has been written to represent wafer, cell, and module costs, which is an decomposition scheme specific to PV, the formulation of costs in terms of usage ratios (ϕ) and input prices (p) is a general one that can describe any technology. ϕ variables generally change as the result of engineering efforts to improve efficiency and materials utilization, while p variables change due to bulk purchasing, scarcity or other market effects [19], or input substitutions.

   At each of the three levels of PV manufacturing costs – wafer production, cell production, and module production (vertical levels in Fig. 2-2) – there are costs for materials, labor,
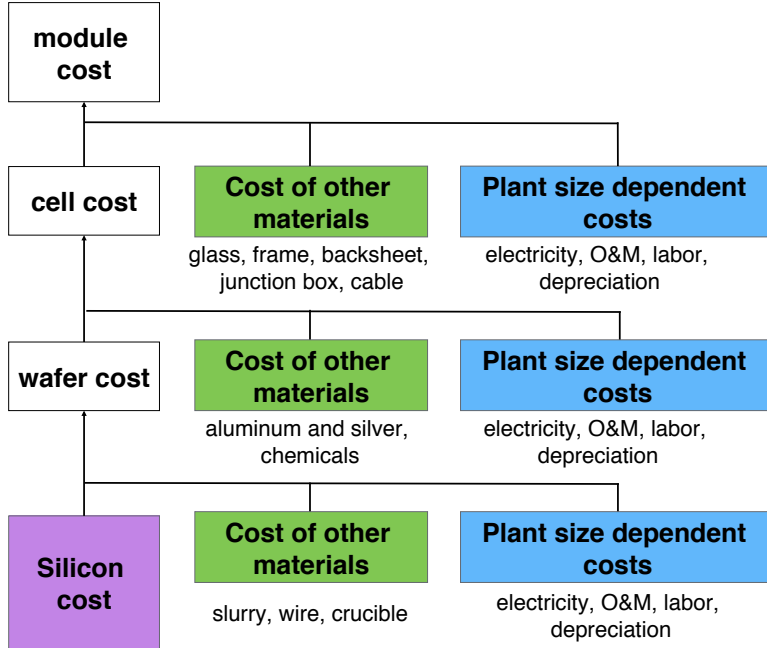
Figure 2-2: Cost components for wafer, cell and module levels (vertical disaggregation) and different input types (horizontal disaggregation).

operation & maintenance, electricity, and depreciation of plant and equipment. Decomposing by level disaggregates the production process for PV modules, but creates challenges here for estimating the sources of cost reduction over time. A consistent categorization of costs is needed for every time period of interest starting with 1980, but such early cost data is scarce. Instead we accomplish this consistency over time by decomposing module production costs into three components by input type: silicon costs, non-silicon material costs, and plant-size dependent costs (horizontal categories in Fig. 2-2). These components are further modeled as described below.

2.2.1 Silicon costs

Historical prices of silicon (i.e. polysilicon) can be obtained from the literature [35, 88, 8] or from industry sources [9]. The amount of silicon used per wafer is a function of wafer area, silicon density, silicon layer thickness, and silicon utilization (the fraction of the silicon ingot used in the wafer after accounting for losses). Multiplying by the number of cells and the price of silion, total silicon cost for the module can be expressed as

$$\text{Si cost} = n_{mc}\frac{Ah\rho}{U}p_s = n_{mc}Av\rho p_s. \tag{2.2}$$

Factor	Unit	1980	2001	2012
Plant size (K)	MW/yr	0.125	14	400
Module efficiency (η)	unitless	8%	13%	15%
Polysilicon price (p_s)	2015\$/kg	66	32	21
Wafer area (A)	cm^2	80	150	243
Silicon usage (v) $\equiv$ thickness (t)/utilization (U)	cm	0.25	0.07	0.04
Yield (y)	unitless	75%	88%	95%
Share of materials costs (θ)	unitless	0.58	0.43	0.65
Scaling factor (b)	unitless	0.27	0.27	0.27
Module cost	2015\$/W	22.1	4.1	1.3

References: Plant size: 2012 [9, 41]. Module efficiency: 1980 [8, 9]. Silicon usage: 1980 [89, 8], 2001: [90, 8], 2012: [41]. Share of materials costs: 1980: [91], 2001: [73], 2012: [41]. Scaling factor: all years [73]. Other values shown in the table are obtained from [9].

Table 2.1: Data used to calculate module cost components.

Here n_{mc} is the number of cells per module, A is wafer area, h is wafer thickness, $\rho = 2.33$ g/cm^3 is wafer density, U is silicon utilization, and p_s is the price of polysilicon. We define the combination $v \equiv h/U$, which we refer to as 'silicon usage' for simplicity. The data for these variables are provided in Table 2.1.

2.2.2 Non-silicon materials costs

Non-silicon materials include the crucible used to produce silicon ingots; slurry and wire used for wafer-sawing; aluminum and silver pastes, chemicals and screens used in cell manufacturing; and glass, frame, backsheet, encapsulant, ribbon, junction box and cable used in the module [41]. To a first-approximation, the usage of these materials can be categorized as proportional to wafer area (e.g. aluminum pastes), proportional to module area (e.g. glass), proportional to module perimeter (e.g. frame), or neither (e.g. junction box), so that costs would take the form

$$\text{non-Si materials costs } = c_0 + n_{mc}c_1 A + c_2 A_m + c_3 P \tag{2.3}$$

with A representing wafer area, A_m the module area, P the module perimeter, and the c_i various constants. Because of data limitations, and since most materials costs depend on area, we ignore the fixed and perimeter dependent categories in this expression. Since the

late 1970s wafer area A and module area A_m have increased proportionally,[2] $A \propto A_m$. Thus we simplify Eq. (2.3) to

$$\text{non-Si materials costs} = n_{mc}cA, \tag{2.4}$$

where c is the per-area cost of all non-silicon materials and A is wafer area. Here the non-Si materials costs account for the costs at all of the wafer, cell and module levels. We derive the value of c from estimated materials costs in the three time periods. Based on the literature, the share of materials costs in PV modules varied between 35-65% [73, 41]. We calculate the materials costs using the total module cost and the fraction due to materials, subtract the cost of silicon, and divide out the wafer area to obtain c.

2.2.3   Plant size-dependent costs

We assume that electricity, labor, maintenance and depreciation costs per wafer varies with the plant size due to scale economies. We model this group of costs as

$$\text{plant size-dependent costs} = n_{mc}p_0 \left(\frac{K}{K_0}\right)^{-b}, \tag{2.5}$$

where K_0 is a reference plant size, p_0 represents the total of these costs for a plant with the reference size, and b is the scaling factor. For convenience we take $K_0 = 400$ MW (the value for 2012), though this choice is just a convention since the effects of a different choice of K_0 would be absorbed into a different value for p_0. We use $b = 0.27$ as the scaling factor [73]. We obtain this value by computing the change in labor, capital, utilities and overhead costs between plants of two sizes described in [73]. We obtain p_0 for 2012 from [41]. For 1980 and 2001 we compute p_0 by computing non-materials costs and dividing out the factor $(K/K_0)^{-b}$.

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[2]The relationship between wafer area and module area is given by

$$A_{\text{module}} = \frac{n_{mc}A}{\alpha}$$

where n_{mc} is the number of cells per module and α is the area utilization, the fraction of module area used by cells. Both wafer area and module area increased about three-fold in the last twenty years, while α and n_{mc} have stayed almost constant in a typical module [76, 41].

2.2.4   Final cost equation

The power output of a module K_m is given by

$$K_m = \frac{\sigma n_{mc} A \eta}{\alpha} \tag{2.6}$$

where $\sigma = 0.1$ W/cm^2 is the solar constant, n_{mc} is the number of cells per module, A is wafer area, η is module efficiency, and α is module area utilization. We assume a constant value of $n_{mc} = 72$. Summing the three components of module costs, and dividing by module capacity, total costs are

$$C\left(\frac{\$}{W}\right) = \frac{\alpha}{\sigma A \eta y}\left[Av\rho p_s + cA + p_0\left(\frac{K}{K_0}\right)^{-b}\right]. \tag{2.7}$$

Some wafers, cells, and modules created during production are faulty and must be discarded, leading to waste and additional costs. To account for this we include the production yield y above.[3] We populate Eq. (2.7) with historical data from three snapshots in time: 1980, 2001 and 2012 (Table 2.1). Theoretically one could model all of the cost components including the materials, electricity, labor and so on as dependent on both plant size and wafer area. However, the data to populate such a sophisticated model is not available. Therefore we make a compromise and model the electricity, labor, maintenance and depreciation costs as scaling with plant size, while we model materials costs as dependent on wafer area.

Using the cost equation and the data in Table 2.1, we obtain the three cost components for 1980, 2001 and 2012. The cost components are illustrated in Fig. 2-2 and their values are shown in Table 2.2. While all of the cost components have gone down in units of \$/W, their shares of total cost have varied. In particular silicon has became a smaller fraction of total cost over time, while non-silicon materials have become a larger fraction. The share of the plant-size dependent costs increased between 1980 and 2001 and then decreased after 2001.

Our decomposition variables are similar to [8] (and one of the time periods we consider (1980-2001) is the same as in [8]), though there are a few important differences which are summarized here. We include the contribution of non-silicon material costs, which are not considered in [8]. To avoid double-counting the reductions from efficiency improvements, we model silicon usage in units of g/module instead of g/W. Similarly we model plant

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[3]Wafer, cell and module production each have individual process yields, though for simplicity we represent overall yield with one value.

Cost component	1980		2001		2012	
	2015$/W	Percentage	2015$/W	Percentage	2015$/W	Percentage
Silicon cost	5.70	26%	0.41	10%	0.12	9%
Non-silicon materials cost	7.14	32%	1.34	33%	0.72	55%
Plant size-dependent cost	9.29	42%	2.33	57%	0.46	35%
Total module cost	22.13		4.08		1.30	

Table 2.2: Cost components in 1980, 2001 and 2012. Total module costs are obtained from [9].

output in units of modules/year instead of W/year. The share of costs that we find to be plant size-dependent and area-dependent are different. In [8], all costs are modeled as being plant-size dependent while we model only non-materials costs as plant-size-dependent, based on [73]. Also based on [73] we use a higher exponent for scale-dependent costs, $b = 0.27$ versus $b = 0.18$ in [8]. Therefore, compared with [8] our plant scale variable affects a smaller fraction of total module costs, while influencing this fraction more strongly. We similarly model all materials costs as area-dependent, and all non-materials costs as non-area-dependent. As a result a much larger fraction of costs are independent of wafer area in our model, 35-60% depending on the period versus 4% in [8]. Other differences in the modeling approach used here and in [8] are discussed at the end of Section 2.3.

2.3 Attributing cost changes to variables

How much of the cost reduction in PV modules came from each variable in Eq. (2.7)? Here we outline a general approach for computing these contributions from an equation for costs, with the derivation given in the SI. Identifying the determinants of a change in technology costs is more challenging than obtaining snapshots of cost components over time for two reasons. First, one must unravel the network describing how cost components (e.g. non-silicon materials costs) depend on input variables (e.g. wafer area). A second challenge is to decompose cost changes in discrete time.

To address these challenges, we first write down (through knowledge of a technology) an equation for cost as a function of a vector of explanatory variables (EVs):

$$C(\mathbf{r}^t) = \sum_i c_i(\mathbf{r}^t). \tag{2.8}$$

C is the cost of the technology and $\mathbf{r}^t$ is the vector of EVs at time t. The total cost is a sum over several cost components c_i that depend on the EVs. Often the cost components can be written as products of functions of the EVs, as is the case with Eq. (2.7), so that we can write

$$c_i(\mathbf{r}^t) = c_{i0} \prod_j g_{ij}(r_j^t) \tag{2.9}$$

where $g_{ij}(r_j^t)$ gives the dependence of the ith cost component on the jth variable. The prefactor c_{i0} combines any other constants that do not depend on the EVs. In the SI we show that the change to total cost is approximately

$$\Delta C \approx \sum_j \left(\sum_i \tilde{c}_i \, \Delta \ln g_{ij} \right) \equiv \Delta C_{\text{approx}}, \tag{2.10}$$

where $\tilde{c}_i \equiv \sqrt{c_i(\mathbf{r}^1)c_i(\mathbf{r}^2)}$ is the geometric average of the cost component i in the two time periods, and $\Delta \ln g_{ij} = \ln g_{ij}(r_j^2) - \ln g_{ij}(r_j^1)$. Eq. (2.10) implies that the contribution of the jth variable is

$$\Delta C_j = \sum_i \tilde{c}_i \, \Delta \ln g_{ij}. \tag{2.11}$$

Eq. (2.11) provides an estimate of how much cost reduction the jth variable is individually responsible for.

In our case, the EVs are $\mathbf{r}^t = \left(A^t, \eta^t, y^t, K^t, p_s^t, v^t, c^t, p_0^t \right)$. The cost components in Eq. (2.7) can be written in the form of Eq. (2.9) as

$$c_1(\mathbf{r}) = \left(\frac{\alpha \rho}{\sigma} \right) v p_s \eta^{-1} y^{-1} \tag{2.12}$$

$$c_2(\mathbf{r}) = \left(\frac{\alpha}{\sigma} \right) c \eta^{-1} y^{-1} \tag{2.13}$$

$$c_3(\mathbf{r}) = \left(\frac{\alpha}{\sigma K_0^{-b}} \right) p_0 K^{-b} A^{-1} \eta^{-1} y^{-1}, \tag{2.14}$$

which are (from top to bottom) silicon costs, non-silicon materials costs, and plant-dependent costs. Then Eq. (2.11) can be computed to form the estimates for individual variables. For

example, the module cost change due to the change in efficiency is

$$\Delta C_\eta = \sum_{i=1}^{3} \tilde{c}_i \Delta \ln \eta^{-1} = \left[\sum_{i=1}^{3} \sqrt{c_i(\mathbf{r}^1) c_i(\mathbf{r}^2)} \right] \left(\ln \frac{\eta^1}{\eta^2} \right). \tag{2.15}$$

To complete the approach, we make one final modification to Eq. (2.11). ΔC is a non-linear function of variable changes Δr_j; however, ascribing portions of ΔC to particular variables necessarily means making a linear approximation. This in turn means that the sum over ΔC_j (i.e. ΔC_{approx}) can be greater or less than the actual change in cost ΔC. Our goal is to score the relative importance of different EVs, not to characterize the non-linearity of ΔC, so in computing the contributions of EVs we normalize Eq. (2.11) as follows:

$$\Delta C_j^{\text{norm}} = \frac{\Delta C}{\Delta C_{\text{approx}}} \Delta C_j. \tag{2.16}$$

This normalization guarantees that the sum over ΔC_j^{norm} sum to ΔC, and percentages based on ΔC_j^{norm} sum to 1.

An important departure from the method of [8] is that we start with a cost equation first rather than beginning directly with cost change equations. This two-step approach has significant advantages. It ensures that our cost change equations are consistent with a realizable cost model, whose values can be directly compared with actual costs. A cost model shows explicitly how variables jointly determine total cost, making it easier to see what modeling assumptions are being made. It also helps to avoid double-counting or undercounting the effects of explanatory variables on costs, because the dependence of cost on each variable has been fully accounted for in the cost model.[4]

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[4]As an example of how double-counting can occur, silicon usage in PV modules is sometimes expressed in units of grams per watt. However, silicon usage per watt can decrease either because of a reduced silicon need *per wafer*, or because of an efficiency improvement. Efficiency of PV modules improved at the same time that silicon needs *per wafer* decreased. As a result, silicon usage *per watt* has changed more than silicon usage *per wafer* has. If the full cost reduction benefit of higher efficiency were already counted elsewhere, then the silicon-usage benefit of higher efficiency will be double-counted.

Double-counting is less likely to occur if the analysis of cost changes starts with an equation for cost. In constructing this equation, the grams-per-watt units of silicon usage would have to be reconciled with the watts units of efficiency $\times$ wafer area $\times$ the solar constant to recover the correct units for cost. Once this reconciling of units is done, the cost change equations that are derived from the cost equation will automatically avoid double-counting as well.

Figure 2-3: Contribution of the low-level mechanisms to module cost decline in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). Mechanisms are listed in the order of decreasing contribution for the 1980-2001 period.

2.4 Results and discussion

In this section we first discuss the *low-level mechanisms* of module cost reduction, which refer to changes to variables in the cost equation. We then relate the low-level mechanisms to *high-level mechanisms* of cost reduction, which refer to processes at the level of institutions arising from human efforts.

2.4.1 Low-level mechanisms of cost reduction

Figure 2-3 and Table 2.3 show the changes in module cost due to each variable in the two periods, 1980-2001 and 2001-2012, and the entire period, 1980-2012. Improving efficiency was the largest contributor in the first period, responsible for 29% of the cost reduction. In the second period, module efficiency was only the fourth most significant factor, and its contribution dropped to 13%. Efficiency increased at the wafer and cell levels through many improvements, such as surface passivation [81], anti-reflective coating [92], and texturing of the wafers [93, 94], and at the module level with improvements such as a glass structural layer laminated design [81].

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Cost change due to:	1980-2001		2001-2012		1980-2012	
	$\Delta 2015\$/W$	Percentage	$\Delta 2015\$/W$	Percentage	$\Delta 2015\$/W$	Percentage
Δ Efficiency	-5.20	29%	-0.35	13%	-5.55	27%
Δ Non-Si materials costs	-3.66	20%	-0.43	15%	-4.09	20%
Δ Wafer area	-3.37	19%	-0.54	20%	-3.92	19%
Δ Silicon usage	-2.22	12%	-0.14	5%	-2.36	11%
Δ Plant size	-2.04	11%	-0.86	31%	-2.90	14%
Δ Yield	-1.71	9%	-0.19	7%	-1.90	9%
Δ Silicon price	-1.28	7%	-0.10	4%	-1.39	7%
Δ p0	1.45	-8%	-0.17	6%	1.28	-6%
Change in module cost	-18.05	100%	-2.78	100%	-20.83	100%

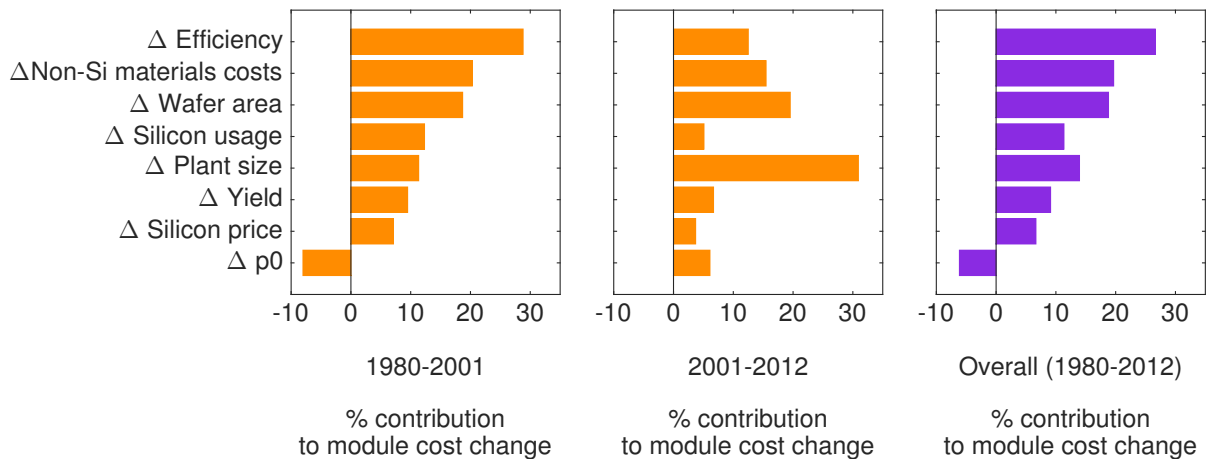Table 2.3: Contribution of the low-level mechanisms to module cost decline in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). Mechanisms are listed in the order of decreasing contribution for the 1980-2001 period. Cost changes due to the low-level mechanisms and their percentage contributions are normalized as explained in Eq. 2.16 in Section 2.3.

The second most significant factor in 1980-2001 was lower per wafer area costs of non-silicon materials, contributing 20% of the cost decline. The contribution of this factor in 2001-2012 was 15%. Non-silicon materials include substances such as as glass, laminate, and metal paste that become embedded in the module as well as slurry and wire used during production. The cost of these materials has been reduced by various process and module design improvements. For example, the cost of slurry used in wafer cutting may be reduced by recycling, with recycling rates up to 80% reported [95].

Increasing wafer area was an important factor in both periods. Wafer area almost doubled from 80 cm^2 to 150 cm^2 in 1980-2001, and grew significantly again to about 240 cm^2 by 2012. A doubling of wafer area, given a fixed number of cells per module, means that each module assembled produces twice as much power. Material costs are mostly proportional to area, but other assembly costs are insensitive to area [96, 8], so that larger wafer area yields cost savings.

Process improvements led to increasing yields in wafer, cell and module production. Overall yield increased from 75% in 1980 to 95% in 2012. The change in yield contributed 9% and 7% to the module cost decline in 1980-2001 and 2001-2012, respectively. Reduced handling of wafers, cells and modules due to automation, and improvements in processes such as wafering, help to increase yield [95]. We note that other improvements (such as larger wafer sizes) can decrease yields [94], so that yield considerations can be a limiting factor for otherwise cost-saving practices.

Decreasing silicon usage also contributed to module cost reductions. Silicon usage depends

on wafer thickness h and silicon utilization U. To study the total cost reduction from both variables, we define the combination $v \equiv h/U$. In 1980-2001 wafer thickness decreased from about 500 μm to 250 μm while silicon utilization increased from about 20% to 35%. Reduced thickness and higher utilization contributed about equally to the silicon cost reduction in this period. Silicon usage continued to decrease in 2001-2012, though it had a less significant cost impact. The industry developed thinner wafers both to reduce the cost of silicon and to increase conversion efficiency [92]. Silicon utilization also increased, though losses remain high, with about 50% of entering silicon lost during slicing of wafers from silicon ingots. Decreasing thickness contributed about 70% of silicon cost reduction in this period while utilization contributed the remaining 30%.

Changes in polysilicon price contributed about 7% and 4% of the module cost decline in 1980-2001 and 2001-2012, respectively. The endpoints of our analysis lie on either side of a temporary period of silicon shortage in 2005-2008, during which polysilicon prices surged. Before this period, most polysilicon was used by the semiconductor industry. The PV industry used wafers rejected by the semiconductor industries, which has higher purity requirements [90]. Around 2006 polysilicon demand by the PV industry surpassed that of the semiconductor industry and polysilicon producers responded by increasing capacity. While more than 80% of the global polysilicon production was consumed by the semiconductor industry before 2000 [97], about 90% went to manufacturing PV cells as of 2012 [98].

The pre-factor p_0 in Eq. (2.5) provides the level of plant-size dependent costs for a plant of a fixed size K_0, thus accounting for the overall level of electricity, labor, capital and depreciation costs at each time. The change in p_0 was estimated to have increased cost in the 1980-2001 period and decreased cost in the 2001-2012 period. As described in Section 2.2 we calibrate p_0 in 1980 and 2001 by requiring non-material costs in our cost model to match values from our data. We regard the variable with caution since changes are difficult to interpret and it is likely to propagate uncertainty in the data. However, its effects are among the smallest in both periods.

Finally, increasing manufacturing plant sizes resulted in scale economies through shared infrastructure, reduced labor requirements, higher yield, and better quality control [99]. Typical plant sizes have scaled up with the industry, starting from 0.125 MW in 1980 and growing to 14 MW in 2001 and to 400 MW in 2012. Plant size became an especially significant factor in the more recent period, contributing almost a third of the decline in module cost.

In Section A.2 of the Supporting Information we estimate the sensitivity of our results to the uncertainty in the input variables shown in Table 2.1. We conclude that overall our results are robust to changes in the variables.

Our findings show some similarities to earlier reported results [8], as well as some differences. Similar to [8] we find that the contribution of increasing module efficiency to cost reduction in the 1980-2001 period was around 30%. While [8] finds the sources of cost declines to be heavily concentrated in plant size and module efficiency changes, we find cost-reducing effects were spread across a number of variables. In [8] the costs of non-silicon materials are not considered, though we find that non-silicon material costs contributed as much to cost reduction as silicon did in this period. We obtain a lower estimate for the contribution of plant size in this period (11% versus 46%), and larger contributions for wafer area (19% versus 3%), silicon consumption (11% versus 3%) and yield (9% versus 2%). We find a roughly similar magnitude for silicon price (7% versus 12%).

2.4.2 High-level mechanisms of cost reduction
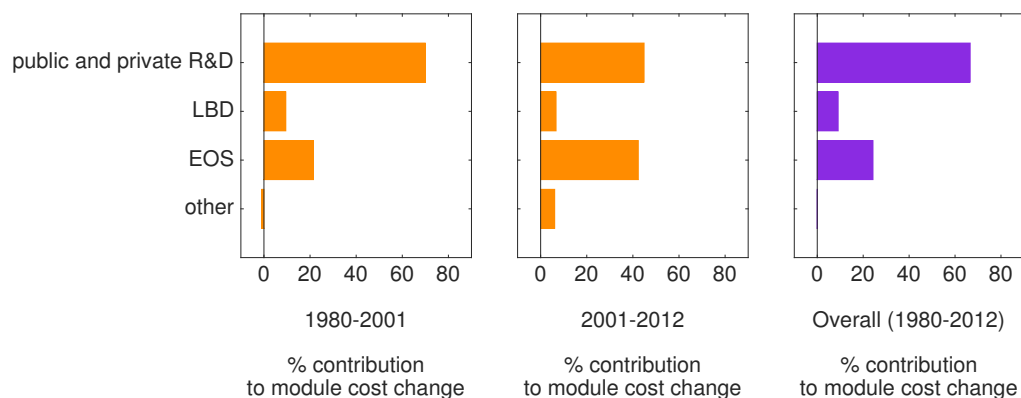
Figure 2-4: Percentage contribution of the high-level mechanisms to module cost decline in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). R&D = Research and development, LBD = Learning-by-doing, EOS = Economies of scale, Other = other mechanisms such as spillovers. We categorize the changes that require a lab setting or a nonroutine production activity (e.g. experimental production line) as being caused by R&D [100, 101]. We consider an improvement to have been made by LBD if it was achieved as a result of repeated routine manufacturing activity and if it was incremental in nature [100]. Changes that result from increases to the scale of the module manufacturing plant we categorize as EOS.

Low-level cost reductions were driven by various 'high-level' mechanisms such as research and development, learning-by-doing, and economies of scale. Estimating the contributions of

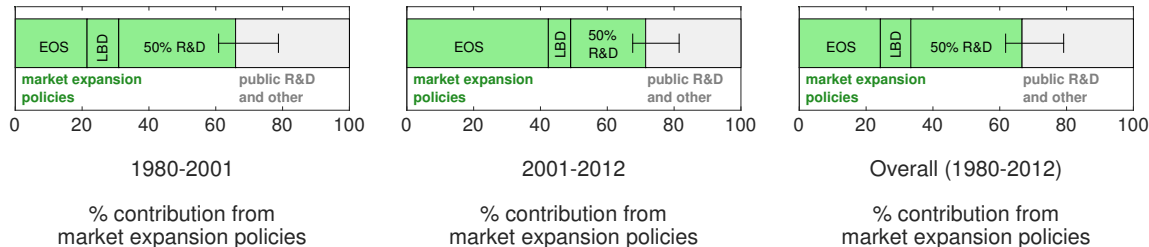Figure 2-5: Percent contribution of market expansion policies (e.g. feed-in-tariffs, renewable portfolio standards) to module cost reduction in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). Scale economies, learning-by-doing, and private R&D were all stimulated by market expansion. Our data does not let us separate the effects of private and public R&D. To accommodate this, we add 50% of total R&D contributions to the contributions of scale economies and learning-by-doing. This effectively assumes that 50% of R&D improvements came from private R&D (roughly commensurate with the share of R&D expenditures in clean energy [7, 102, 103, 104]). Uncertainty bars show the total contribution from market expansion policies that would result under the alternate assignments of low-level mechanisms to high-level mechanisms shown in Fig. A-12 without accounting for uncertainty in the private R&D estimate.

these mechanisms is useful because they align more closely with the policy levers often used to drive down cost. To estimate how much each contributed to cost reduction in PV modules (Fig. 2-4), we categorize each low-level variable according to which high-level mechanism was most responsible for its change. In Section A.3 of the Supporting Information we perform a sensitivity analysis to test the effect of these assumptions. Our conclusions about the relative importance of different high-level mechanisms are robust to various schemes for relating low-level and high-level mechanisms (see Fig. A-12).

Changes that require a lab setting or a nonroutine production activity (e.g. experimental production line) are labeled as being caused by research and development (R&D) [100, 101]. R&D can result in improvements to either the manufacturing process or the technology being produced. We consider an improvement to have been made by learning-by-doing (LBD) if it was achieved as a result of repeated routine manufacturing activity and if it was incremental in nature [100]. Cost changes that result from increases to the module manufacturing plant scale, and from volume purchases of materials or scale economies in materials supplier industries, we categorize as economies of scale (EOS).

Based on this we categorize improvements to module efficiency, wafer area and silicon usage under R&D. Improvements to cell efficiency were largely achieved by R&D done at national labs, universities and companies. Closing the gap between cell and module

efficiencies also required R&D to improve module assembly processes such as encapsulation and interconnections. Larger wafer area was achieved through R&D on single crystal growing and multicrystalline ingot casting. Wafer thickness and silicon utilization improved though manufacturing techniques such as wire-sawing that were improved through R&D. LBD may have been an additional driver of wafer area and silicon usage, which are affected by the efficiency of the manufacturing process.

Yield likely improved mainly through LBD, as advances in quality control of wafers and cells reduced rejects and increased automation reduced excess handling. R&D may have played a role, though we expect that improving yield mainly involved repeated routine manufacturing activity.

The increasing size of module plants brought about economies of scale (EOS), as manufacturers simultaneously prepared for higher demand [8] and looked for better access to capital [77]. Larger plants realized cost savings from spreading out the costs of shared infrastructure across greater output and from physical or geometric scaling relationships [105, 106]. In our model we assume all non-material costs realize scale benefits so that increasing plant sizes lowers the cost per watt of labor, capital equipment, and electricity.

Silicon prices were driven by different developments over time. Until the mid-2000s, demand for silicon wafers by the PV industry was met mainly with wafers rejected by the semiconductor industry. The availability of silicon was a positive externality of semiconductor production and not a result of R&D, LBD, or EOS in the PV industry. We therefore categorize silicon price's high-level mechanism as 'other' for 1980-2001. The PV industry surpassed the semiconductor industry in silicon demand around 2006 [107], leading to a price spike and supply shortage. To maintain supply, the PV industry developed its own production of polysilicon. In this period knowledge spillover and scale economies were important. Know-how of producing single crystal silicon ingots and slicing wafers was acquired from the semiconductor industry by the PV industry, which rapidly scaled-up its own capacity. For 2001-2012 we therefore choose EOS as the main high-level mechanism for decreasing silicon price.

Decreases to non-silicon materials costs were important sources of cost reduction in both time periods. Non-silicon materials costs can be decomposed into material usage (mass/area) times material price (dollars/mass). We propose that R&D helped reduce materials usage through new module designs, while EOS led to the decreasing prices due to volume purchases

or scale economies in materials supplier industries. We assign decreases in non-silicon materials costs equally to R&D and EOS, and explore the effect of other assignments in Fig. A-12.

Finally we choose 'other' as the high-level mechanism for the change in p_0. p_0 includes different types of costs (electricity, labor, capital and depreciation) and multiple high-level mechanisms can affect it. For example, the labor costs component of p_0 can be reduced through LBD. We do not have the information to break down p_0, and therefore cannot quantify the high-level mechanisms governing it. However, this issue does not affect the results much since the module cost change due to the change in p_0 has been small.

Adding the effects of low-level variables, we estimate the percent changes in module cost due to R&D, LBD, and EOS in the two time periods (Fig. 2-4). In the Supporting Information, we consider other plausible categorizations of low-level variables and show the maximum and minimum values achieved with these alternate categorizations. Fig. A-12 shows two alternative cases that include recategorizing c, A and v. These two alternative categorizations are meant to reflect the lowest and highest values R&D, EOS and LBD can take, so that robust conclusions can be drawn.

Our estimates show a strong impact from R&D. R&D played a dominant role in the first period, improving multiple low-level variables that reduced cost significantly. (Table 2.3.) R&D's impact is high in the second period as well. LBD is estimated to have had a small impact, though we show in Fig. A-12 that LBD's impact could be higher to the extent that it contributed to improvements in wafer area and silicon usage.

Scale economies changed from being a minor contributor in the first period to a significant one in the second. Though plant sizes grew far more in percentage terms during the first period, and were responsible for significant cost reductions in absolute terms, cost reductions overall were dominated by R&D-driven efficiency, wafer area, and material usage improvements. These improvements slowed down in the second period (Table 2.1), permitting EOS to contribute a larger share.

Private R&D, learning-by-doing and scale economies were all stimulated by market expansion (e.g. through feed-in-tariffs, renewable portfolio standards). Unfortunately our data does not let us separate the effects of private and public R&D, however we know that the expenditure share of each is roughly 50% [7, 102, 103, 104]). If 50% of R&D improvements came from private R&D, then market expansion would have contributed about 67% of cost
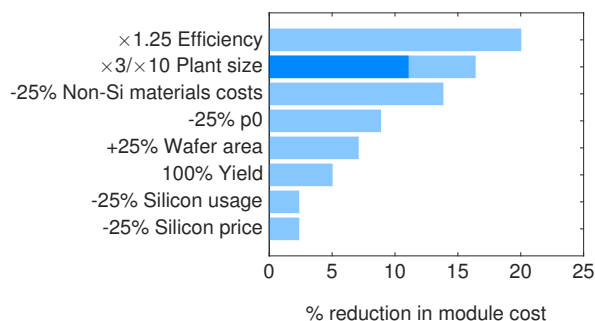
Figure 2-6: Module cost reductions from one-at-a-time changes to low-level variables. The reduction in module cost below the 2012 value is shown for each one-at-a-time variable change. Most variables are adjusted up or down by 25%, in a direction that reduces cost. Yield was changed from 95% to 100%. Plant size is increased by a factor of 3 (dark blue) and a factor of 10 (light blue).

reduction over both periods. These results are shown in Fig. 2-5, where uncertainty bars reflect the range in contribution from market expansion policies that would result under the alternate assignments of low-level mechanisms to high-level mechanisms given in Fig. A-12. These results show clearly that PV is an example of a technology where market expansion played a significant role in stimulating innovative activity and driving down costs [7, 108].

Some cost reductions came from improvements made outside of the PV industry, and were not stimulated by PV market expansion. We make a rough estimate of the upper bound on these effects using the variables that were affected by outside developments. p_0 includes equipment costs in module manufacturing, and some equipment improvements (e.g. wire-sawing) took place in other industries and were transmitted to module manufacturing as knowledge spillovers. Some reductions in non-silicon materials costs may have come from improvements in other industries that yielded price reductions. As noted earlier the price of silicon was affected by developments in the semi-conductor industry. Summing the cost reductions from these three variables, we estimate that at most 20% of PV's cost reduction came from developments outside the PV industry in 1980-2012.

2.4.3 Prospective cost reductions

Considering the various low-level and high-level causes of historical cost declines, how effective would different strategies be at reducing module costs going forward? To gain insight we perform two simple analyses to assess how influential each low-level and high-level mechanism is for reducing costs under our model. In the first analysis, each low-level variable is changed
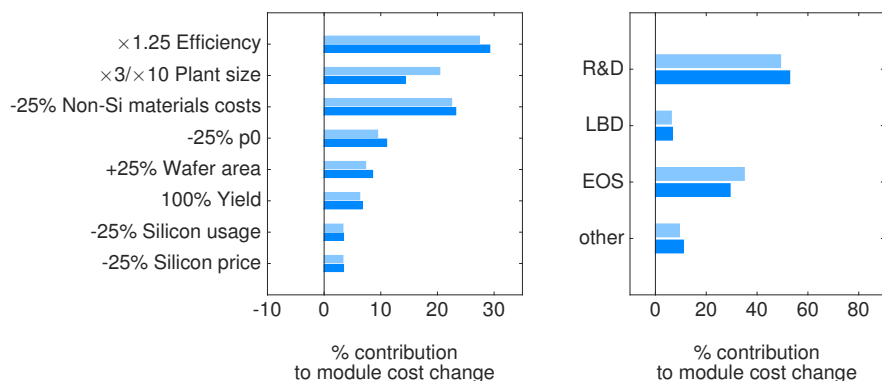
Figure 2-7: Percent contributions to module cost reduction below the 2012 value in a scenario where several low-level variables are changed simultaneously. Left: Percent contributions of low-level mechanisms from changing all variables at the same time by the amounts shown. Separate bars are shown for the cases where plant size increases by a factor of 3 (dark blue) and a factor of 10 (light blue). Right: Percent contributions of each high-level mechanism. R&D = Research and development, LBD = Learning-by-doing, EOS = Economies of scale, Other = other mechanisms such as spillovers.

one-at-a-time, starting from its 2012 value, in a direction that reduces cost. With the exceptions of yield and plant size we change each variable by the same percentage of $\pm 25\%$ to see how much cost reduction results. While different variables are not equally likely to realize a given percentage improvement, this approach lets us see how strongly each variable influences cost. To avoid using an unphysical yield above 100% instead of raising it by 25% we set yield equal to 100%. Plant size historically grew by very large factors far exceeding 25% – 114-fold in 1981-2001, and 29-fold in 2001-2012, and a 25% increase would not be expected to achieve much cost reduction. Instead we consider a 3-fold and a 10-fold increase in plant size. The latter increase would result in plant sizes of about 4 GW/year, roughly double the size of the largest plants in China currently. The results are shown in the left panel of Fig. 2-6. The most influential variables are efficiency, plant size, and non-silicon materials costs. Plant-size contributes substantially, though as plants become larger it may become more difficult to increase plant sizes by factors large enough to realize significant further gains.

High-level mechanisms often stimulate improvements in several low-level variables at the same time, and therefore we also model the simultaneous occurrence of multiple low-level mechanisms. To assess the cost change contribution of each low-level variable, we need to use the cost change equations developed in Section 2.3. (This is in contrast to the one-at-a-time

changes to low-level variables described above, whose contributions to cost change can be computed by comparing total costs at each snapshot in time.) In this second analysis we alter all low-level variables simultaneously by the amounts given above. We then group the cost changes from these variables by high-level mechanism in the same way as in the second period of our historical analysis. The results[5] are shown in Fig. 2-7. Changing all variables at once, with a 10-fold increase in plant size, module costs decline to 44% of the 2012 value. As was observed historically, combined public and private R&D accounts for most of the decline in this scenario.

Our model can be used as a tool to perform prospective analyses to guide future engineering and policy efforts. The above analysis shows one scenario in which high-level mechanisms drive several low-level mechanisms. In this scenario, summing the percent contributions of learning-by-doing and scale economies, in the case of a 10X plant size increase, about 40% of total cost reduction results from mechanisms related to market-expansion (or roughly 65% if we assign 50% of future R&D-related improvements to the private sector, commensurate with the past share of private R&D funding [7, 102, 103, 104]).

Several scenarios could be developed to prospectively investigate the effects of low-level mechanisms, public R&D funding strategies, market-expansion policies, private R&D, and other firm-level strategy. Expert elicitation could be used to assess the potential for changing low-level variables in the cost equation. (The quantitative framework can enable the elicitation to focus on detailed variables that technical experts are familiar with, and may therefore help to elicit more reliable information from experts than has traditionally been achieved [87, 109].) Using this information, an exploration of the effects of different combinations of high- and low-level mechanisms could inform decisions in the public and private sectors. This approach could be applied not only to PV modules, but PV systems, energy storage, and other technologies, as well as performance metrics other than cost.

2.5 Conclusions and policy implications

PV module costs declined dramatically in the last forty years. To identify the reasons, we advance an analysis method that bridges top-down, high-level analyses of technology cost

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[5]In the 10X plant size case, plant size and non-Si materials costs swap places in the ranking of their effects. This can happen since changing all variables at once has different effects on cost than changing variables one-at-a-time and then aggregating their effects.

evolution with bottom-up engineering models. The method begins with a cost equation relating a technology's costs to a set of low-level explanatory variables, e.g. technical performance characteristics such as efficiency or material usage. Cost change equations are then derived to estimate each variable's contribution. These variables explain cost changes 'at a low-level', and we term changes to these variables low-level mechanisms of cost reduction. Other processes like R&D, learning-by-doing, and scale economies may instigate several low-level mechanisms and drive down costs as a whole. We term these high-level causes of cost reduction.

We find that cost reductions in PV modules were fairly evenly distributed across a number of low-level mechanisms, which may help explain why this technology experienced relatively steady cost reductions over the past three decades. We estimate that changes to efficiency contributed 27% to the cost reduction from 1980-2012, non-silicon materials costs 20%, wafer area 19%, plant size 14%, silicon usage 11%, yield 9%, and silicon price 7%.

Several high-level mechanisms were important. These include public and private R&D and economies of scale, which contributed an estimated 67% and 24%, respectively, of the cost decline between 1980 and 2012. Learning-by-doing, defined here as incremental and resulting from a repeated, routine manufacturing process (e.g. not requiring an experimental production line), contributed 9% of the cost decline during this period.

Looking across both the 1980-2001 and the 2001-2012 periods, our findings suggest that the key drivers of decreasing costs have been changing over time. Economies of scale in particular have had a greater impact more recently, and likely offer an avenue for further cost reductions. Notably, the typical 2012 plant size in our data set has been surpassed by several new Chinese plants with typical sizes of 1-2 GW/year [77]. However there may be a limit to how much plant sizes will grow, and savings from economies of scale may be exhausted over time.

R&D, both public and private, was a key driver of module cost reduction historically and can be valuable going forward in improving module efficiency and reducing materials use. Improvements to module efficiency in particular would help cut the per-watt cost of all cost components of PV modules (as well as PV systems). Variables that might face limitations in the short term are manufacturing yield, which is already close to 100%, and wafer area, which is constrained by yield considerations.

Market-expansion policies have played a central role in driving down the costs of PV

modules, with private R&D, economies of scale, and learning-by-doing together contributing an estimated 67% of the cost decline in PV modules between 1980 and 2012. This finding contributes to an ongoing debate on the effectiveness of market-expansion policies, as complements to publicly-funded R&D [69]. In the case of PV, our analysis shows definitively that private sector activity, which was incentivized by government policies in various nations [84], was critically important for driving down costs. Additionally, our findings support the importance of public R&D to complement private sector activity, which may focus more on refinements to technology and manufacturing rather than the more major innovations needed as the limits to incremental improvements are reached [69, 31]. These results add insight to earlier findings from correlational analyses on the importance of market expansion in driving energy patenting (as a proxy for innovative activity) in recent years [7], with public R&D having played the dominant role in the 70s and 80s.

Looking forward, market expansion policies can continue to support cost declines, through a virtuous, mutually-reinforcing cycle of technology improvement and emissions reductions [84]. However, our results suggest that these policies should be complemented by public R&D to reduce the risks of exhausting the improvement potential of current-generation, silicon-based module technology, by exploring devices based on other abundant semiconductor materials with the potential for lower processing costs [19].

In this work we provide a reconstruction of trends in PV modules across time using three representative points in time, drawing from a variety of sources. It is important to note that the data used in this work has uncertainties, for example due to the incomplete sampling of firms. Nevertheless we provide a framework for modeling costs and cost changes that can be populated with the best available data.

This analysis can be helpful in guiding engineering efforts, the formulation of energy and climate policy, and research investments by government and the private sector. The method outlined here can be applied to many technologies to understand the reasons for past changes in cost or other performance, and to explore promising opportunities for future improvement.

Chapter 3

Metal production requirements for rapid photovoltaics deployment

If global photovoltaics (PV) deployment grows rapidly, the required input materials need to be supplied at an increasing rate. In this paper, we quantify the effect of PV deployment levels on the scale of metals production. For example, we find that if cadmium telluride {copper indium gallium diselenide} PV accounts for more than 3% {10%} of electricity generation by 2030, the required growth rates for the production of indium and tellurium would exceed historically-observed production growth rates for a large set of metals. In contrast, even if crystalline silicon PV supplies all electricity in 2030, the required silicon production growth rate would fall within the historical range. More generally, this paper highlights possible constraints to the rate of scaling up metals production for some PV technologies, and outlines an approach to assessing projected metals growth requirements against an ensemble of past growth rates from across the metals production sector. The framework developed in this paper may be useful for evaluating the scalability of a wide range of materials and devices, to inform technology development in the laboratory, as well as public and private research investment.[1]

3.1 Introduction

Photovoltaics (PV) is a low-carbon technology that has the potential to reduce greenhouse gas emissions if deployed at large scale. [110, 111, 4] As of 2012, PV provides only 0.4% of

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[1]This chapter has been published in *Energy and Environmental Science* [19] with co-authors James McNerney, Robert L. Jaffe and Jessika E. Trancik.

the world's electricity. [112] Its deployment is growing rapidly, however, at an average rate of 30% per year, [5] as the technology steadily improves and costs decline. [113, 114, 115, 7, 31]

The future growth of PV has been estimated in various energy scenarios, based on projections of energy demand and the cost and performance of technologies in the future. Various international organizations, [55, 56] environmental agencies and industry associations, [57, 58] energy companies and other corporations [59, 60] and academic institutions and researchers [61, 62] have contributed to this literature. Another group of studies focuses on resource constraints and the potential for future PV deployment. For example, various researchers have analyzed the material constraints on PV deployment that are imposed by annual metal production levels or reserves [53, 13, 18, 54] and have discussed the potential for increasing PV deployment by reducing the material intensity of PV technologies. [21, 43, 54, 45]

While these studies address the production scale of metals eventually needed, they do not directly address the time frame over which scaling up should be achieved. In this paper, we ask whether metals production can be scaled up at a pace that matches the rapidly increasing PV deployment levels put forward in aggressive low-carbon energy scenarios. Based on the projected PV deployment levels in 2030, we estimate the growth rates required for metals production to satisfy the metal demand by the PV sector. We present a new perspective on the metal requirements of PV deployment by comparing the required growth rates with the growth rates observed in the past by a large set of metals (the full set of metals for which yearly production data is available for all years in the period 1972 to 2012). (See Section B.1 of Appendix B for details.)

We include in our analysis the absorber layer materials of three PV technologies manufactured and sold today: crystalline silicon (c-Si) technology (roughly 90% of annual PV production today) [80] and two thin-film PV technologies, cadmium telluride (CdTe) and copper indium gallium diselenide (CIGS) (with roughly 5% and 2% of annual PV production today), [80] building on our earlier, preliminary results. [20] Whereas c-Si is based on an abundant metal, silicon, CdTe and CIGS utilize metals that have low crustal abundance and are obtained as byproducts of other metals' production.

In this paper we aim to provide a thorough analysis of the required growth rates for silicon in c-Si, tellurium in CdTe, and indium, gallium and selenium in CIGS to meet a range of projected PV growth scenarios. To complement this analysis of past and projected metals

growth rates, we also compare the projected levels of metals production to their estimated scalability potential based on metals reserves. The approach developed in this paper may also be useful for studying the scalability potential of other technologies as well, in light of the production growth requirements of raw materials.

3.2 Methods

We estimate the growth rates required for metals production to meet the metal demand associated with projected global PV deployment levels in 2030. These projected levels are based on a number of published energy scenarios ranging from low to high PV deployment (Table 3.1). We note that providing a high proportion of the total electricity through PV would require energy storage technologies that would also entail material requirements. [116] This paper concentrates on the materials used in PV technologies but could be extended to analyze energy storage technologies.

The analysis begins with estimating the required annual production in 2030 for each PV metal of interest. We then calculate the annual growth rate needed for the metals production to reach the required level in 2030. To estimate the required metal production in 2030, we consider the projected demand for the metal by both the PV sector and non-PV end-use sectors of the metal,

$$P_\beta = X_\alpha I_{\alpha\beta} + N_\beta(1 + n_\beta)^{18} \tag{3.1}$$

where

P_β required production for metal β in 2030 [metric tons/year (t/y)]

X_α deployment for PV technology α during 2030 [GW/y]

$I_{\alpha\beta}$ intensity of metal β for PV technology α [t/GW]

N_β metal β used by non-PV end-uses in 2012 [t/y]

n_β annual growth rate in non-PV end-uses of metal β [unitless]

The projected demand for a metal β by a PV technology α in 2030 is determined by the projected annual deployment level of the PV technology in 2030, X_α, and the anticipated material intensity of metal β in 2030, $I_{\alpha\beta}$. We calculate the annual PV deployment in 2030, X_α, by using the cumulative installed PV capacity for 2030 projected by the energy scenarios

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Table 3.1: Cumulative Installed PV Capacity Projections for 2030.

Energy Scenario	Cumulative installed PV capacity (GW)	Approximate % of global electricity from PV
IEA WEO[a]	720	3
Solar Generation 6[b]	1850	8
GEA[c]	3000	13
Shell[d]	5500	24

[a] 450 scenario [55]
[b] Paradigm shift scenario [58]
[c] GEA-supply, conventional transportation, full portfolio scenario [61]
[d] Scramble scenario [59]
Note: Installed capacity figures rounded to nearest ten GW. Approximate percentage of global electricity is calculated assuming 15% capacity factor for PV [58] and a total global electricity generation of 30000 TWh in 2030. [55]

(Table 3.1) and assuming a constant percent annual growth from 2012 to 2030. The material intensity, $I_{\alpha\beta}$ (in g/W or t/GW), for a metal in a PV module is given by

$$I_{\alpha\beta} = \frac{t_\alpha \rho_\alpha w_{\alpha\beta}}{\sigma \eta_\alpha U_{\alpha\beta} y_\alpha} \tag{3.2}$$

where

t_α thickness of absorber layer for PV technology α [μm]

ρ_α density of layer for PV technology α [g/cm^3]

$w_{\alpha\beta}$ mass fraction of metal β within the layer for PV technology α [unitless]

η_α module efficiency for PV technology α [unitless]

σ solar constant [1000 W/m^2]

$U_{\alpha\beta}$ utilization fraction of metal β in manufacturing PV technology α [unitless]

y_α yield in cell and module manufacturing for PV technology α [unitless]

For each PV metal, we consider a range of estimates for material intensity in 2030. Table 3.2 provides the parameters used to obtain these estimates and the resulting high, medium and low material intensity values. The ranges for material intensity considered are 10-30

Table 3.2: Parameters for Material Intensity and the Resulting Material Intensity, $I_{\alpha\beta}$, for Each Element.

Elements	Cases	t_α (μm)	η_α (%)	$U_{\alpha\beta}$ (%)	y_α (%)	ρ_α (g/cm^3)	$w_{\alpha\beta}$ (%)	$I_{\alpha\beta}$ (t/GW)
	high	2	14	75	73			28
In in CIGS	medium	1.2	15.7	80	90	5.75	22	13
	low	1.1	20	95	98			7
	high	2	14	75	73			9
Ga in CIGS	medium	1.2	15.7	80	90	5.75	7	4
	low	1.1	20	95	98			2
	high	2	14	30	85			161
Se in CIGS	medium	1.2	15.7	60	90	5.75	50	41
	low	1.1	20	95	98			17
	high	2.5	11.7	50	85			156
Te in CdTe	medium	2	14	70	90	5.85	53	70
	low	1	18	95	97			19
	high	2.5	11.7	50	85			138
Cd in CdTe	medium	2	14	70	90	5.85	47	62
	low	1	18	95	97			17
	high	180	14.8	45	95			6629
Si in c-Si	medium	120	18	55	98	2.33	100	2882
	low	50	20.5	90	99			638

In, Ga, Se: t_α high [43, 45]; t_α medium, t_α low [45]; η_α high [117]; η_α medium, ρ_α, $w_{\alpha\beta}$ for In, $w_{\alpha\beta}$ for Ga [43]; η_α low [118]; $U_{\alpha\beta}$ high for In, $U_{\alpha\beta}$ high for Ga [43], other $U_{\alpha\beta}$ values [118]; $w_{\alpha\beta}$ for Se [119]; y_α high for In, y_α high for Ga [43], other y_α values [118].

Te, Cd: t_α high, ρ_α, $w_{\alpha\beta}$ for Te [43]; η_α high, η_α low [42]; t_α medium, t_α low, $U_{\alpha\beta}$ high for Te, $U_{\alpha\beta}$ low for Te, y_α high, y_α medium [118]; η_α medium [45]; $U_{\alpha\beta}$ medium for Te [14]; y_α low [120]. $U_{\alpha\beta}$ values for Cd are assumed to be the same as Te. $w_{\alpha\beta}$ for Cd is 1-$w_{\alpha\beta}$ for Te.

Si: ρ_α [41]; all remaining parameters [40].

(a) Indium (b) Gallium (c) Selenium
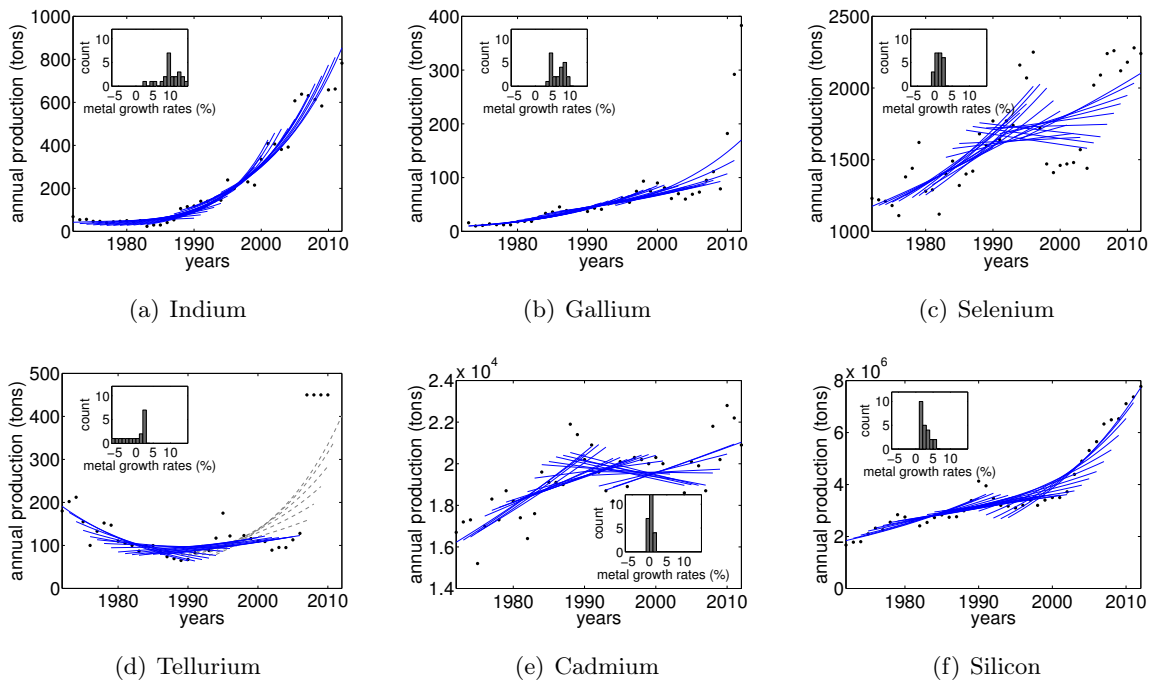
(d) Tellurium (e) Cadmium (f) Silicon

Figure 3-1: Annual production of metals over time, 1972-2012. Black points show the actual production data, while blue lines are obtained by fitting a line to the natural logarithm of the production data (using the least squares method) for each 18-year period in 1972-2012. The slope of the each fitted line represents the annual growth rate for that 18-year period. The inset in each figure is the histogram of the annual growth rates obtained by this curve fitting method. The goodness-of-fit varies substantially across the metals and time periods investigated. The method of reporting tellurium production data changed in 2007, resulting in an arbitrary jump. [121] Therefore the Te data for the last 6 years are not taken into account when estimating the growth rates. This is indicated by the gray color used for the last 6 fitted lines.

t/GW for In, 2-10 t/GW for Ga, and 20-160 t/GW for Se in CIGS; 20-160 t/GW for Te and 20-140 t/GW for Cd in CdTe; and 640-6630 t/GW for Si in c-Si when material losses during manufacturing are considered. The high material intensity estimate corresponds to today's level.

The demand by non-PV end-uses of each metal in 2030 is estimated by using the median of the historical growth rates of that metal over all 18-year periods between 1972 and 2012. To account for the variability in the historical growth rates and the uncertainty regarding the future of the non-PV end-uses of the metal, we also calculate a confidence interval around the median growth of the non-PV end-uses defined by the 1st and 3rd quartiles of the distribution of historical growth rates over all 18-year periods between 1972-2012.

We calculate the growth rate, r_β, required for the metals production in 2012 to reach the required level in 2030 by assuming a constant percentage annual growth rate and using equation (3.3):

$$P_\beta = P0_\beta \times (1 + r_\beta)^{18} \tag{3.3}$$

where

$P0_\beta$ production of metal β in 2012 [t/y] (from [122, 123, 124, 125, 126, 127])

P_β production of metal β in 2030 [t/y] (found in eq. 3.1)

After obtaining the required growth rates, r_β, we compare them to historical growth rates of metals production in order to determine whether the required growth rates have historical precedent. When studying the historical growth rates, we use a large set of metals to obtain a more complete picture of the metals production sector. We obtain the annual global production values for 32 metals for the last 40 years from the U.S. Geological Survey. [122, 123, 124, 125, 126, 127] These represent all metals for which continuous yearly production data is available.

We study material resources at the purity grade reported by the US Geological Survey. (See Table B-1 in Appendix B.) We note that byproduct metals such as Te are generally tracked at higher levels of purity than primary metals such as Si, since only the refined byproduct is globally traded. Because of this, we carry out an additional analysis on metallurgical grade Si, a higher purity form that is the precursor to most (97%) Si used

in solar cells [128, 129, 130], to see whether this partially-refined material with smaller production scale is able to support deployment of Si-based PV. This analysis also limits the raw Si resource, since currently metallurgical grade Si is produced more selectively from silica deposits with relatively low starting level of impurities. [131] We note that data on MG-Si is limited to the period from 1990 - 2012, and that data prior to 2004 excludes production by China, further limiting the number of observations. To maintain consistency with other metals, in Figures 3-1-3-4 we use total production of Si given in the USGS data, for which a full 40 year history of most recent production data is available.

We calculate the historical annual growth rates for each metal for all overlapping 18-year periods between 1972-2012. Annual growth rates are calculated based on 18-year time horizons to match the time horizon of the metals growth projections considered (2012-2030). Because we are interested in growth rates that are sustained over all possible 18-year periods, we measure the growth rates over overlapping periods rather than disjoint periods. The average annual growth rate of metals production over each 18-year period is estimated by fitting a straight line to the natural logarithm of the production over time using the least-squares method (Figure 3-1). This is not meant to be a high-fidelity model and we emphasize that the goodness-of-fit varies substantially across the metals and 18-year time periods studied. This level of fidelity is appropriate for answering the following question: If we approximate past and future growth in metals production as following an exponential trend over an 18-year period, how do future required growth rates compare to those observed in the past?

3.3 Results and Discussion

In this section, we first present historical growth rates in the production of metals. Next, we show the growth rates required for the PV metals to reach various projected annual PV installation levels in 2030, and compare these to historical growth rates. Third, we briefly discuss constraints on scaling up the production of byproduct metals based on the production levels of their host metals, as well as the estimated metals reserves.
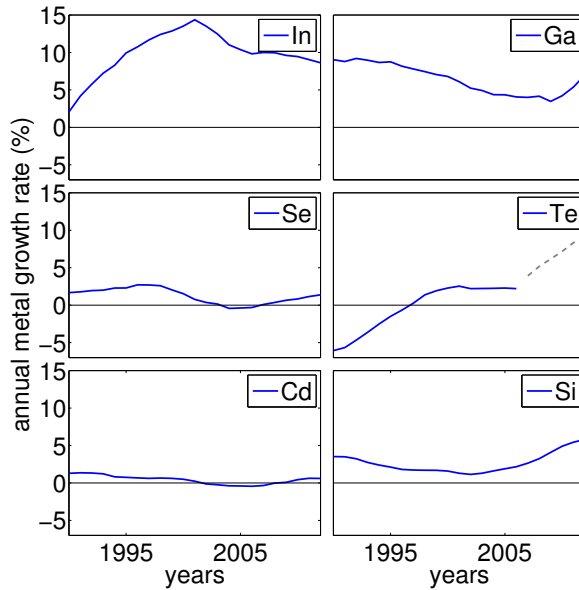
Figure 3-2: Historical growth rates over time are shown for the metals of interest. Growth rates are calculated and plotted in a backward looking manner: The growth rate corresponding to a year is calculated using the production values from the previous 18 years. Reporting of the Te production data changed in 2007, [121] therefore the data for the last 6 years are not taken into account when estimating the growth rates.

3.3.1 Historical Growth Rates

Figure 3-1 shows the annual production values for a set of PV metals over time (1972-2012). The inset in each plot shows a histogram of the annual growth rates for the corresponding metal over all 18 year periods. As can be seen in Figure 3-1, the variability in annual growth rates differs across metals but the distribution of growth rates is constrained to a fairly narrow range, falling below 10% growth per year for these metals with the exception of In.

The change in growth rates over time are different for each PV metal (Figure 3-2). In and Ga have experienced growth rates that are mostly above 5% per year, which is high compared to the other four metals. In, Ga, and Te growth rates have changed significantly over time, unlike Se and Cd rates, which have fluctuated within a small range between -1% and 3% per year. Si growth rate has also been lower and more stable compared to In, Ga, and Te, and recently increased to 5% per year.

To gain a broader picture of the metals production industry, we also obtain the growth rates for the 32 metals available in the USGS database (Figure 3-3). Figure 3-3(a) shows the

histogram of the aggregated growth rates observed by the set of 32 metals over all 18-year periods in 1972-2012. We see that the median growth rate is 2.3% per year. A growth rate of 9% per year at the 95th percentile of the aggregated growth rate distribution is marked with a vertical dashed line in Figure 3-3(a). We interpret 9% per year as an upper end of business-as-usual growth. If a growth rate of 9% per year is sustained over an 18-year period, the annual production will increase by almost a factor of 5 over this period. Also important to our analysis is the maximum growth rate that has been sustained over an 18-year period, which is 14.7% per year.

(a) Histogram of historical growth rates   (b) Historical growth rates over time
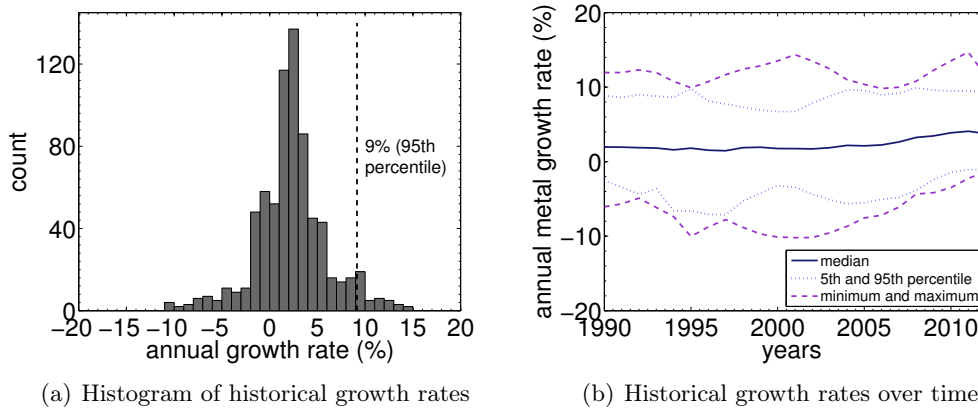
Figure 3-3: **(a)**: Histogram shows the distribution of the historical annual growth rates of production of 32 metals observed in 1972-2012 over 18-year periods. Growth rates are calculated by fitting lines to the natural logarithm of the production values in each of the 18-year periods in 1972-2012. The median 18-year average annual growth rate is 2.3%. **(b)**: 18-year average annual growth rates in metals production have been almost constant over time for the 32 metals studied. Annual growth rates are backward looking: they are calculated using the production values from the previous 18 years. The solid midline is the median of the growth rates of 32 metals for each year. The blue dotted lines show the 5th and 95th percentiles. The dashed purple lines show the minimum and the maximum growth rates observed. Note: The data coming from the last 6 years of Te production are excluded from both panel (a) and panel (b) due to a change in the reporting of the Te production data in 2007. [121]

Figure 3-3(b) shows how the historical growth rates change over time. We observe that the median 18-year average growth rate has been mostly stable over time. An upward trend is observed in the median as well as the interval between the 5th and 95th percentiles after 2005. Even with this upward trend in recent years, the growth rates have been stable, and the median growth rate stayed below 5% per year.

Using overlapping time periods to obtain the 18-year average annual growth rates places

greater weight on years falling in the middle of the time span considered (1972-2012). However we note that this does not introduce a bias in the histogram shown in Figure 3-3(a), as the annual production growth rates across the aggregated set of metals trend neither up nor down over the period considered (1972-2012), as shown in Figure B-3 in Appendix B.

3.3.2 Comparison of Projected and Historical Growth Rates

Figure 3-4 shows the annual growth rates required for the production of PV metals to meet the demand of a wide range of annual PV installation levels in 2030. The lower and upper ends of each colored band in Figure 3-4 are based on growth in non-PV end-uses at rates defined by the 1st and 3rd quartiles of the distribution of their historical 18-year average growth rates.

When explaining the results, we focus on the medium material intensity case and the annual PV installation level corresponding to the "Solar Generation 6, paradigm shift"[58] scenario. The Solar Generation 6 [58] scenario projects a relatively modest growth in PV installations. In this scenario, the cumulative installed capacity reaches 1850 GW in 2030, [58] and generates around 2430 TWh in a year assuming an average capacity factor of 15%. If the total annual global electricity generation in 2030 is 30000 TWh, [55] then PV supplies around 8% of the world's electricity in this scenario. When we assume that PV installation grows at a constant percentage annual growth rate starting from about 100 GW cumulative installed capacity in 2012, the annual PV installations in 2030 would be 275 GW to reach the 1850 GW cumulative installed capacity in 2030. In Figure 3-4, the vertical line marked with the "8% SolarGen6" corresponds to this annual installation level, and 8% refers to the portion of the global electricity provided by PV.

If CIGS provides all of the 275 GW annual installations projected by the Solar Generation 6 [58] scenario in 2030, the required growth rate for In is approximately 14% per year for the medium intensity case, as shown in Figure 3-4(a). This rate is almost unprecedented considering that the highest growth rate that has been observed historically by a large group of metals is 14.7% (as shown in Figure 3-3(a)). 14% per year is also high compared to In's recent growth rates, where In production has been growing at a rate lower than 10% per year (Figure 3-2). A growth rate of 14% per year means that In production increases from 780 t/y in 2012 to 8250 t/y in 2030, which is over a factor of 10 increase. In this scenario, the annual Ga and Se production each needs to grow at 11% per year, as shown in Figure

3-4(b) and Figure 3-4(c). These growth rates are greater than the majority of the historical growth rates experienced by all metals (Figure 3-3(a)). For Se, the projected 11% per year is significantly higher than the growth rates that Se has experienced in the last forty years (Figure 3-2), and corresponds to an increase in annual production of 2240 t/y in 2012 to 14660 t/y in 2030. On the other hand, the required growth rate for Ga, 11% per year, is slightly above what Ga has been experiencing in the recent years (Figure 3-2). This rate means that Ga production increases from 380 t/y in 2012 to 2490 t/y in 2030.

If we constrain metals growth rates to the maximum historical rate of 14.7%, the annual CIGS deployment levels in 2030 would be limited by In to 340 GW. Se and Ga would allow the annual CIGS deployment to be up to 580 GW and 700 GW, respectively, if CIGS were not limited by In.

If CdTe provides 8% of the global electricity generation in 2030 corresponding to the Solar Generation 6 [58] scenario, in which case the annual CdTe installation in 2030 is 275 GW, Te production needs to grow at 23% per year for the medium material intensity case as shown in Figure 3-4(d). 23% per year is significantly higher than the highest historical growth rate observed for all of the 32 metals (Figure 3-3(a)). 23% per year growth rate corresponds to a more than fortyfold increase in the annual Te production - from 500 t/y in 2012 to 20760 t/y in 2030. Cd, on the other hand, requires only 4% per year growth rate in this scenario (Figure 3-4(e)) - an increase from 20900 t/y to 42340 t/y. Historically, Cd production has been growing at very low rates and even decreased over sustained time periods as can be observed in the negative rates in Figure 3-2. 4% growth per year is relatively low compared to the required growth rates of other byproduct metals.

The maximum CdTe deployment in 2030 would be determined by Te, if Te growth rate does not exceed the maximum historically observed growth rate (14.7% per year) observed by all of the 32 metals. In this case, the annual CdTe deployment in 2030 would be limited to 80 GW. Cd would allow up 3600 GW annual CdTe deployment, if there were no constraints imposed by Te.

The median historical growth rates for In and Ga are $n_{In} = 10\%$ and $n_{Ga} = 6.8\%$, are on the higher end of the historical growth rates of all metals. Since we project the growth of non-PV end-uses based on the historical growth rates and the share of non-PV end-uses is very high compared to PV uses, the non-PV demand for both In and Ga is projected to be high. In comparison, a larger fraction (40%) of Te is used for PV compared to In and Ga,

which have only up to 5% of their production dedicated to PV uses. For this reason, the required Te growth rates are more directly related to the level of PV installations than CIGS metals are as seen in Figure 3-4.

Instead of CIGS or CdTe, if all of the 275 GW annual PV installation comes from c-Si, Si production needs to increase only by 2.5% per year (Figure 3-4(f)). This growth rate is close to the median historical growth rate observed for all metals, 2.3% per year. Unlike byproduct metals, the increasing PV deployment does not cause much increase in the required growth rates for Si. This is mainly due to the fact that PV constitutes only a tiny fraction of Si's end-uses. For the medium material intensity case, the required growth rate for Si does not exceed 5% per year up to 1000 GW of annual deployment. For all annual deployment levels explored in this analysis (up to 6000 GW per year in 2030, supplying 100% of forecasted electricity consumption) the required growth rates for Si stay within the range of historical growth rates observed for all metals. (We estimate that silver production for use in contacts for c-Si cells can supply high levels of c-Si PV deployment (up to 80% of global electricity by c-Si in 2030) without exceeding historical growth rates. See Appendix B for details. Silver might also be replaced with other materials.) [15, 132, 133] We find the same results using only metallurgical grade Si (see Methods section) as the basis for Si growth rate measurements, rather than all Si. Applying the same analysis to this alternative measure of useable Si production, in Appendix B, we find that required growth rates remain within the historical range with 100% of global electricity supplied by Si-based solar cells.

It is worth noting that although the growth rates are lower for Si, the increase in the amount of annual Si production from 2012 to 2030 is two to three orders of magnitude higher compared to other PV metals (In, Ga, Te, Se) because it is produced at a much larger scale. A growth rate of 2.5% per year correspond to an increase in Si production from 7.8 millions t/y in 2012 to 12.2 million t/y in 2030.

3.3.3 Discussion of Constraints on Metals Production Growth

In, Ga, Se, Te, and Cd have low crustal abundances and are extracted economically today only as byproducts of other 'host' metals. However a significant quantity of byproduct metal is never extracted from the mined ore. Below we briefly discuss the scalability potential of byproduct metals if they were recovered with 100% efficiency from the mined mineral at today's production levels of host metals, and compare these production levels to those

(a) Indium, $n_{In} = 10\%$ (b) Gallium, $n_{Ga} = 6.8\%$ (c) Selenium, $n_{Se} = 1.4\%$

(d) Tellurium, $n_{Te} = 1.4\%$ (e) Cadmium, $n_{Cd} = 0.6\%$ (f) Silicon, $n_{Si} = 2.2\%$

■ high material intensity   ■ medium material intensity   ■ low material intensity
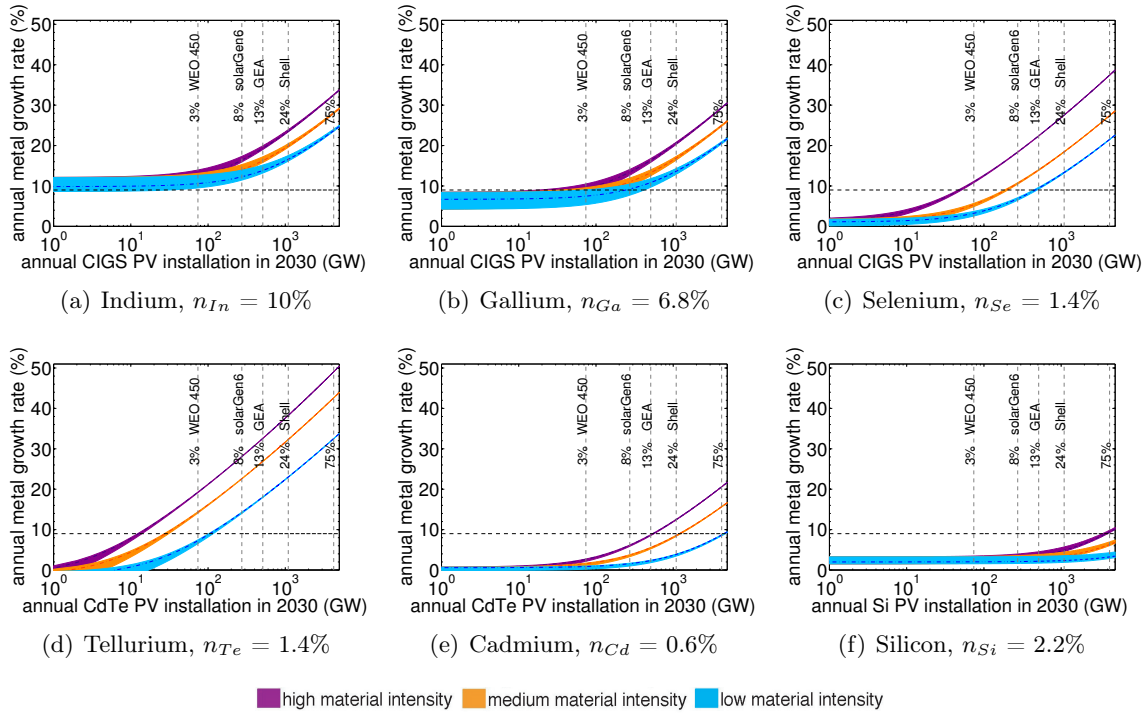
Figure 3-4: Required growth rates for metals production to reach a range of annual PV installation levels in 2030. The bands with different colors show the required growth rates for different levels of material intensities given in Table 3.2. The lower and upper ends of each band are obtained by assuming that the non-PV end-uses grow at rates equal to the 1st and 3rd quartiles, respectively, of the historical growth rate distribution of that metal over each 18-year period between 1972-2012. The median of the 18-year average growth rates observed between 1972-2012 for each metal, (n), is shown below each plot. The vertical lines indicate the assumed annual installation level for the PV technology corresponding to each energy scenario. The percentage on the left of the scenario names indicate the fraction of global electricity generation coming from PV. The energy scenarios originally report only the cumulative PV installations. By assuming a constant percent annual growth rate, we calculated the annual installation level in 2030. The horizontal line at 9% growth rate corresponds to the 95th percentile of the historical growth rates for all 32 metals as shown in Figure 3-3.

required to meet 8% of global electricity (corresponding to the Solar Generation 6 scenario.) [58] We also compare the projected metals production requirements to estimates of global metals reserves. We note, however, that the reserves estimates are revised over time to reflect newly identified mineable deposits, and therefore should not be considered fixed constraints on metals production. [134, 135]

We find that for a scenario in which 8% of the global electricity in 2030 is provided by PV (CIGS, CdTe, or c-Si), and under the assumption of medium material intensity, the required levels of annual production for In, Te, and Se exceed the estimated potential production levels for today by large amounts. The required annual Te production in 2030 also exceeds the Te reserves, [136] while the required annual In production in 2030 approaches the estimated In reserves. The cumulative production by 2030 would far exceed the reserves for In and Te. Ga and Si production are less constrained as discussed further below.

The amount of annually recoverable In is 1350 t/y based on the average In content of the zinc ore, sphalerite (ZnS),[63] and the annual zinc production of 13.5 million tons in 2012. [122] The required annual In production in 2030 to meet 8% of electricity demand (~8300 t/y) is about 6 times the annually recoverable In (1350 t/y), and close to the estimated global In reserves (11000 t). [137]

The potential Te and Se production can be estimated to be around 1430 t/y and 5500 t/y, respectively, based on the average Te and Se content of the anode in the electrolytic copper refineries [138] and the global electrolytic copper refinery production in 2011. [139] The required production for Te to meet 8% of electricity demand in 2030 (~20800 t/y) is an order of magnitude larger than the potential production (~1400 t/y) and almost equal to the estimated reserves (24000 t). [136] The required production for Se in 2030 (~14700 t/y) is more than twice the potential recoverable amount (~5500 t/y). The estimated Se reserves (120000 t) [136] would be sufficient for around 8 years, at the required 2030 annual production levels.

The amount of Cd that is potentially recoverable from zinc ores can be estimated to be about 40500 t/y, based on the average Cd content of the zinc ore, sphalerite (ZnS), [63] and the annual zinc production of 13.5 million tons in 2012 [122]. For Cd, the required production in 2030 for the Solar Generation 6 scenario [58] (~42300 t/y) is also above the potential production (~41000 t/y); however, the difference is proportionately less compared to In, Te, and Se. If the required level of annual Cd production is sustained, the estimated

Cd reserves (500000 t) [136] would be sufficient for around 12 years.

Ga has the highest crustal abundance among all of the byproduct metals analyzed in this paper. Ga availability can be estimated to be 12500 t/y based on the average content of bauxite ores, [140] and the annual bauxite production in 2012, 250 million tons. [122] The required Ga production in 2030 for the Solar Generation 6 scenario [58] (~2500 t/y) is almost an order of magnitude below the estimated maximum recoverable Ga based on today's bauxite production levels (~12500 t/y), and much lower than the estimated Ga reserves (400000 t). [141]

Unlike the byproduct metals discussed above, Si is abundant: it comprises about 28% of the Earth's crust as a constituent of various minerals. [142] Although the U.S. Geological Survey does not report quantitative estimates of Si reserves, it states that the reserves are ample. [136] If the annual Si production grows at its historical average annual growth rate of 2.2% (as shown in Figure 3-1), then the annual Si production in 2030 will reach 11.5 million t/y in 2030. This is only 6% lower than the annual Si production level required by the Solar Generation 6 scenario [58] in 2030, which is 12.2 million t/y.

3.4   Conclusion

Continued rapid growth in PV deployment could require significant growth in the supply of some metals. In this paper, we estimate the growth rates needed in metals production to match PV deployment projections in 2030 for a range of future energy scenarios. We compare the required growth rates for six PV metals (In, Ga, Se, Te, Cd, and Si) with the historical growth rates observed for a large set of metals. We also compare the required production levels of the byproduct metals to their scalability potential based on metals reserves estimates.

The annual growth rates required for the byproduct metals (In, Ga, Te, and Se) production to satisfy the energy scenario-projected PV demand levels in 2030 are either unprecedented or fall on the higher end of the historical growth rates distribution. Growth projections for CdTe {CIGS} to supply 3% {10%} or greater electricity demand by 2030 would require unprecedented metals production growth rates for Te {In}. These estimates are for the medium material intensity case. The required metals growth rates will be even higher if material intensity remains at today's levels, the 'high materials intensity' case. In contrast,

our results suggest that c-Si technology can provide up to 100% of global electricity in 2030 without Si production exceeding the historical growth rates observed across a large set of metals.

The scalability potential of In, Te, and Se also fall short of the required production levels for these metals in 2030 based on estimated metals reserves. Ga has a higher scalability potential based on its higher abundance in bauxite ores. The Cd supply does not appear to be constraining because of its higher abundance in ores and decreasing demand by non-PV uses due to its toxicity. Finally, Si supply restrictions do not appear to pose a binding scalability constraint, due to the abundance of this metal.

This paper focuses on three main PV technologies that have been commercialized, CdTe, CIGS and c-Si. We find that at least one of these technologies, c-Si, is scalable based on the analysis of required metals production growth rates and Si availability. When the high processing costs of Si are considered, there is still room for improvement and possibly the introduction of non-Si based PV technologies, in order to reduce module costs. This study highlights, however, the importance from a scalability perspective of reducing the material intensity of other PV technologies (for example by using concentrators), or utilizing earth abundant materials. These general insights apply to a range of existing and future PV technologies.

In this paper, the required metals growth rates reported rely on estimates of the future demand for non-PV end-uses, based on the range of observed historical growth rates of these metals. We note that if non-PV end-uses grow more rapidly or slowly than observed historically, the comparison of projected and historical growth rates to meet PV scenarios would change.

The analysis of required growth rates in the context of historical growth rates provides a new perspective for assessing the raw material needs for future energy deployment scenarios. This approach can also be useful for analyzing the materials requirements of other technologies, to assess their scalability and inform technology development and research investment. We note that while the availability of raw materials is a necessary condition for scaling up technology production, other factors including production energy requirements [143, 128, 129] and the regional distribution of resources [131], should also be considered in an analysis of sufficient conditions for scalability.

Chapter 4

Criticality signals from metal price fluctuations with a focus on photovoltaics

Renewable energy technologies such as photovoltaics (PV) have an exceptional track record of falling costs and growing deployment. However, questions remain as to whether materials availability could prevent the cost-effective production of these technologies. This work focuses on a particular definition of metals criticality, which is the cost riskiness that metals bring to the technologies they are used in, and develops an approach that can serve as a first-pass assessment. We first characterize and compare the price dynamics of a wide set of metals. We find that the median price of byproduct metals are 45 times higher than the median price of major metals on average across all years over the period 1973-2012, while the median price volatility of byproduct metals was 69% higher than the median price volatility of major metals. We then evaluate the cost riskiness of PV technologies by treating a technology as a portfolio of metals. We find that PV technologies such as CdTe and CIGS that rely on byproduct metals, which show high price volatility and prices, may face higher cost riskiness, whereas other technologies such as perovskites would be expected to be less risky. The cost-riskiness metrics proposed in this work can be readily applied to other technologies.

4.1   Introduction

Despite past improvements, there may be scalability constraints that could slow down the cost trend and growth of PV. A scalability constraint that is relevant for PV is materials availability [13, 14]. Materials are important inputs and constitute a significant share of PV costs. Some of the current PV technologies use rare metals, whose availability and prices are risky. This is mainly because they are obtained as byproducts of major metals such as copper and zinc [21, 22, 23]. Being byproducts, their price and availability are dictated by the economics of major metals [24, 25, 26, 27].

Previous studies have identified possible materials constraints across many sectors of the economy and have shown that this may cause risks for companies, countries and regions [46, 47, 48, 49, 50, 51]. In general, these studies described metals as 'critical' if they are essential to industry and difficult to substitute, but sourced from few and politically unstable regions. Across these studies different definitions and indicators of criticality have been used [68]. Many metals used in technologies that can play a role in the transition to a low-carbon economy, such as PV, wind turbines and electric cars, have been deemed critical [63, 64, 65, 66, 67]. However, past studies have not analyzed how material availability risks may affect technology costs.

Here we assess materials availability risks from the perspective of technology costs, by introducing the concept of *cost riskiness*. This is the risk that input materials may bring to the technologies they are used in due to changes in material prices. Changes in price can act as an indicator of risks in the metals production system because price can become volatile due to physical unavailability, speculation or imperfect information. These changes can introduce added uncertainty and risks for producers, consumers and other stakeholders [144]. Metals that have inelastic supply (e.g. due to complex or inflexible production processes or limited excess supply) or metals that have inelastic demand (e.g. since they are essential, difficult to substitute, or represent a small portion of the overall cost of the product they are used in) may have higher price fluctuations in the case of demand and supply shocks, respectively. Price volatility has been proposed as an indicator of criticality in a few studies [145, 146]; however, it has not been investigated from the perspective of technology cost riskiness before.

To analyze cost riskiness, we use currently available data on metals prices and explore

signals in the price behavior that can indicate the risks of using certain metals in a technology. Specifically we ask: How do different metals compare in terms of price dynamics (averages and fluctuations around the averages)? How much cost riskiness may PV technologies experience due to their input metals?

We compare metals based on their price dynamics by using historical data for 35 metals over a 40-year period (1973-2012). We quantify the low-frequency changes in the historical price data from moving averages and the high-frequency changes from volatilities. We then apply these metrics to several PV technologies, including those that have been commercialized and those that are being developed in the labs, to compare their cost riskiness due to the metals they employ. Although we focus on PV here, the cost-riskiness metrics we propose can be used to evaluate any technology and make comparisons across technologies. The insights from this analysis can be used to inform the developments of technologies.

In Section 4.2, we describe the methods and data used to obtain the cost-riskiness metrics. We discuss how metals compare in terms of price dynamics, and apply the cost-riskiness metrics to the metals used in PV technologies in Section 4.3. We conclude in Section 4.4.

4.2 Methods

4.2.1 Description of the data

We obtain global yearly price and production data from the U.S. Geological Survey publications [147], which are available to the public. We include many metals in our dataset to get a broad picture. Our dataset includes 33 metals and 2 metal groups (platinum group metals and rare earth elements), ranges from major industrial metals to metals produced at smaller scales and used in more specialized applications, and captures most of the important metals which are produced, traded, and used worldwide. This dataset covers 38 of the 62 naturally occurring metals/metalloids. Only 9 metals that are included in the USGS database were not included in our analysis due to incomplete data. In Appendix C we provide more information about the reasons for including or not including certain metals.

Besides comparing metals on an individual basis, we also want to identify the differences between certain groups of metals. Therefore, we categorize the metals in our dataset as shown in Table 4.1. Our analyses will especially highlight the characteristics of major metals and byproduct metals. We categorize metals as 'major metals' if they are the primary products of

Table 4.1: Metal groups in this study. We categorize metals as 'major metals' if they are the primary products of their mines. Metals that are 100% obtained as byproducts are in the 'byproducts' category, while 'others' are those that may be obtained as byproducts or primary products of a mine. Note that the data is at the aggregate level for rare earth elements and platinum group metals.

Major metals	Byproducts	Others
Aluminum	Arsenic	Cobalt
Chromium	Bismuth	Vanadium
Copper	Cadmium	Beryllium
Lead	Gallium	Niobium
Magnesium	Germanium	Lithium
Manganese	Indium	Mercury
Nickel	Rhenium	Molybdenum
Silicon	Selenium	Antimony
Strontium	Tellurium	Tantalum
Tin	Thallium	Tungsten
Zinc	Rare earth elements	Silver
	(15 lanthanides,	Gold
	yttrium, scandium)	Platinum group metals
		(platinum, palladium,
		rhodium, ruthenium,
		osmium, iridium)

their mines. Metals that are 100% obtained as byproducts are in the 'byproducts' category, while 'others' are those that may be obtained as byproducts or as primary products of a mine.

For major metals, both price and production data are available at the USGS website starting from as early as 1900. For other metals, data may start later. In order to compare metals on an equal time frame, our analysis focuses on 1973-2012 as this is the period for which data are available for all of the metals in our dataset.

4.2.2 Description of the cost-riskiness metrics

We analyze metal price dynamics over time and across metals by quantifying the low- and high-frequency changes as described below. To quantify the low-frequency changes, we calculate the moving average. Given a price sequence[1] for a metal for 1973-2012, $\{p_t\}_{t=1}^{40}$, we calculate a moving average sequence using a time window of interest. Using shorter time windows would reveal the fluctuations more, while longer time windows would emphasize the overall trend. Say, the time window is 20 years, then the moving average sequences for the price, $\{MA_t\}_{t=1}^{21}$, are found in the following formula:

$$MA_t = \frac{1}{20} \sum_{i=t}^{t+19} p_i. \tag{4.1}$$

We also obtain the moving average sequence for the production data when we compare metals in terms of low-frequency price and production changes in Section 4.3. The moving average for production is obtained by using the same procedure as above.

To characterize the short-term variations in price, we calculate volatility. The volatility of a price series is commonly calculated as the standard deviation of period-over-period changes in prices [148, 52, 144]. We start by calculating the year-to-year changes in prices. Given a price sequence for a metal for 1973-2012, $\{p_t\}_{t=1}^{40}$, the yearly price change sequence, $\{\rho_t\}_{t=1}^{39}$ is obtained by taking the first difference of the logarithm of the price sequence:

$$\rho_t = \ln p_{t+1} - \ln p_t. \tag{4.2}$$

The logarithmic differences can also be interpreted as yearly percentage changes in price when they are small. The volatility for a price change sequence with length n is the standard

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[1]Note that the yearly prices are deflated to their real values in 2012 by using the GDP deflator.

deviation of the yearly changes:

$$\sigma_t = \sqrt{\frac{\sum_{t=1}^{t=n} (\rho_t - \bar{\rho})^2}{(n-1)}}. \tag{4.3}$$

4.2.3 Application of the cost-riskiness metrics to technologies

For a technology, we can evaluate the price trend and price volatility of its metals individually. However, in order to compare PV technologies that are composed of multiple metals, we need a method to combine the cost riskiness of individual metals. To our knowledge only one previous study attempted to analyze the risks due to input metals at a technological level by combining the risks of individual metals [149]. In this work we treat each technology as a portfolio of metals and obtain an aggregate score for a technology by weighting the price and price volatility of its individual metals.

The expected average price of the portfolio (i.e. a PV technology) is the weighted sum of the individual metal's prices:

$$p_{tech} = \sum_i m_i p_i, \tag{4.4}$$

where p_i is the price of metal i [2012\$/t] and m_i is the material intensity of metal i [t/GWp] in the technology.

The weighted price is similar to the 'vulnerability to supply restriction' dimension of criticality used in previous studies (e.g. [50]). When price is weighted by material usage, it shows the economic importance of the metals for the technology, therefore the economic consequence that could be suffered in case of a supply disruption. A similar weighting approach can be used to obtain the economy-wide importance of a metal by weighting the price by the economy-wide usage.

The price volatility of the portfolio (i.e. a PV cell technology) is shown in Eq. 4.5. This time we use the mass fractions of metals in the technology as weights to represent their proportional effect on the technology. The weighted price volatility is determined not only by the price volatilities of the individual metals but also how their yearly price changes correlate with each other. If they are perfectly uncorrelated, the technology's price variance is the sum over all metals of the square of the fraction of the metal in the cell times the metals' price variance. If there is a correlation, the second term adds to or subtracts from the first term.
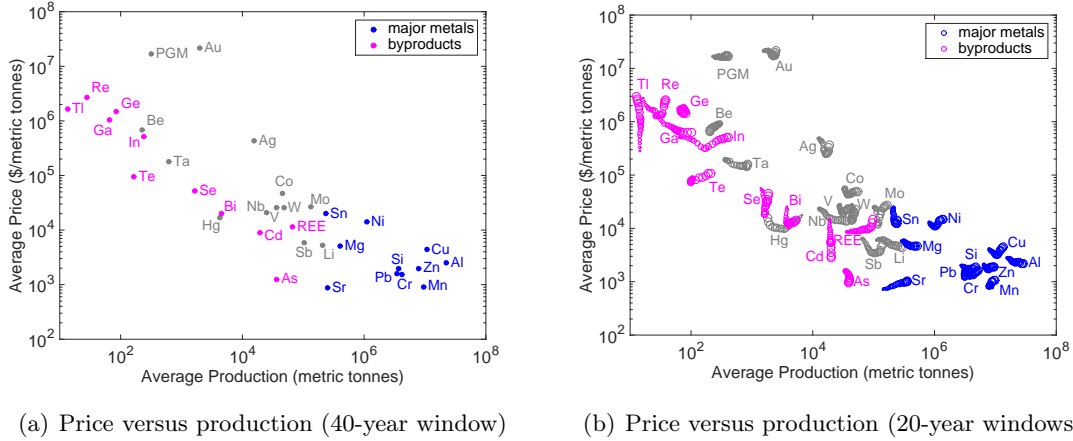
(a) Price versus production (40-year window) (b) Price versus production (20-year windows)

Figure 4-1: Average price versus average production for 1973-2012, using **(a)** a 40-year window and **(b)** overlapping 20-year windows. Major metals are shown in blue, byproduct metals are in magenta, and other metals are in gray. Annual price and production data are collected from the U.S. Geological Survey publications [147]. Prices are in real 2012 USD. Note that there has been limited movement across the x-axis over time. The relationship between price and production is $p \sim d^{-0.57}$ in (a) and $p \sim d^{-0.56}$ in (b), where p is price and d is production.

$$\sigma_{tech} = \sqrt{\sum_i w_i^2 \sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j \sigma_i \sigma_j \rho_{ij}}, \qquad (4.5)$$

where w_i is the mass fraction of metal i, σ_i is the price volatility of metal i, and ρ_{ij} is the correlation coefficient of yearly price changes of metal i and j.

4.3 Results and Discussion

4.3.1 Low-frequency changes: Moving averages

When we analyze the low-frequency changes (moving averages) in price, we observe differences across metals. Plotting the average price against average production for the 40 year-period between 1973 and 2012 (Figure 4-1(a)) shows that average production and average price are negatively correlated across metals. This plot identifies a group of high-price and low-production metals in the upper left corner of the plot, and a second group with low price and high production in the lower right corner. Byproduct metals (in magenta) appear close to the upper left with their low production levels and high price. Major metals (in blue) are

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on the lower right corner due to their high production and low price levels.

The difference between the average prices of byproducts and major metals has persisted over time. When the median price level is plotted over time for different metal groups (Figure 4-2(a)) for a sliding time window of 20 years, we see that on average across all years the median price of byproduct metals are 1.65 orders of magnitude higher (45 times more) than the median price of major metals.

When we pool all of the price values obtained by using 20-year sliding windows (Figure 4-2(b)), we observe that byproducts have a wider distribution with a higher median. While only 9% of the major metals (1 metal out of 11) has median price above the median of all metals combined, 64% of the byproduct metals (7 metals out of 11) have medians that exceed the median for all metals. Note that very similar results are obtained when we use shorter sliding windows such as 5-year windows.

Another result that emerges from Figure 4-1(b) is that movement along the production axis (x-axis) has been limited. In the 40 year-period between 1973 and 2012, no metal has moved from very low production to very high production. This has implications for scalability of technologies utilizing byproduct metals. Studying these past trajectories can provide context for changes in production and price needed to widely adopt new technologies.

4.3.2   High-frequency changes: Volatility

Figure 4-3 ranks metals based on their price volatility calculated for the 40-year time window of 1973-2012. We observe that metal groups differ in price volatility as well: Major metals (blue) tend to have lower price volatility on average compared to other metals, while more byproduct metals (magenta) rank among the highest.

Next we explore how the price volatilities of different metal groups change over time. We calculate the price volatility of each metal for 20-year sliding time windows in 1973-2012. We then plot the median value obtained from all metals in each metal group in a given year (Figure 4-2(c)). We see that on average across all years, the median price volatility of byproduct metals are 69% higher than the median price volatility of major metals.

When we pool all of the price volatility values obtained by using 20-year sliding windows (Figure 4-2(d)), we observe that byproducts have a wider distribution with a higher median. While only 9% of the major metals (1 metals out of 11) has median price volatility above the median of all metals combined, 73% of the byproduct metals (8 metals out of 11) have
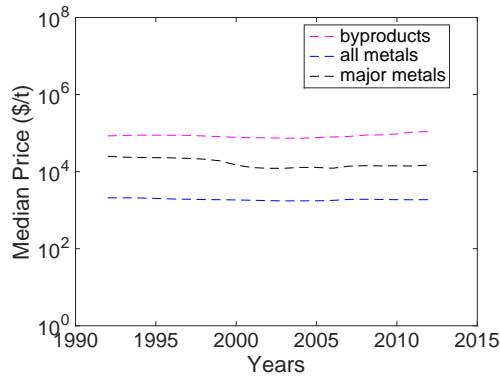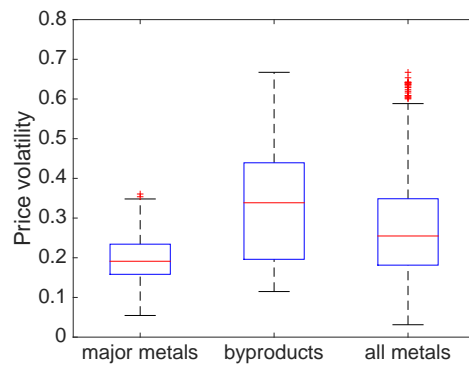
(a) Price: Median over time
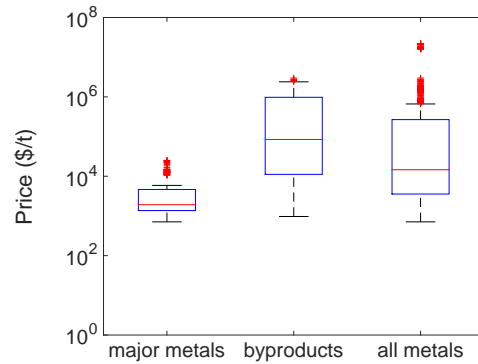
(b) Price: Boxplot for all years
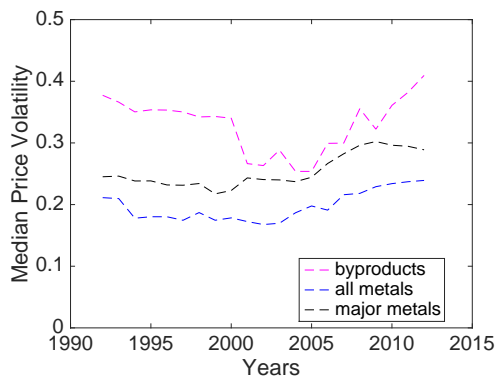
(c) Price volatility: Median over time

(d) Price volatility: Boxplot for all years

Figure 4-2: **(a)** Median price for metal groups over time. The median value shown refers to the median of the average prices obtained for each metal at the end of a 20-year time window. Note the logarithmic scale. **(b)** Boxplots of average prices obtained for each metal for each 20-year sliding window in 1973-2012. **(c)** Median price volatility for metal groups over time. The median value shown refers to the median of the volatility value obtained for each metal at the end of a 20-year time window. **(d)** Boxplots of volatilities obtained for each metal for each 20-year sliding window in 1973-2012. Prices are in 2012 real USD.
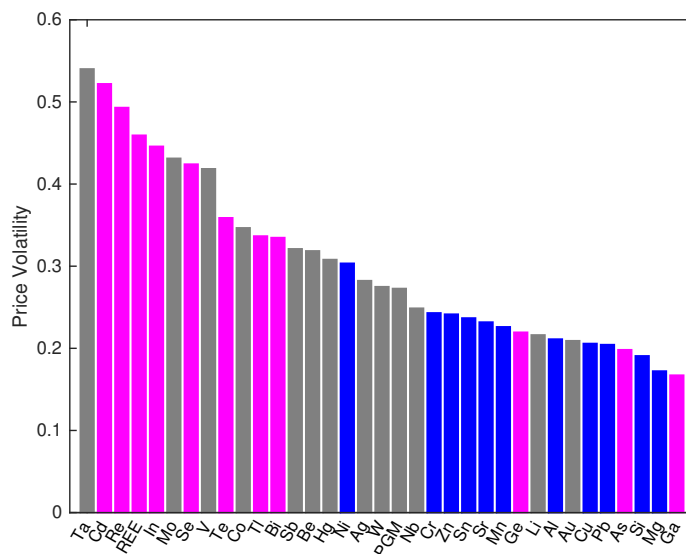
Figure 4-3: Price volatility for 1973-2012, using a 40-year window. Major metals are shown in blue, byproduct metals are in magenta, and other metals are in gray. Price volatility is the standard deviation of the logarithmic price returns obtained for the period 1973-2012. Annual price data was collected from the U.S. Geological Survey publications [147]. Prices have been converted to real 2012 USD before volatility was calculated.

medians that exceed the median for all metals. Note that similar results are obtained when we use shorter sliding time windows, such as 5-year windows.

Major metals, which are produced at larger scales as shown in Fig. 4-1(a) and Fig. 4-1(b), have higher natural abundances and more established production channels and markets. These metals may have benefited from the learning effect and economies of scale to a greater extent than the metals that are produced in low quantities.

4.3.3 Application of cost-riskiness metrics to photovoltaics (PV) technologies

As deployment of PV increases, rapid growth in PV manufacturing will require production of sufficient amount of PV materials in a cost-effective and timely manner [19]. Studying the cost riskiness of PV technologies can be especially useful for informing early-stage technologies in terms of scalability.

In this section we compare PV technologies based on the cost riskiness due to the metals they employ. We calculate aggregate cost-riskiness scores for each technology as described in

Section 4.2. Table 4.2 shows the data and cost-riskiness metric values for the metals used in the PV technologies included in our analysis. Although we demonstrate our cost-riskiness metrics on PV cell technologies here, the method can be applied to PV modules and systems or other technologies.

We calculate the cost-riskiness metrics for metals used in the absorber layers of both commercial and emerging PV cell technologies. The commercialized technologies include crystalline silicon (c-Si) (both single- and multi-crystalline), gallium arsenide (GaAs), III-V multijunction (MJ) solar cells, and three thin-film technologies, namely hydrogenated amorphous silicon (a-Si:H), cadmium telluride (CdTe), and copper indium gallium diselenide (CIGS). The emerging PV cell technologies that we analyze include copper zinc tin sulfide (CZTS), colloidal perovskites and quantum dot photovoltaics (QDPV).[2]

Figure 4-4 shows the weighted price plotted against weighted price volatility for each PV technology. We find that the thin film technologies CdTe and CIGS have relatively high price volatilities mainly because of their reliance on byproduct metals. GaAs, CIGS, III-V MJ, c-Si have higher weighted prices, because they use byproduct metals with high prices or the material intensity is high (for c-Si). Note that the weighted price is in units of dollar per GW generated. Since power depends on conversion efficiency, as technologies get more efficient, material usage per GW and the weighted price can go down. CZTS, perovskites and QD cells cells have lower weighted prices and price volatilities because of their use of abundant metals; however, they have not been fully commercialized.

Note that these are preliminary results to demonstrate the method and they will be refined further. In future work we will revisit the assumption that the purity level of a metal as it is used in PV and the price and production for that particular purity level are consistent.

4.4 Conclusion

In this paper we focused on a particular definition of metals criticality, namely the risks that metals can cause to technologies. We asked what signals we can get from metal price behavior that indicate the risks of using these materials in a technology. To answer this question, we developed an approach for analyzing cost riskiness based on the low- and high-frequency

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[2]There are other emerging PV cell technologies that we exclude from the analysis. Organic photovoltaics use carbon in their absorber layer. Since carbon is not a metal and not included in our dataset, we exclude this technology. Dye-sensitized solar cells use ruthenium, which is a minor platinum group metal (PGM). We exclude this technology since we do not have data on individual PGMs.

Table 4.2: Average price and price volatility for the metals used in the absorber layers of various PV technologies. Technology scores are the weighted sums of individual metal scores as explained in Section 4.2.

Technologies and materials	Material intensity[a] (t/GWp)	Price[b] (2012$/t)	Mass fraction	Price volatility[b]
sc-Si (single crystal)				
Si	1455.625	1819	100%	0.121
mc-Si (multicrystalline)				
Si	2015.481	1819	100%	0.121
GaAs				
Ga	22.528	747067	49%	0.154
As	23.920	1416	51%	0.173
III-V MJ [d]				
Ga	0.029	747067	1%	0.154
As	0.042	1416	1%	0.173
In	0.047	473925	1%	0.452
Ge	4.797	1584214	98%	0.177
a-Si:H				
Si	57.532	1819	100%	0.121
CdTe				
Cd	29.443	5864	48%	0.585
Te	31.392	84518	52%	0.277
CIGS				
Cu	8.222	3742	16%	0.178
In	14.856	473925	28%	0.452
Ga	9.022	747067	17%	0.154
Se	20.434	31251	39%	0.364
CZTS				
Cu	20.933	3742	40%	0.178
Zn	11.127	1876	21%	0.197
Sn	19.807	15272	38%	0.187
Perovskite[e]				
Pb	2.413	1438	100%	0.181
QD				
Pb	12.711	1438	100%	0.181

[a] Material intensities were obtained from [3], which assumed record-efficiency or representative device structures, current record lab-cell efficiencies, and 100% materials utilization and manufacturing yield. These are optimistic assumptions; actual materials utilization has been estimated to range from 15-70% for a-Si:H, 60-80% for CIGS, and 90-99% for CdTe [3].

[b] Price and price volatility values reported here are the median of the values obtained by using 20-year sliding windows over time.

[c] Weighted scores for technologies are the weighted sums of individual metal scores.

[d] This technology utilizes mirrors or lenses to concentrate light on a small area and increase efficiency. To obtain the specified material intensity, a concentration ratio of 500 is assumed for III-V MJs [3].

[e] Perovskites also use carbon in their absorber layer. Since carbon is not a metal and not included in our dataset, we excluded carbon. Similarly, sulfur in CZTS and QD was excluded from our analysis.
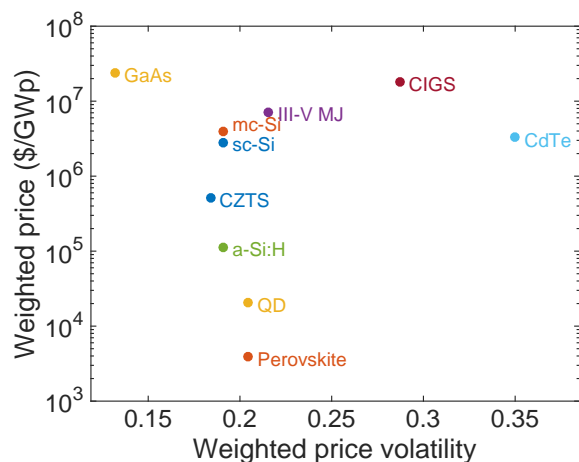
Figure 4-4: Weighted price versus weighted price volatility scores for PV technologies. For numerical results and weights given to individual metals, see Table 4.2.

changes in historical metals prices. This approach can serve as a first-pass assessment of metals criticality from the perspective of technology costs (such as PV costs).

We found that we already observe signals of riskiness for certain metals. We highlighted the differences between major metals and byproducts in terms of their price trends and the fluctuations around these trends. Our analysis showed that on average byproducts have higher price volatilities and higher average prices than major metals.

We then developed a method for evaluating the cost riskiness that metals bring to technologies and demonstrated this method on different PV technologies. We found that technologies such as CdTe and CIGS, which rely on byproduct metals with particularly high price volatility as well as high prices, may face higher risks, whereas other technologies such as perovskites perform well in terms of these cost-riskiness measures.

Although we focused on PV here, the approach can be applied to any technology and can allow making comparisons across technologies. We can use the insights gained to inform the development of and investment in technologies.

Appendices

Appendix A

Supporting Information for Chapter 2

A.1 Derivation of Eq. (2.10)

The change in the technology's cost is given by

$$\Delta C(\mathbf{r}) = \sum_i \Delta c_i(\mathbf{r}). \tag{A.1}$$

Assuming cost components can be written in the form of Eq. (2.9), we have

$$\Delta c_i(\mathbf{r}) = c_{i0}\, \Delta\left(\prod_j g_{ij}(r_j) \right). \tag{A.2}$$

We wish to express the finite difference of a product of variables in a more convenient form. For infinitesimal changes, the product rule says

$$d(x_1 x_2 x_3 \ldots) = (dx_1)x_2 x_3 \ldots + x_1(dx_2)x_3 \ldots + \cdots. \tag{A.3}$$

A similar rule can be derived for Δ. The derivation is simpler if we first derive a rule for

applying Δ to an exponential. The change in e^x can written in terms of Δx as

$$\Delta e^x = e^{x_2} - e^{x_1}$$
$$= e^{\bar{x} - \frac{1}{2}\Delta x} - e^{\bar{x} + \frac{1}{2}\Delta x}$$
$$= e^{\bar{x}}\left(e^{+\frac{1}{2}\Delta x} - e^{-\frac{1}{2}\Delta x}\right)$$
$$= e^{\bar{x}} \cdot 2\sinh\left(\frac{1}{2}\Delta x\right) \tag{A.4}$$

where for the second line we defined $\bar{x} \equiv \frac{1}{2}(x_1 + x_2)$. In the limit $x \to 0$, we have $\sinh x \to x$, and we recover the rule $d(e^x) = e^x\,dx$. Using Eq. A.4, the change in a product of variables can be written as

$$\Delta\prod_i x_i = \Delta e^{\sum_i \ln x_i}$$
$$= e^{\overline{\sum_i \ln x_i}} \cdot 2\sinh\left(\frac{1}{2}\sum_i \Delta \ln x_i\right) \tag{A.5}$$

where $\overline{\sum_i \ln x_i}$ denotes the arithmetic average of $\sum_i \ln x_i$ in the two time periods. The exponential factor can be written more simply as a geometric average:

$$e^{\overline{\sum_i \ln x_i}} = e^{\frac{1}{2}\left(\sum_i \ln x_i^1 + \sum_i \ln x_i^2\right)}$$
$$= e^{\sum_i \ln \sqrt{x_i^1 x_i^2}}$$
$$= \prod_i \sqrt{x_i^1 x_i^2}. \tag{A.6}$$

Writing the geometric average of x in the two time periods as $\tilde{x}_i \equiv \sqrt{x_i^1 x_i^2}$, we can write

$$\Delta\left(\prod_i x_i\right) = \left(\prod_i \tilde{x}_i\right) \cdot 2\sinh\left(\frac{1}{2}\sum_i \Delta \ln x_i\right). \tag{A.7}$$

Eq. (A.7) defines a product rule for the Δ operator.

Returning to Eq. (A.2) and using the rule just derived we find

$$\Delta c_i = c_{i0}\left(\prod_j \tilde{g}_{ij}\right) \cdot 2\sinh\left(\frac{1}{2}\sum_j \Delta \ln g_{ij}\right) \tag{A.8}$$

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where $\tilde{g}_{ij} \equiv \sqrt{g_{ij}(r_j^1) \cdot g_{ij}(r_j^2)}$ is the geometric average value of $g_{ij}(r_j^t)$ from the two time periods. Since c_{i0} is a constant that does not vary between the two periods, the product $c_{i0} \prod_\alpha \tilde{g}_{i\alpha}$ is the geometric average of the ith cost component, $\tilde{c}_i \equiv \sqrt{c_i(\mathbf{r}^1) \cdot c_i(\mathbf{r}^2)}$. Thus, we can write Eq. (A.8) more simply as

$$\Delta c_i = \tilde{c}_i \cdot 2 \sinh\left(\frac{1}{2} \sum_j \Delta \ln g_{ij}\right). \tag{A.9}$$

Given Eq. (A.1) the total cost change is therefore

$$\Delta C = \sum_i \tilde{c}_i \cdot 2 \sinh\left(\frac{1}{2} \sum_j \Delta \ln g_{ij}(r_j)\right). \tag{A.10}$$

This formula gives an exact relationship between ΔC and the Δg_{ij}. However we cannot use it to decompose ΔC into contributions from each variable r_j, because the sum over variables j is trapped inside the argument of the sinh. When $\sum_j \Delta \ln g_{ij}$ is small, one can make the approximation $\sinh x \approx x$, and Eq. (A.10) becomes

$$(\Delta C)_{\text{approx}} \approx \sum_i \tilde{c}_i \sum_j \Delta \ln g_{ij}(r_j)$$
$$\approx \sum_j \left(\sum_i \tilde{c}_i \Delta \ln g_{ij}(r_j)\right). \tag{A.11}$$

Since this derivation assumes that $\sum_j \Delta \ln g_{ij}$ is small, ideally one would use it to estimate changes over periods of time that are short enough that variable changes small. Estimates of cost change attributions over longer time periods can then be formed by chaining together changes over shorter periods.

A.2 Sensitivity analysis for low-level mechanisms

In this section we estimate the sensitivity of our cost change results to uncertainty in the input variables of Table 2.1. We vary each variable in each of the three time periods by $\pm 20\%$, for a total of eight cases, and recompute the list of cost change contribution in both periods. We take the minimum and maximum of the changes in each variable out of these
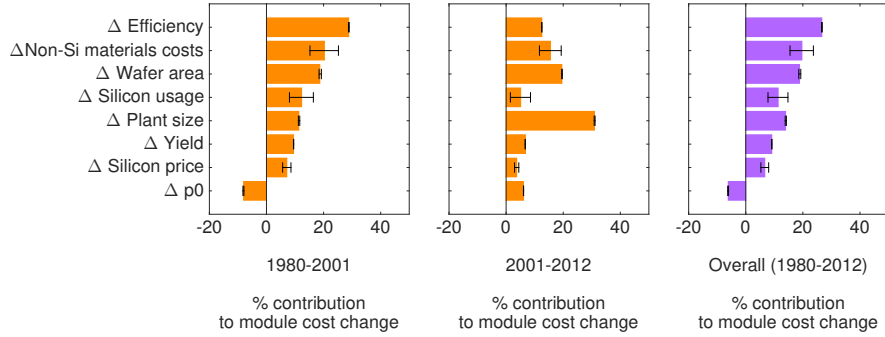
Figure A-1: Sensitivity analysis for silicon usage, v. We vary silicon usage in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

eight cases to produce error bars.[1]

Figure A-1 shows how the percent contributions change when silicon usage v is varied. Since contributions must sum to 100% changing v affects the relative contributions of both v and all other variables to a greater or lesser extent. Figures A-2-A-9 show the same analysis for other variables and the scaling factor, b. Fig. A-10 shows the contributions when all variables are varied by $\pm 20\%$, except for yield, which is varied by $\pm 3\%$ of its value in all years and module efficiency which is varied by $\pm 5\%$ of its value in 2001 and 2012 to ensure the 2012 is always higher than the 2001 efficiency. We conclude that the results are sensitive to module efficiency, while not very sensitive to changes in other variables and the scaling factor, b. We find that a smaller change in efficiency during a period is associated with larger changes in non-silicon materials and p_0, and in some scenarios with more modest assumptions about efficiency improvement, we find that the relative contributions of efficiency and non-silicon materials switch places Fig. A-3. In these scenarios, both efficiency and non-silicon materials continue to play significant roles in cost reduction. Furthermore, conversion efficiency estimates may be fairly reliable because of standard testing procedures.

We perform an additional sensitivity analysis on the silicon price in 1980, which has a wide range of values across different sources. Figure A-11 shows sensitivity analysis results when the silicon price in 1980 is varied. Various sources report a silicon price higher than our central value of 66 2015\$/kg, which would result in a larger contribution of a falling silicon

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[1]An exception is yield, which is varied by $\pm 3\%$ of its value in all years to ensure that it does not exceed 100%. To prevent efficiency from decreasing over time in our sensitivity tests, we limit the variation of efficiency such that module efficiency is varied by $\pm 5\%$ of its value in 2001 and 2012.
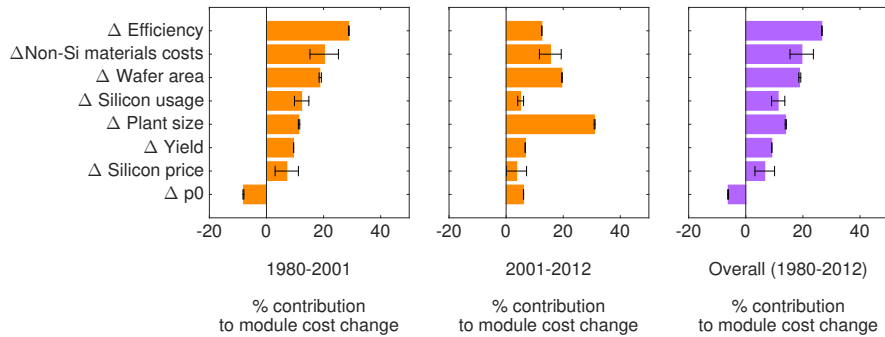
Figure A-2: Sensitivity analysis for silicon price, p_s. We vary silicon price in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.
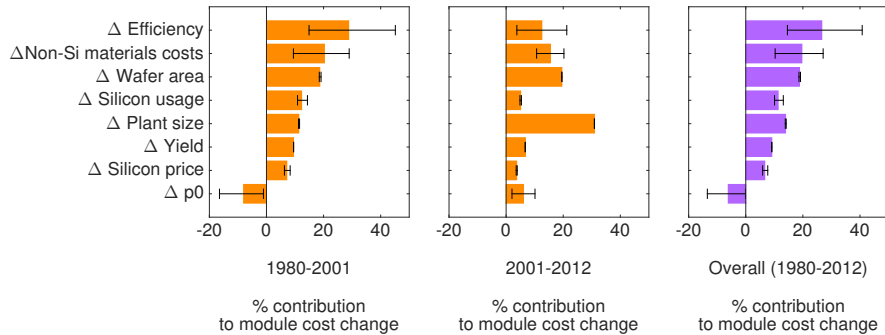

Figure A-3: Sensitivity analysis for module efficiency, η. Note that module efficiency in 1980 (8%) is varied by $\pm$ 20% of its value (resulting in lower and upper bounds of 6.4% and 9.6%), while module efficiency in 2001 and 2012 by $\pm$ 5% of its value to prevent efficiency from decreasing over time in our sensitivity tests (resulting in lower and upper bounds of 12.35% and 13.65% for 2001, and 14.25% and 15.75% for 2012.) We recompute the list of cost change contributions of low-level mechanisms in both periods for a total of eight cases. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.
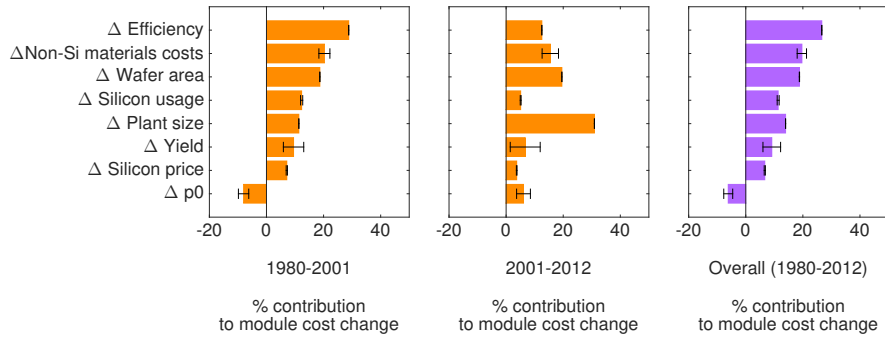
Figure A-4: Sensitivity analysis for yield, y. We vary yield in 1980, 2001, and 2012 by 3% of its value, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanism out of these eight cases. Note that yield is varied by $\pm 3\%$ of its value in all years to ensure that it does not exceed 100%.
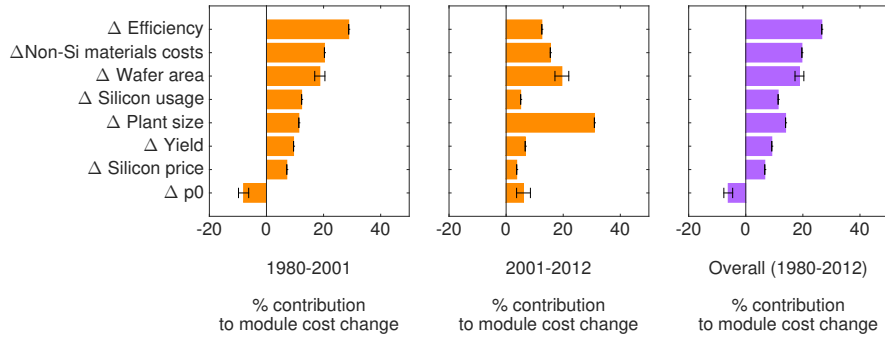

Figure A-5: Sensitivity analysis for wafer area, A. We vary wafer area in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.
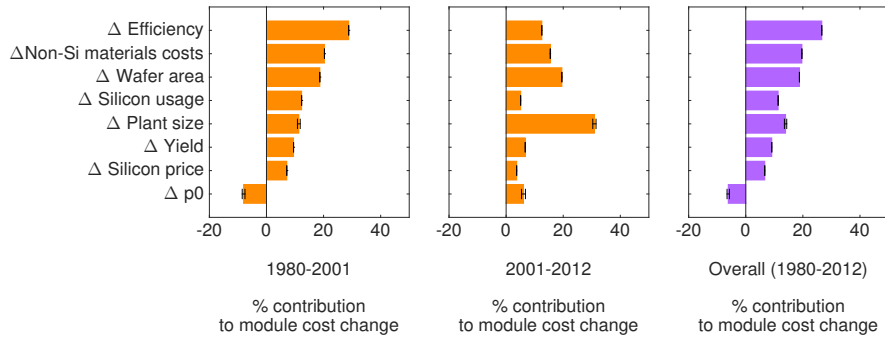

Figure A-6: Sensitivity analysis for plant size, K. We vary plant size in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.
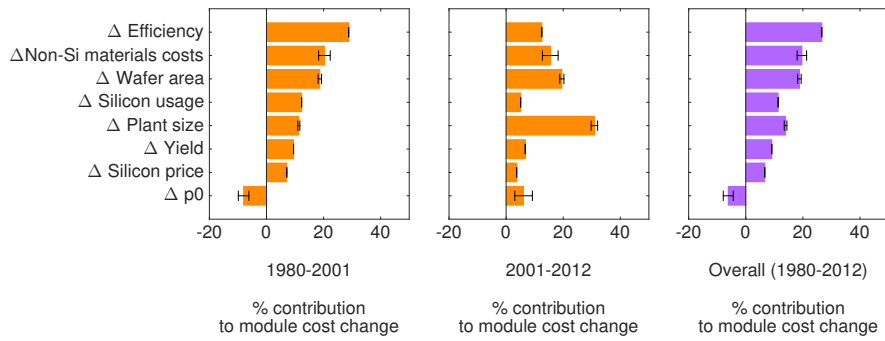
Figure A-7: Sensitivity analysis for share of materials costs, θ. We vary the share of materials costs in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.
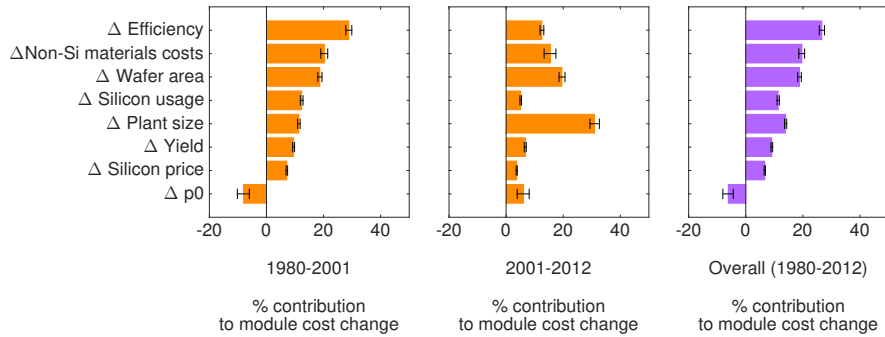

Figure A-8: Sensitivity analysis for module price, C. We vary module price in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

Figure A-9: Sensitivity analysis for scaling factor, b. We vary the scaling factor in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.
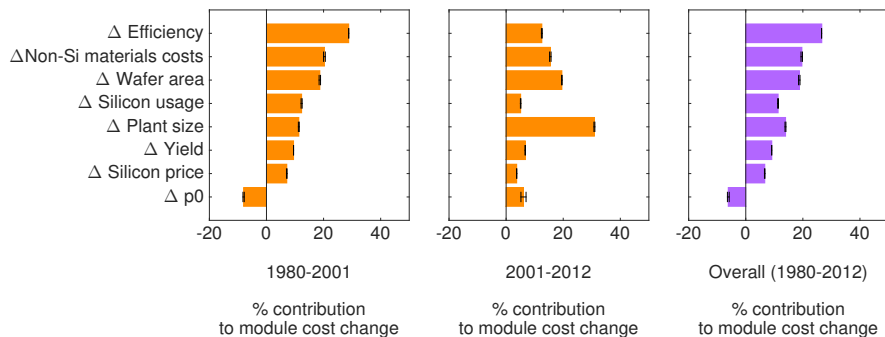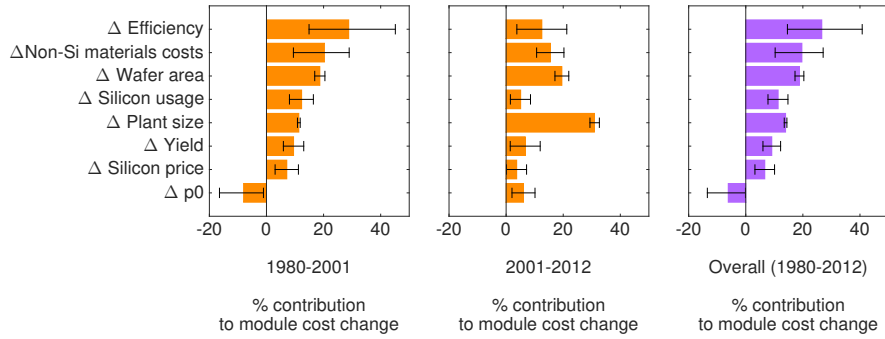
Figure A-10: Contributions to cost reduction with error bars representing scenarios in which all variables are varied relative to the central scenario by $\pm 20\%$, except for yield, which is varied by $\pm 3\%$ of its value, and efficiency, which is varied by $\pm 5\%$ of its value in 2001 and 2012 to prevent efficiency from decreasing over time.
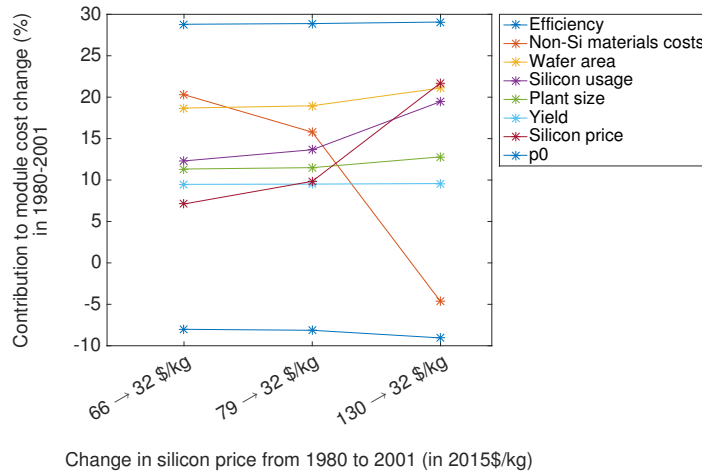

Figure A-11: Percentage contribution of low-level mechanisms to module cost change when silicon price in 1980 is varied from the central scenario assumption of 66 2015\$/kg.

price to module cost change. At the same time, the contribution of non-Si materials costs would be lower. The rest of the list would stay mostly unchanged. Thus total materials costs (silicon and non-silicon) are always significant, while the relative importance of silicon and non-silicon costs can change depending on value used for the 1980 silicon price.

A.3 Sensitivity analysis for high-level mechanisms

In the main text we propose a primary assignment for each variable. Here we show the high-level results would change for different assignments of low-level variables to high-level mechanisms. Table A.1 shows the alternate assignments that result in the lowest and highest

Low-level Mechanisms	High-level Mechanisms		
	Primary Assignment	Case ★	Case ◊
Δ Efficiency	R&D	R&D	R&D
Δ Non-Si materials costs	0.5 R&D, 0.5 EOS	R&D	EOS
Δ Wafer area	R&D	R&D	0.5 R&D, 0.5 LBD
Δ Silicon usage	R&D	R&D	0.5 R&D, 0.5 LBD
Δ Plant size	EOS	EOS	EOS
Δ Yield	LBD	LBD	LBD
Δ Silicon price	other (1980-2001) EOS (2001-2012)	other (1980-2001) EOS (2001-2012)	other (1980-2001) EOS (2001-2012)
Δ p0	other	other	other

Table A.1: Assignment of low-level mechanisms to high-level mechanisms. The primary assignments lead to the bars given in Fig. 2-4. Alternative assignments (★ and ◊ cases) reflect assignments with the lowest and highest values of R&D, EOS and LBD, and correspond to the star and diamond cases in Fig. A-12.

values of R&D, EOS and LBD. Fig. A-12 shows the results of these assignments.

Figure A-13 shows the percentage contribution of all high-level mechanisms when low-level variables are given an alternate assignment one-at-a-time. Wafer area and silicon usage were originally assigned to R&D. Here we assign 50% of these variables to LBD and 50% remains assigned to R&D. Non-Si materials costs were originally assigned equally to R&D and EOS. Here we consider a 100% assignment to R&D and a 100% assignment to EOS. We find that in 1980-2001 and 1980-2012 R&D remains the most important mechanism. LBD gains importance to the extent that wafer area and silicon usage were LBD-driven. EOS can potentially become almost equal to R&D in the second period.

Figures A-14 - A-16 explore high-level contributions when multiple low-level variables may be reassigned as shown in Tables A.2-A.4. Figure A-17 shows the results from all combinations of reassignments. To allow extreme cases to be observed more easily, Figure A-14 shows only combinations of reassignments that result in a minimum or maximum contribution for R&D. Figures A-15 and A-16 do the same for LBD and EOS, respectively. R&D never switches places with any other mechanisms in the first period. It can switch places with EOS in the second period. LBD can switch places with EOS in the first period. It does not switch places with any mechanism in the second period.
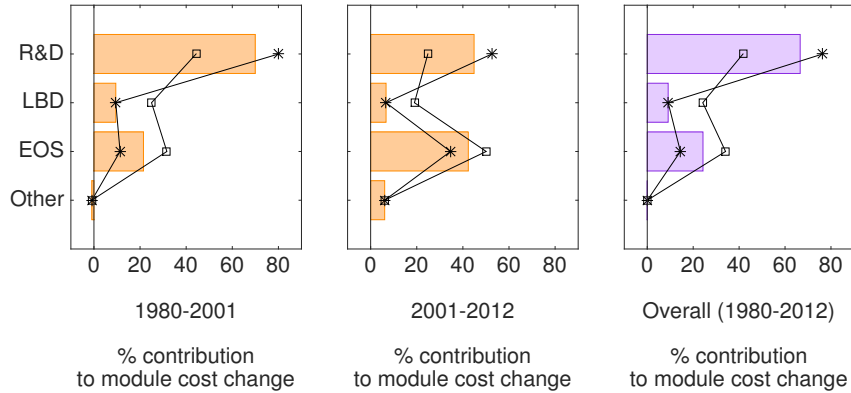
Figure A-12: Percentage contribution of the high-level mechanisms to module cost decline in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). R&D = Research and development, LBD = Learning-by-doing, EOS = Economies of scale, Other = other mechanisms such as spillovers. We categorize the changes that require a lab setting or a nonroutine production activity (e.g. experimental production line) as being caused by R&D [100, 101]. We consider an improvement to have been made by LBD if it was achieved as a result of repeated routine manufacturing activity and if it was incremental in nature [100]. Changes that result from increases to the scale of the module manufacturing plant we categorize as EOS. Assignments of low-level mechanisms are given in Table A.1. Bars show the results under the primary assignment, while the ★ and ◊ cases show the results under alternative assignments.
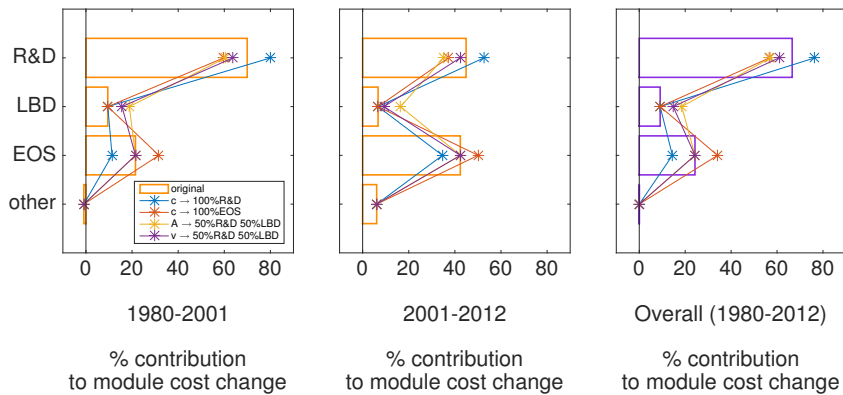

Figure A-13: Possible percentage contribution of high-level mechanisms in each period. Lines with markers link high-level contributions under alternate assignments of low-level variables to high-level mechanisms. Reassignments are made one-at-a-time. Non-Si materials costs (c) were originally assigned equally to R&D and EOS, and we consider two possible reassignments, to R&D only and to EOS only. Wafer area (A) and silicon usage (v) were originally assigned to R&D, and here we also consider a case where they are assigned to LBD and R&D equally.

Low-level mechanisms	Original	(1)	(2)
Δ Non-Si materials costs	0.5 R&D 0.5 EOS	R&D	EOS
Δ Wafer area	R&D	R&D	0.5 R&D 0.5 LBD
Δ Silicon usage	R&D	R&D	0.5 R&D 0.5 LBD

Table A.2: Alternate assignments of three low-level mechanisms to high-level mechanisms to achieve the lowest and highest possible contributions of R&D. Note that other low-level mechanisms remain in their primary high-level mechanisms. The contributions of the high-level mechanisms in each case are shown in Figure A-14
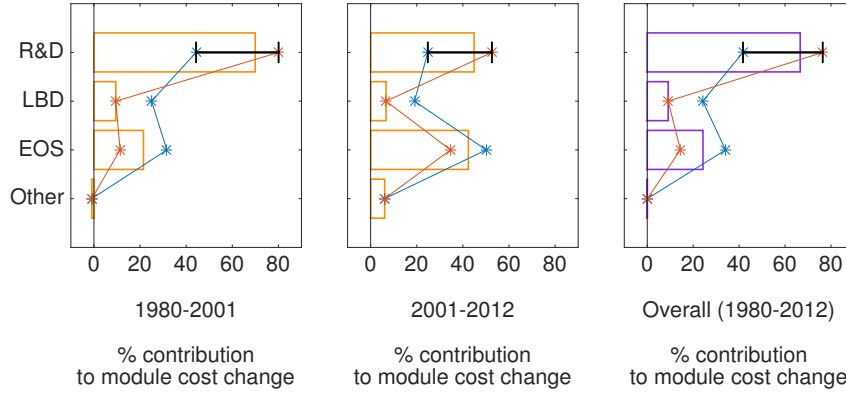

Figure A-14: Possible percentage contribution of high-level mechanisms under the highest and lowest cases for R&D. Horizontal bars show the contribution of the primary mechanisms. Lines with markers link results under alternate assignments. The lowest case for R&D is obtained when both wafer area (A) and silicon usage (v) are moved to LBD from their original assignment to R&D; and non-Si materials costs (c) are assigned to EOS in place of their original assignment to 50% R&D and 50% EOS. The highest case for R&D is obtained when both wafer area (A) and silicon usage (v) remain in R&D, and non-Si materials costs (c) are assigned to R&D only.

Low-level mechanisms	Original	(1)	(2)	(3)	(4)	(5)
Δ Non-Si materials costs	0.5 R&D 0.5 EOS	0.5 R&D 0.5 EOS	R&D	EOS	R&D	EOS
Δ Wafer area	R&D	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	R&D	R&D
Δ Silicon usage	R&D	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	R&D	R&D

Table A.3: Alternate assignments of three low-level mechanisms to high-level mechanisms to achieve the lowest and highest possible contributions of LBD. Other low-level mechanisms remain in their primary assignments. High-level contributions for each assignment are shown in Figure A-15.
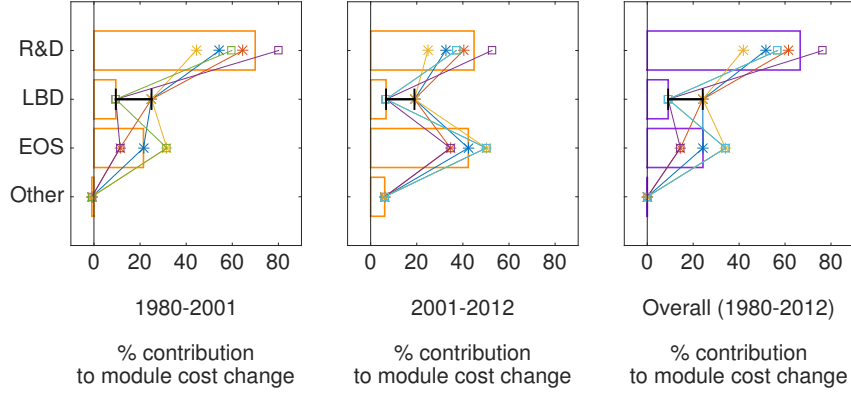
Figure A-15: Possible percentage contribution of high-level mechanisms under highest and lowest cases for LBD. Horizontal bars show the contribution of the primary mechanisms. Lines with markers link results under alternate assignments. The lowest case for LBD is obtained when both wafer area (A) and silicon usage (v) remain in their original assignment to R&D. The highest case for LBD is obtained when both wafer area (A) and silicon usage (v) are moved to LBD from their original assignment to R&D.

Low-level mechanisms	Original	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Non-Si materials costs	0.5 R&D 0.5 EOS	EOS	EOS	EOS	EOS	R&D	R&D	R&D	R&D
Δ Wafer area	R&D	R&D	0.5 R&D 0.5 LBD	R&D	0.5 R&D 0.5 LBD	R&D	0.5 R&D 0.5 LBD	R&D	0.5 R&D 0.5 LBD
Δ Silicon usage	R&D	R&D	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	R&D	R&D	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	R&D

Table A.4: Alternate assignments of three low-level mechanisms to high-level mechanisms to achieve the lowest and highest possible contributions of EOS. Other low-level mechanisms remain in their primary assignments. High-level contributions for each assignment are shown in Figure A-16.
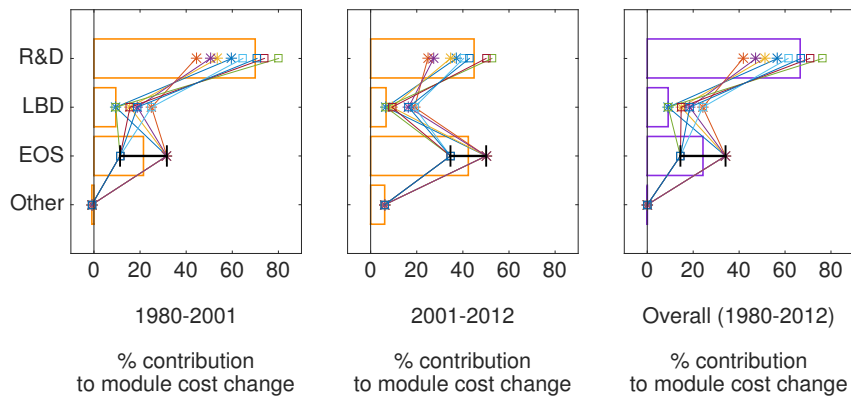
Figure A-16: Possible percentage contribution of high-level mechanisms under highest and lowest cases for EOS. Horizontal bars show the contribution of the primary mechanisms. Lines with markers link results under alternate assignments. The lowest case for EOS is obtained when non-Si materials costs (c) are assigned to R&D rather than their original assignment of 50% R&D and 50% EOS. The highest case for EOS is obtained when non-Si materials costs (c) are assigned to EOS only.

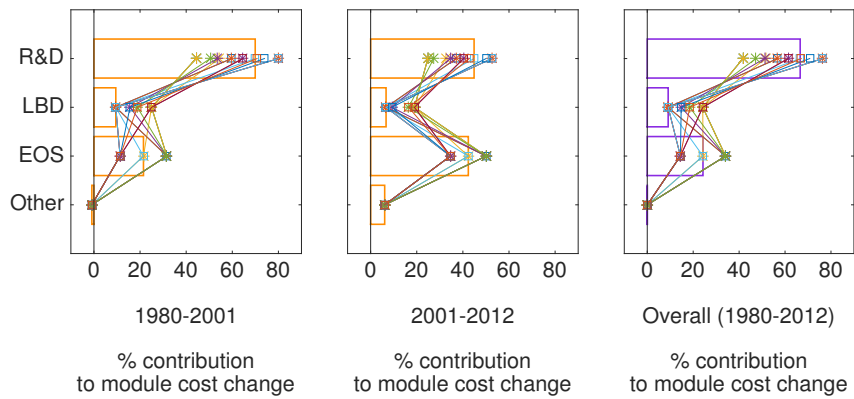Figure A-17: Possible percentage contributions of high-level mechanisms in each period. Contributions here are obtained by reassigning multiple variables at once from primary mechanisms to secondary mechanisms, based on all cases shown in Tables A.2-A.4, and Figures A-14-A-16. Horizontal bars show the contribution under the primary assignment used in the main text. Lines with markers link results under alternate assignments.

Appendix B

Supporting Information for Chapter 3

B.1 Metals Analyzed for Historical Growth Rates

We analyze the growth rates in the historical production of 31 metals and 1 metal group: Ag, Al, As, Au, Be, Bi, Cd, Co, Cr, Cu, Ga, Ge, Hg, In, Mg, Mn, Mo, Nb, Ni, platinum group metals, Pb, Re, Sb, Se, Si, Sn, Sr, Ta, Te, V, W, Zn. Metals are chosen on the basis of available data from the U.S. Geological Survey. Elements whose production are reported in gross weight (e.g. oxides) are not included in this analysis (B, Fe, Li, Ti, Zr, rare earth elements). Other elements are not included due to lack of world production data (Cs, Hf, Th, Tl), although USGS provides other information for these elements.

B.2 Purity of metals tracked by US Geological Survey

Metals are produced and traded at a variety of purity levels based on market standards. For many byproducts the raw material has already been partially refined to higher levels of purity. See Table B.1.

B.3 Analysis of MG-Si

Purity grade reported by the US Geological Survey (USGS) varies. (See Table B.1.) Byproduct metals such as Te are generally tracked at higher levels of purity than primary metals such as Si, since only the refined byproduct is globally traded. Because of this, we carry out an additional analysis on metallurgical grade Si (MG-Si), a higher purity form of Si that is

Metal	Range of purity in production data
In	$99.97\% - 99.99\%$
Ga	$99.99\%- - 99.999999\%$
Se	$90\%+$
Cd	$99.95\% - 99.99\%$
Te	99.99%
Si	$55\% - 99.99\%+$
MG-Si	$98 - 99\%$

Table B.1: Purity of metals tracked by the US Geological Survey. Source: [150, 151, 152, 153, 98]

the precursor to most (97%) Si used in solar cells [128, 129, 130], to see whether this similarly partially-refined material with smaller production scale is able to support deployment of Si-based PV. This analysis also limits the raw Si resource, since currently metallurgical grade Si is produced more selectively from silica deposits with relatively low starting level of impurities [131].

We obtain data for MG-Si from the USGS, which publishes world production of MG-Si starting in 1990. (Fig. B-1.) Beginning in 2005, the production data for MG-Si began including production from China, leading to a significant jump upward in the data series. As in the case of tellurium, due to this change in the method of reporting we do not use data prior to 2005. The most recent data year is 2012, and has production noticeably higher than the rest of the series. We note that recent commodity summaries [154, 155, 98] have often revised the most recent year's production as new data becomes available, which may explain the jump in 2012. Because it is not clear that the method of reporting is the same for this year we have removed it. From 2005 to 2011, the average growth rate in MG-Si is 2.7% per year. Below we also report the results if we do not make these exclusions and instead use all data from 1990 to 2012.

Most production (around 80%) is used to produce silicones, aluminum alloys, and chemicals, while about 20% is used to produce polycrystalline Si [54]. Of the amount that goes toward polycrystalline Si, around 90-93% is used by the solar industry [156, 98], with the remainder going to the semiconductor industry. Thus we estimate that about 82% of the 2012 production represents non-PV end uses of MG-Si.

Required growth rates for MG-Si are shown in Fig. B-2. Under a medium material intensity, when non-PV end uses of MG-Si grow at 2.7%, required growth rates exceed the historical rates when providing above 100% of electricity generation. Even if we take the
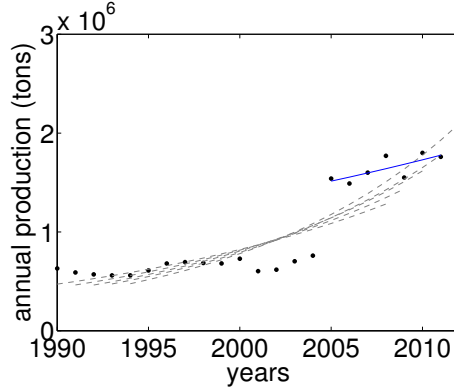
Figure B-1: Historical production of MG-Si (gross weight), 1990-2012. Black points show the actual production data obtained from USGS mineral yearbooks from 1994 to 2012. Lines are obtained by fitting a line to the natural logarithm of the production data (using the least squares method) for each 18-year period in 1990-2012. The slope of the each fitted line represents the annual growth rate for that 18-year period. The method of reporting MG-Si production data changed in 2008, resulting in an arbitrary jump from 2004 to 2005. The most recent value (2012) is also artificially high. See text for discussion. Only the 2005-2011 period is used here to estimate the average annual growth rate (blue fitted line).

MG-Si data at face value and include years before 2005 and the year 2012 for measuring the MG-Si growth rate, the median growth rate over all 18 year periods is 6.8% per year. In this case, required growth rates still exceed the historical rates only when providing above 100% of electricity generation.

B.4   Historical Year-To-Year Growth Rates

See Figure B-3.

B.5   Required Growth Rates for Silver

See Figure B-4 for estimates of the required growth rates for silver. The current material intensity for silver used in c-Si technology is estimated at 57 metric tons/GW [41]. This is used for the high material intensity case in Figure B-4. The medium intensity case of 47 tons/GW is calculated based on an efficiency improvement in the c-Si technology from 14.8% to 18% in 2030 [40]. The low intensity case is estimated by using a contingency scenario from the literature [157], in which silver is almost completely eliminated from the c-Si technology. By using this paper's prediction of a tenfold decrease in silver intensity per cell area and considering an efficiency improvement of about 40% compared to today [40], the low intensity
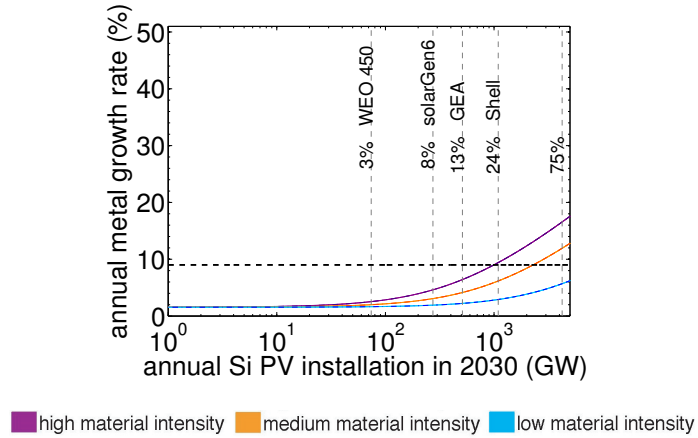
Figure B-2: Required growth rates for MG-Si to reach a range of annual PV installation levels in 2030. Non-PV end uses of MG-Si are assumed to grow at the historical growth rate for MG-Si between 2005 and 2011 ($n_{MG-Si} = 2.7\%$). The bands with different colors show the required growth rates for different levels of material intensities given in Table 3.2. See caption of Fig. 3-4 for additional detail.
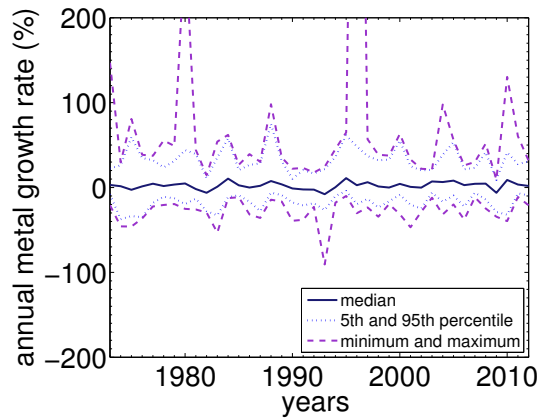
Figure B-3: Year-to-year growth rates in metals production have no apparent trend up or down over time. The solid midline is the median of the growth rates of 32 metals for each year. The blue dotted lines show the 5th and 95th percentiles. The dashed purple lines show the minimum and the maximum growth rates observed.

case is estimated at 4 tons/GW.

Figure B-4: Required growth rates for silver for a range of material intensity estimates and annual c-Si deployment levels in 2030. The lower and upper ends of each band are obtained by assuming that the non-PV end-uses grow at rates equal to the 1st and 3rd quartiles, respectively, of the historical growth rate distribution of that metal over each 18-year period between 1972-2012.

Appendix C

Supporting Information for Chapter 4

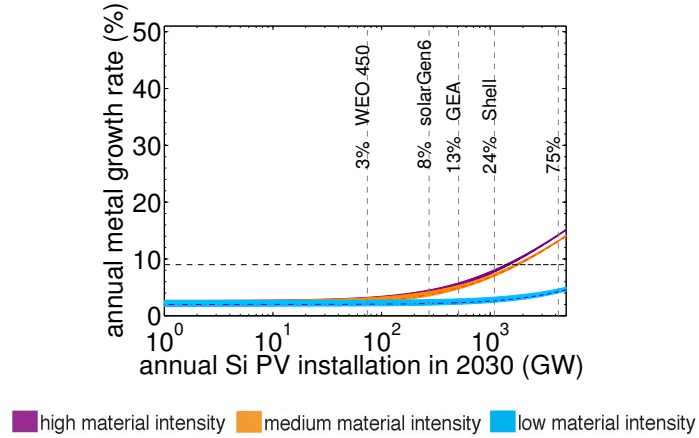**Metals that are included and that are not included in the study**

Metals marked blue are included in the study, and others are not included in the study. Metals in *italics* are in the USGS database but not covered by our study due to various reasons: barium, boron, cesium, hafnium, titanium (no world production reported) and sodium, potassium, iron and zirconium (production reported in gross weight, metal content is not clear). We also include selenium, a nonmetal, due to its use in PV, as well as the 17 rare earth elements (lanthanides, yttrium, scandium). In total we cover 38 of the 62 naturally occurring metals/metalloids, and 56 elements out of the 118 elements in the periodic table.

Alkali metals	Alkaline earth metals	Transition metals		Post-transition metals	Metalloids
Lithium	Beryllium	*Titanium*	Rhodium*	Aluminum	*Boron*
Sodium	Magnesium	Vanadium	Palladium*	Gallium	Silicon
Potassium	Calcium	Chromium	Silver	Indium	Germanium
Rubidium	Strontium	Manganese	Cadmium	Tin	Arsenic
Cesium	*Barium*	*Iron*	*Hafnium*	Thallium	Antimony
Francium	Radium	Cobalt	Tantalum	Lead	Tellurium
		Nickel	Tungsten	Bismuth	Polonium
		Copper	Rhenium		
		Zinc	Osmium*		
		Zirconium	Iridium*		
		Niobium	Platinum*		
		Molybdenum	Gold		
		Technetium	Mercury		
		Ruthenium*	9 elements that don't occur naturally		
		*included in 'platinum group metals'			

Note: The category of metals that are not included in our study and not included in the USGS database is very small: Rubidium (low production, 2-4 ton/yr), francium, radium, technetium, polonium (all extremely rare, radioactive) and 9 other metals that don't occur naturally.

Other elements that are not included in our study are: nonmetals (11 elements out of 12, since selenium is included), noble gases (6 elements), actinides (15 radioactive elements) and 6 new elements with unknown chemical properties. Element groups are obtained from Los Alamos National Laboratory website, http://periodic.lanl.gov/metal.shtml

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