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A Retrospective Analysis of Circular Economy and Industrial Decarbonization Metrics in the United States, 1998–2022

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ABSTRACT

While technical strategies for industrial decarbonization can be synergistic with those supporting a circular economy, metrics for decarbonization and circularity are distinct (and not necessarily correlated). We analyze time-series data for the period 1998–2022 synthesized from multiple U.S. governmental datasets, including new input/output data from the Bureau of Economic Analysis's 2023 Comprehensive Update of the National Economic Accounts, to take a "pulse check" on decarbonization and circularity metrics in the United States. This includes a retrospective analysis of trends in industrial emissions intensity over time (based on historical Manufacturing Energy Consumption Survey data) and correlations with salient economic metrics for 18 U.S. manufacturing industries. Some industries are reducing their emissions much faster than others, and we show that this pace of change—at least for certain industries—has to do with industry growth rates as well as predictable lock-in effects related to investments in capital assets. The analysis is extended to an initial exploration of interconnectedness between industry growth, material flows, and indicators relevant to the circular economy. We leverage data from economic input–output tables to assess the intensiveness of virgin material use in U.S. manufacturing supply chains, and comment on the usefulness of these measures as high-level indicators for circularity and circularity potential.

1 | Introduction

1.1 | Motivation

Industrial decarbonization opportunity analyses have tended to assess emissions reduction potential by making "adjustments" to the way materials have been, and are currently, processed. However, these interventions often presume that the linear flow of materials from primary extraction to intermediates to final products will remain the same. It has become increasingly clear that simple adjustments to the status quo will be insufficient to achieve deep decarbonization of the manufacturing sector, where "deep decarbonization" is defined as the complete (or nearly complete) elimination of Scope 1, 2, and 3 emissions that originate from production activities. An expansive transformation of the industrial sector is needed—and this transformation

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must consider not only energy efficiency but also resource efficiency. Materials circularity will become an increasingly important lever for deep decarbonization.

The tendency of decarbonization analyses to focus on "adjustments to what is" (e.g., improving energy and/or material efficiency of existing industrial operations and equipment) as opposed to explorations of "what could be" (e.g., transforming supply chains and manufacturing methods to replace virgin material inputs with end-of-life scrap) is not surprising given the substantial body of data on energy and carbon intensities for existing production processes. Forecasts for improvements can be extrapolated from such data at scales ranging from discrete unit processes, to facility-level equipment, to supply chain-level activity. Conversely, available data and methods for assessing the emissions implications of materials circularity, especially where transformational change would be necessary to realize such circularity, are much more limited.

It is from that basis that we seek to explore whether a retrospective analysis of existing U.S. governmental datasets might reveal insights into factors that have contributed to differences in the rates of decarbonization across industries, and to what extent these differences could be traced to operational investments and process shifts. First, we examine the relationship between industrial capital expenditure and subsequent emissions shifts. Then, we use an input–output approach to examine the level of integration of scrap/secondhand material in supply chains and how this relates to decarbonization outcomes. This historic context could provide a stronger foundation from which to forecast potential emissions reductions and economic barriers for hypothetical deep decarbonization scenarios involving a transition away from our current linear "take-make-waste" paradigm and toward a more circular economy.

1.2 | Review of Related Work

There is a robust body of literature on the relationship between economic factors and their impact on environmental outcomes such as greenhouse gas emissions, pollution, and ecosystem disruption. This includes, for example, over 30 years of discussion in the global literature related to the validity and usefulness of the environmental Kuznets curve (EKC), first introduced in the 1990s as a tool for assessing the relationship between emissions and economic growth. The EKC hypothesis posits that as an economy develops, pollution initially increases until the economy reaches a certain size threshold (often measured by gross domestic product per capita), at which point the trend reverses and pollution begins to decline, producing an inverted U-shaped curve known as the EKC. A number of reviews have been published on the EKC theory, including two excellent ones by David Stern [1, 2]. In general, there is strong evidence that emissions tend to increase most rapidly with early economic growth and there is also some evidence that emissions typically taper off as growth continues to increase. However, explanatory factors other than the EKC effect are generally present, such as technology investment and reallocation of production activities in a region or country as the economy develops (e.g., moving away from high-emissions agriculture and primary manufacturing activities to increase emphasis on knowledge- and technology-intensive industries and services) [3]. As a result, it would be misguided to expect that the EKC effect alone could be a significant driver toward decarbonization, especially at a global scale. Nonetheless, a useful insight from the EKC literature is the ubiquitous observation of environmental performance degradation during periods of rapid structural change in an economy, such as the introduction and advancement of new industries in a developing country. Considering the potential scale of equipment and technology changeover needed to transition to a circular economy, it is possible that this observation may have parallels for circularity even in developed economies (i.e., it is possible that certain environmental measures could get worse—or appear to look worse—before they get better). For example, the emissions of a U.S. industry may increase when re-shoring production, even if the life-cycle emissions of the goods produced decrease. Likewise, quantities of apparent waste may appear to increase if end-of-life materials are retained for future production value rather than exported and eliminated from the economy.

A large swath of policy literature has examined the relationship between manufacturing activity and emissions of six "criteria" air pollutants regulated by the U.S. Clean Air Act (42 USC. Ch. 85). Since 1990, criteria (regulated) pollutants in the U.S. have included carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter (PM_{10} and $PM_{2.5}$), sulfur dioxide (SO_2), volatile organic compounds (VOCs), and lead (Pb). Limits for these six pollutants are set by the Environmental Protection Agency (EPA). Importantly, this list *excludes* the greenhouse gases carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O); and as a result, most policy studies do not treat decarbonization directly. Even so, some of the findings may be relevant in extension. For example, Shapiro and Walker [4] found that manufacturing emissions of CO, NO_x, PM_{10}, $PM_{2.5}$, SO_2, and VOCs (criteria pollutants) each dropped by at least 60% over the period 1990–2008 (i.e., after the 1990 amendments to the Clean Air Act), while real manufacturing output grew by over 30%. Meanwhile, manufacturing emissions of CO_2 (not a criteria air pollutant) changed relatively little over the same period, highlighting the effects of regulation. Through statistical decomposition, the authors found that the changes in criteria pollutant emissions could be mostly attributed to reductions in pollution intensity within individual industries, rather than an overall decline in production or a reallocation of production across industries.

Another of our interests for this study relates to the role of industrial capital expenditures in either slowing or accelerating progress toward decarbonization and/or material circularity. On the one hand, capital investment is essential for decarbonization, as asset turnover is necessary to phase out fossil-fuel-burning industrial assets and transition to electrified equipment and low-carbon fuels and feedstocks [5]. Retrofitted carbon management technologies (e.g., carbon capture, storage, and utilization) are also capital-intensive. Such investments are key to the decoupling of manufacturing production activities from emissions. But on the other hand, the "wrong" capital investment may commit decades of greenhouse gas emissions due to technology lock-in effects [6]. Agnolucci et al. [7] found that in the UK, capital expenditures made in response to policies that incentivized investment in capital assets without regard to environmental factors (e.g., to promote economic growth and productivity) had an adverse impact on nearly all of the greenhouse gases and criteria pollutants the authors studied. They concluded that "investing in new capital equipment and machinery should not per se be considered equivalent to investing in cleaner technologies," and that policymakers should consider this in the design of incentives for capital financing. In a study of firms in the Netherlands over the period 2000–2008, Brinkerink and co-workers [8] showed that after a large capital equipment investment, firms tend to increase their absolute energy use but reduce their energy intensity (energy consumption per unit of output), suggesting both production expansion and more energy-efficient equipment. The authors did not explore how much of the energy increase could be attributed to planned expansion of production activities (that may have motivated the new capital investment in the first place) versus potentially unplanned rebound effects (related to the lower cost of use for more energy-efficient equipment).

Metrics to measure progress toward a circular economy are still being actively discussed in the literature [9]. Many authors have observed, rightly, that it is challenging to define a single index or bounded set of indicators that reasonably captures all of the key factors contributing to a circular economy [10–14] or the relationship between circularity and environmental performance [15]. Nonetheless, existing indicators can provide useful insights, even if not comprehensive. One example is the circularity index (CI) shown in Equation (1), which Jonathan Cullen introduced in 2017 [16]. The index is defined as the product $\mathrm{CI} = \alpha\,\beta$, where α is a supply parameter defined by the ratio of recovered end-of-life material (i.e., the recycling rate) to the total material demand, and β is a technical feasibility parameter that compares the energy requirement of material recycling to that of primary production.

Circularity index:

$$\mathrm{CI} = \alpha\,\beta \tag{1}$$

where α = supply of recovered end-of-life material/total material demand (capped at 1). $\beta = 1$ – (energy required for material recovery/energy required for primary production).

Monetary cost is not included in this definition, and this metric does not quantify the effects of circularity strategies other than recovery and recycling. Cullen's circularity index is highest when the supply of end-of-life material is plentiful, and when that end-of-life material can be readily processed (from an energy standpoint) into usable material of comparable quality to the primary (non-recycled) material. A circularity index of $\mathrm{CI} = 1$ would indicate perfect circularity based on recycling. Such a value is recognized by Cullen as unachievable in practice, but still useful as a theoretical benchmark. The CI has been assessed for a number of key materials (steel, plastic, aluminum, titanium, concrete, paper, cobalt, nickel) on a global level [16, 17]. Today, aluminum has both the highest overall CI value and the highest technical feasibility for recycling (β), while paper has the highest supply of recovered material (α); but no material has yet achieved an overall index above $\mathrm{CI} = 0.25$ [17]. The Ellen MacArthur Foundation reported that in Europe, 95% of the original raw material and energy value of manufactured goods is lost via discarded materials and only 5% is captured through recovery efforts, including both recycling and waste-based energy recovery [18].

While there is room for progress in recycling and material recovery, awareness is increasing that a multifaceted circularity strategy (involving approaches other than recycling) is critical for transformative advancement toward a circular economy. In 2024, the International Organization for Standardization (ISO) published the first international circular economy standards (the ISO 59000 family), intended to "harmonize the understanding of the circular economy and to support its implementation and measurement." [19] ISO 59020 defines 13 distinct circularity indicators across five indicator categories (inflows, outflows, energy, water, and economic)—six of which are specified as "mandatory" elements of a circularity assessment. For example, the required inflow metrics quantify the amount of reused, recycled, virgin renewable, and virgin non-renewable content incorporated into a product system; whereas the required outflow metrics quantify the fraction of the resulting product system that can actually be reused, recycled, or returned to the biosphere at end of the life. Optional metrics quantify other aspects of circularity, such as product lifetime, water use and recirculation, renewable energy, and material productivity.

Many groups have identified input–output (IO) analysis techniques—including environmentally extended IO methods—as well-suited for the study of the circular economy (see e.g., McCarthy et al. [14], Donati et al. [20], or Hawkins et al. [21]). Since IO methods quantify economic transactions between industries, these techniques can be leveraged to trace material inputs as they move through supply chain networks. Robust, long-range economic data are available in national input–output accounts; indeed, these are the same datasets used by government economists to calculate gross domestic product (GDP) and other key indicators for the national economy. In the United States, these underlying economic data are reported by the U.S. Bureau of Economic Analysis (BEA), with historical data available from 1947 forward [22]. EPA presently develops and maintains the leading environmentally extended input–output (EEIO) model for the United States, USEEIO [23–25]. In USEEIO, the environmental extension in the USEEIO model is based on emissions reported in the EPA's annual *Inventory of U.S. Greenhouse Gas Emissions and Sinks* [26]. Recently, DOE's Industrial Efficiency and Decarbonization Office initiated work to develop a new environmentally extended IO tool specialized for industrial decarbonization scenario modeling. Now publicly available as a beta version, DOE's Environmentally Extended Input–Output for Industrial Decarbonization (EEIO-IDA) tool [27, 28] includes user-adjustable parameters to simulate changes in the electric grid and industrial technology adoption, aligning with the four pillars of industrial decarbonization defined in DOE's *Industrial Decarbonization Roadmap* and follow-on work: energy efficiency; industrial electrification; low-carbon fuels, feedstocks, and energy sources; and carbon capture, utilization, and storage [29, 30]. Top-down IO-based models such as these can probe the complex interplay between environmental, economic, and physical dimensions of industrial activities.

2 | Methods

The analysis began with a data curation process to collect environmental and economic data for the U.S. manufacturing sector, subdivided into 18 distinct manufacturing industries based on three-digit North American Industry Classification System (NAICS) codes. We synthesized data from four U.S. government agencies to compose a panel dataset on industrial electricity and fuel use, energy-related greenhouse gas emissions, capital expenditures, intermediate inputs to production, and gross industry output for each of the 18 industries over the period 1998–2022. For consistency in time series, all monetary values were converted to 2017 chain dollars using BEA industry-specific price indices for gross output, consistent with BEA's 2023 Comprehensive Update. Sources were used as follows to compile the datasets:

- BEA's input–output accounts [22] provided data on real gross output and intermediate inputs for each industry. Specifically, the Use of Commodities by Industry tables were used to assess the breakdown of each manufacturing industry's gross output by its intermediate inputs (purchased materials and services) and value-added components (compensation of employees, gross operating surplus, and taxes) in monetary units. Inputs to manufacturing from the "scrap, used, and secondhand" industry were considered separately from other material inputs to examine circularity. Data were drawn from the BEA's 2023 Comprehensive Update.
- U.S. Bureau of Labor Statistics (BLS) data [31] were used to compile information on capital expenditure by industry. BLS reports annual capital expenditures in monetary units with a further breakdown by equipment, structures, and intellectual property products. In this study, the total investment across all capital assets was adopted as the capital investment of a given industry. The distribution of capital investments across industries in 2022 is shown in Figure 1.
- Industry-specific electricity and energy-related fuel use data were drawn from the U.S. Energy Information Administration (EIA) Manufacturing Energy Consumption Survey (MECS) [32] for all MECS reporting years (1998, 2002, 2006, 2010, 2014, and 2018). Consumption of fuels for non-energy purposes (as feedstocks) was not included in the analysis.
- EPA's Greenhouse Gas Emissions Factors Hub [33] was used as the data source for fuel combustion emissions factors (i.e., to compute the quantity of CO_2, CH_4, and N_2O emissions resulting from each unit of fuel combusted). Non-combustion (life cycle) emissions of fuels were not included. These emission factors were used to calculate energy-related emissions from MECS energy use data. IPCC AR5 100-year global warming potential values [34] were then used to determine the energy-related greenhouse gas emissions in CO_2-equivalent terms.
- EPA Emissions & Generation Resource Integrated Database (eGRID) data [35] were used for electricity generation emissions factors (i.e., the quantity of CO_2, CH_4, and N_2O emissions resulting from each unit of electricity consumed). eGRID currently provides electricity emissions factors for 1996–2022, capturing historical shifts in the grid mix. Emissions factors from eGRID were applied to electricity use data reported in MECS to determine the electricity-related emissions of CO_2, CH_4, and N_2O arising from each industry's electricity use. As with the fuel use emissions, 100-year GWP values (IPCC AR5 [34]) were used to calculate CO_2 equivalence.

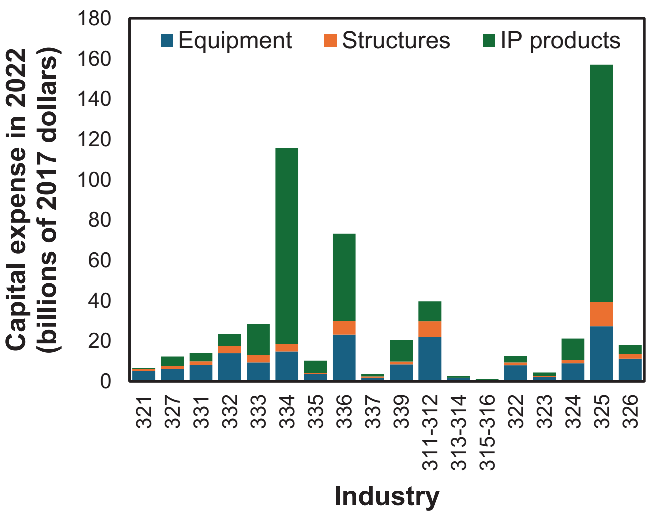

FIGURE 1 | Breakdown of capital expenses by U.S. manufacturing industry (listed by NAICS code) and capital expense category in 2022.

With the exception of the EIA Manufacturing Energy Consumption Survey (MECS), which is fielded only once every 4 years, all listed data sources provide annual data. Since MECS has a 4 year reporting interval, the emissions time series has a 4 year interval, with the most recent reporting year being 2018. The remaining datasets have annual increments, with data available for 1998–2022. For illustrative purposes, Table 1 shows an excerpt of the main dataset for the years 1998 and 2018. The full dataset is provided as Supporting Information for this article.

The prepared dataset was examined in aggregate to assess general trends across the entire manufacturing sector, and individually for all 18 manufacturing industries to draw industry-specific inferences. Considering that emissions and capital expenditures scale, at least to some extent, with industry size, we found it useful to examine emissions and capital expenditures on an intensity basis (per unit of monetary output). We define *emissions intensity* and *capital investment intensity* as shown in Equations (2) and (3), using gross output as the denominator:

$$\text{Emissions Intensity}\left(\frac{\text{kg}}{\$\text{USD}}\right) = \frac{\text{Greenhouse Gas Emissions}\left(\text{kg of CO}_2\text{e}\right)}{\text{Real Gross Output (2017 chain dollars)}} \tag{2}$$

$$\text{Capital Investment Intensity (unitless)} = \frac{\text{Capital Expenditure (2017 chain dollars)}}{\text{Real Gross Output (2017 chain dollars)}} \tag{3}$$

Throughout the analysis, real gross output was used as the primary monetary measure of industry size rather than another commonly used monetary indicator, GDP. Real gross output can be understood as the sum of intermediate inputs

TABLE 1 | Excerpt of the multi-year, multi-industry dataset compiled for analysis.

NAICS code—Industry description	Real gross output (billions of 2017 chain dollars)		Capital investment, all assets (billions of 2017 chain dollars)		Energy-related greenhouse gas emissions (million metric tons CO_2e)	
	1998	2018	1998	2018	1998	2018
321—Wood products	$119	$112	$4	$5	51	36
327—Nonmetallic mineral products	$144	$124	$9	$10	87	68
331—Primary metals	$258	$230	$11	$17	339	175
332—Fabricated metal products	$362	$348	$16	$20	49	23
333—Machinery	$373	$367	$30	$26	25	14
334—Computer and electronic products	$157	$313	$92	$106	30	11
335—Electrical equipment, appliances, components	$152	$118	$8	$10	14	7
336—Transportation equipment	$739	$936	$66	$83	56	31
337—Furniture and related products	$94	$63	$3	$3	10	3
339—Miscellaneous manufacturing	$146	$151	$10	$19	11	6
311FT—Food and beverage and tobacco products	$886	$932	$22	$43	106	100
313TT—Textile mills and textile product mills	$110	$41	$5	$2	35	8
315AL—Apparel and leather and allied products	$93	$19	$2	$1	6	1
322—Paper products	$234	$158	$13	$9	255	174
323—Printing and related support activities	$122	$74	$6	$5	12	6
324—Petroleum and coal products	$424	$471	$13	$31	267	251
325—Chemical products	$718	$708	$72	$135	307	265
326—Plastics and rubber products	$245	$224	$13	$15	44	26

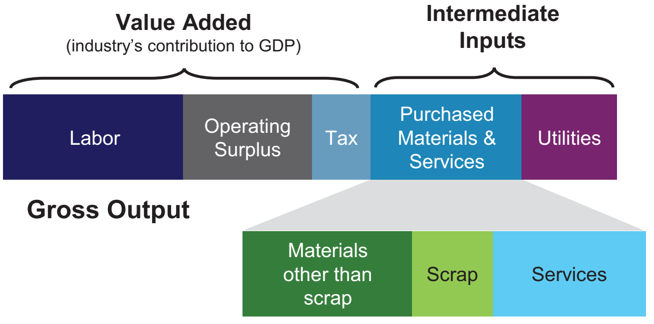

FIGURE 2 | Components of the real gross output of an industry.

purchased by an industry plus the industry's value-add, where value-add is composed of employee compensation, gross operating surplus, and taxes on production (minus any subsidies). As shown in Figure 2, real gross output includes contributions from intermediate inputs that are not counted toward GDP, but are still important components of the industrial activity, especially as related to environmental impacts and material circularity. We further divided intermediate inputs into four

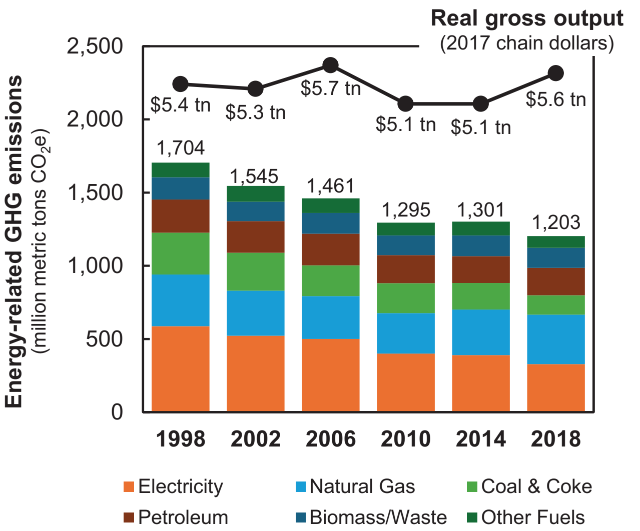

FIGURE 3 | Energy-related (Scope 1 and Scope 2) greenhouse gas emissions and real gross output (in 2017 chain dollars) of all U.S. manufacturing, 1998–2018.

categories: materials other than scrap, scrap, services, and utilities. This subdivision (based on a grouping of intermediate input industries in BEA's "Use of Commodities" tables into these four categories) allowed for a deeper exploration of the physical economy by distinguishing between purchases of physical goods versus intangible services, and between purchases of virgin material versus scrap and secondhand material.

3 | Results and Discussion

3.1 | Industrial Decarbonization Trends

Between 1998 and 2018, the energy-related greenhouse gas emissions of the U.S. manufacturing sector dropped by 29% in the U.S., while real gross output has stayed roughly constant (Figure 3). Historically, most of this reduction has been related to incremental energy productivity improvements rather than major fuel-switching or electrification strategies, evidenced here by the roughly proportional reductions in emissions from each fuel. An exception is the ongoing phase-out of coal, which has been significantly de-emphasized as an industrial energy source across many applications (largely in favor of natural gas).

The rates of emissions reductions and technological/market ecosystem factors contributing to those shifts have varied significantly by industry. This is illustrated by Figure 4, which superimposes data for energy-related greenhouse gas emissions, real gross output, and capital expenditures for 18 different industries. In some industries (like apparel, paper, and nonmetallic minerals), emissions trends have closely followed trends in gross output. In other industries (like primary

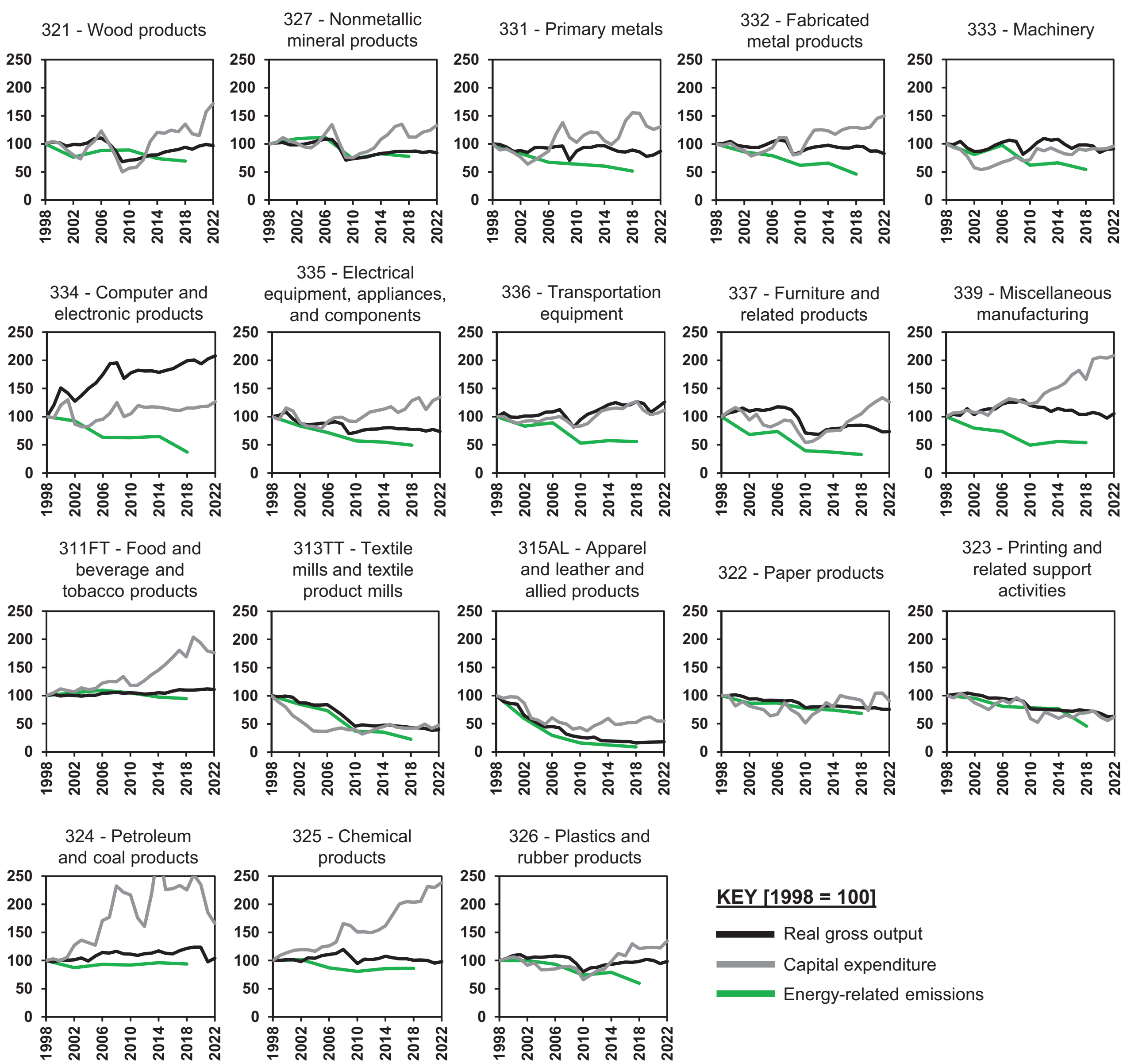

FIGURE 4 | Energy-related greenhouse gas emissions, real gross output, and capital expenditure time-series data for 18 U.S. manufacturing industries for the period 1998–2022 [1998 = 100].

metals, furniture, and transportation equipment), emissions reductions have occurred much faster than the production changes. Trends in capital expenditures for individual industries show that the manufacturing industries that have invested most heavily in capital assets relative to their gross output have seen relatively slower reductions in emissions intensity (emissions per real dollar of output) over the past 20 years (Figure 5a). This is attributed to committed emissions resulting from technology lock-in combined with a historic emphasis on industrial productivity and efficiency (rather than emissions reduction) in assets with lifetimes that are often over 30 years.

Industry size and growth rates were also correlated with emissions trends, as shown in Figure 5b. Industries can be generally grouped into an emissions-intensive category (top half of industries in terms of emissions per unit of gross output) and a lower-emissions-intensity category (the remaining industries). Every industry has reduced its emissions intensity since 1998—but on average, the emissions-intensive industries are reducing emissions relatively more slowly (averaging a 15% improvement since 1998) compared to the lower-emissions-intensity industries (which have averaged a 40% improvement since 1998). For each industry group, there is also a possible correlation between emissions reduction and industry growth: shrinking industries appear to be reducing their emissions more slowly, while growing industries may be reducing emissions relatively more quickly (see downward-sloping trendlines suggested by the shaded regions in Figure 5b). This speaks to a potential agility advantage in growing industries, which may bias them toward faster decarbonization. In growing industries, expansion may incentivize investment in state-of-the-art, lower-emissions equipment for added capacity. The potential benefits of capital equipment investments are potentially much lower in shrinking industries, where reliance on older equipment stocks may continue to meet business needs.

While general trends are observed across the entire manufacturing sector, greenhouse gas emissions are also impacted by industry-specific cost drivers and market conditions impacting technology selection and uptake. An example is the Chemicals industry, which has seen only modest reductions in emissions intensity over the past two decades despite significant investment in capital. A contributing factor may be the "fracking boom" that led to widespread availability of low-cost domestic shale gas in the United States starting in ~2005. This shock coincided with an increase in natural gas usage and a slight *increase* in emissions intensity for the chemicals industry (Figure 6a) even as emissions intensity decreased for the manufacturing sector as a whole (Figure 6b), suggesting a sacrifice in environmental performance to realize a competitive advantage opportunity within the chemicals industry. Investments in fossil fuel-fired equipment, ancillary equipment, and services during this period likely led to long-term carbon lock-in, notwithstanding debates about whether low-cost natural gas may have provided a short-term benefit as a "bridge fuel" by encouraging retirement of coal and oil assets [36, 37]. This example illustrates how new capital investment by manufacturing firms (while essential) can slow or reverse progress toward emissions targets if companies lack business incentives to prioritize environmental impacts in purchasing decisions.

3.2 | Circularity Trends

EPA tracks the fate of municipal solid waste (MSW) in the United States through its Advancing Sustainable Materials Management program, and the agency currently maintains historical data for 1960–2018 [38]. These data show that the fraction of MSW that is "sustainably managed" (recycled or composted) in the U.S. has increased from 6% in 1960 to 32% in 2018 (Figure 7), with the most significant increases seen in the 1990s. Since the turn of the century, recycling rates have increased only a few percent (from 29% in 2000 to 32% in 2018) and the total volume of recycled material has climbed at a rate approximately proportional to the rate of MSW generation.

BEA input–output data show that the increasing supply of recyclables has not yet resulted in major reorganizations of U.S.

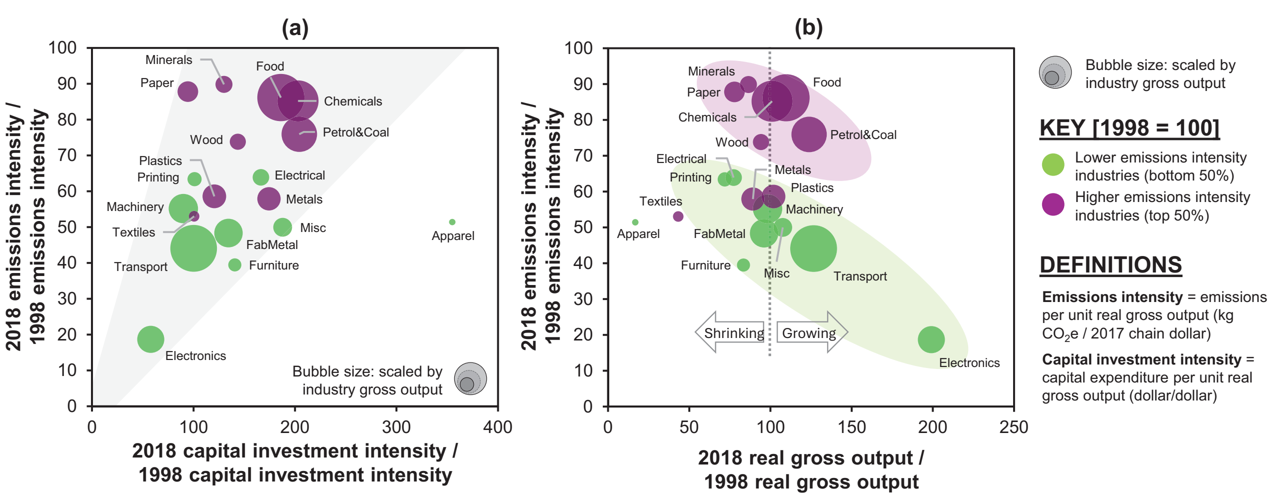

FIGURE 5 | Emissions intensity (emissions per unit of real gross output) versus capital expenditure intensity (capital expenditure per unit of real gross output); and (b) emissions intensity versus real gross output; both for 18 U.S. manufacturing industries [1998 = 100]. Bubble size indicates the industry size in terms of real gross output.

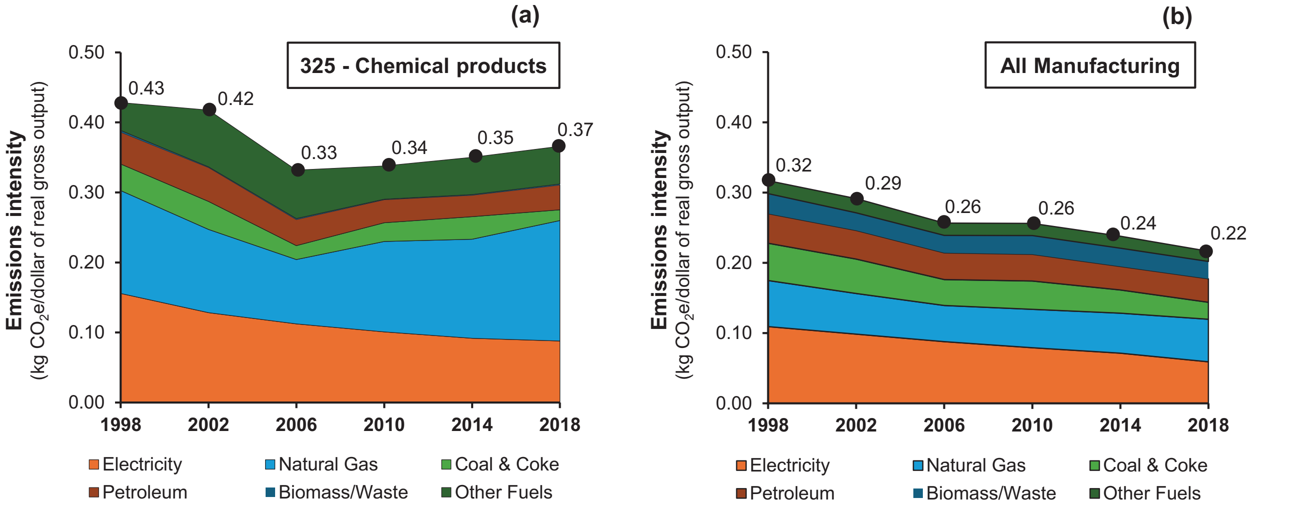

FIGURE 6 | Time series showing the evolution of emissions intensity over time for (a) the U.S. chemicals industry and (b) all U.S. manufacturing (average of all industries) for the period 1998–2022.

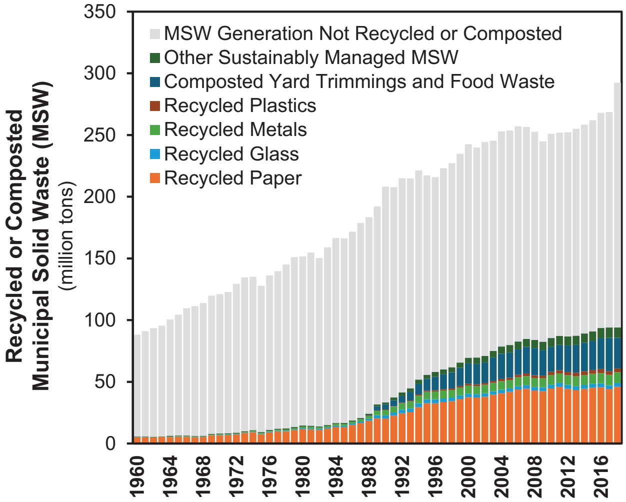

FIGURE 7 | Municipal solid waste generation tonnage and recycling/composting rates in the United States.

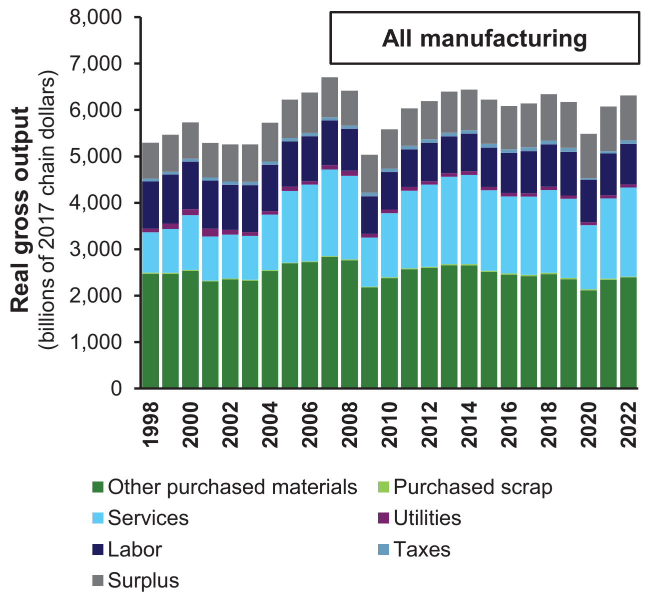

FIGURE 8 | Breakdown of gross industry output for all U.S. manufacturing for 1998–2022, showing little change in raw material requirements to produce a unit of gross output for manufacturing overall.

production systems to take advantage of this supply for most industries. As illustrated in Figure 2, BEA defines the gross output of an industry as the sum of its intermediate inputs (purchased materials and services) plus the industry's value-add (which includes compensation of employees, gross operating surplus, and taxes on production). The intermediate inputs of each industry were further decomposed based on BEA "Use of Commodities by Industry" tables to separate intermediate inputs by category:

- Purchases of raw materials other than scrap: The industry's purchases of virgin physical materials from extractive and manufacturing industries (excluding scrap), defined by BEA IO codes 111CA through 326;
- Purchases of scrap: The industry's purchases of secondary material (interpreted as purchases of the "scrap and secondhand" commodity), defined by BEA IO code "Used"; and
- Purchases of services: The industry's purchases from service industries that do not produce physical materials, defined by all other BEA IO industry codes (42 through GSLE).

A time series of the total gross output of all U.S. manufacturing, broken down in this way to emphasize the contributions of purchased material inputs to the total, is given in Figure 8. The data illustrate that at the sectoral level (all-of-manufacturing), there has been very limited progress toward dematerialization (which would be signaled by a reduced dependence on raw material inputs from extractive and manufacturing industries). Over the past 20 years, the average virgin material input required to produce one unit of gross manufacturing output has

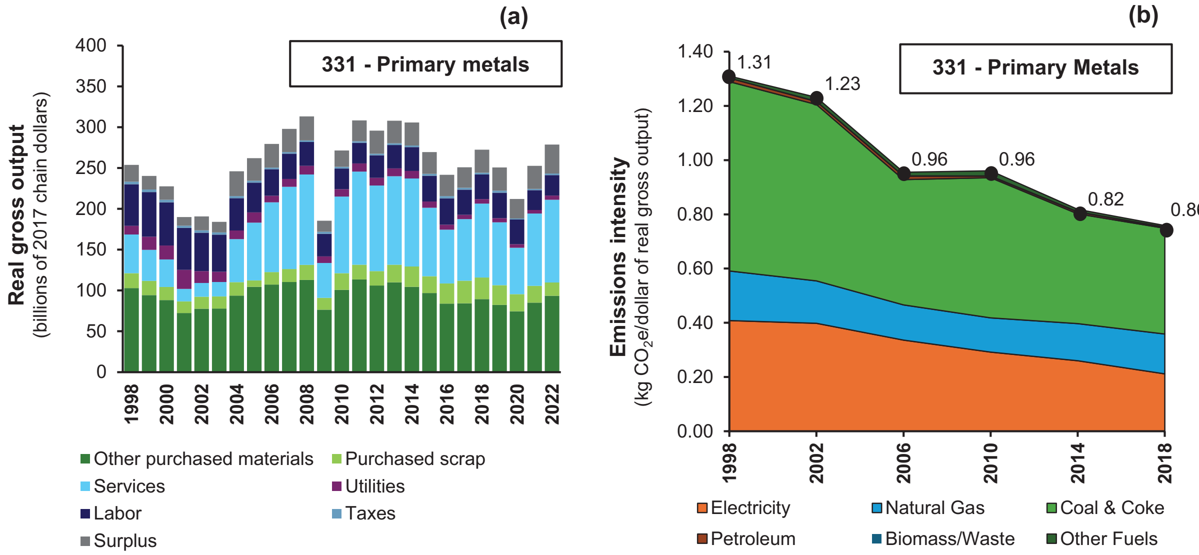

FIGURE 9 | Time series of economic and environmental characteristics of the U.S. primary metals industry for the period 1998–2022: (a) gross industry output decomposition and (b) emissions intensity.

remained steady at about 45 cents per dollar. Scrap inputs contribute less than one-half cent to each dollar of gross manufacturing output.

Only two industries have considerable scrap inputs displacing virgin material: primary metals and paper. Scrap use in primary metals, for example, is related to the modern prevalence of secondary aluminum production and electric arc furnace (EAF) steelmaking from scrap metal. Scrap purchases contribute significantly to this industry's intermediate inputs, as shown in the decomposition of Figure 9a. By mass, the proportion of inputs from scrap would be even higher than the monetary distribution shown, given the low price of scrap metal compared to virgin inputs. The shift away from conventional blast furnace/basic oxygen furnace (BF/BOF) steelmaking toward the electrified EAF process has allowed the primary metals industry to realize major Scope 2 emissions reductions over the past two decades from improvements in the U.S. electrical grid. This has led to a 50% reduction in overall emissions intensity for this industry over the past 20 years, as shown in Figure 9b.

4 | Conclusion

To achieve U.S. industrial decarbonization goals of net-zero emissions by midcentury, an unprecedented level of capital equipment turnover will be required, including retirement of fossil fuel assets and replacement with technologies that provide higher levels of energy efficiency; electrification; utilization of low carbon fuels, feedstocks, and energy sources; and carbon capture, utilization, and storage. Similarly, transformative technology shifts will be needed to dematerialize the economy (by investing in technologies that reduce industrial reliance on raw, virgin material inputs) and move toward a more circular economy. The contrast between the two industries profiled here (chemicals and primary metals) illustrates the complexities and potential for unintended consequences related to technology lock-in:

- In the **primary metals industry**, the replacement of BF/BOF steelmaking equipment with EAF equipment has yielded a **multi-faceted improvement in environmental performance**, including lower virgin material requirements; reduced dependence on fossil fuel; and a rapid reduction in emissions intensity (emissions per unit of gross industry output).
- In the **chemicals industry**, natural gas technologies implemented during the U.S. fracking boom (roughly 2005–2012) capitalized on the competitive benefits of low-cost shale gas availability, but slowed progress toward decarbonization by **locking in a long-term dependence on fossil fuels**.

While these are broad, highly aggregated industries with many technologies and events contributing to the net outcomes, these examples illustrate that new capital investment alone does not guarantee positive environmental outcomes, particularly if the new capital equipment offers only incremental efficiency improvements over the capital equipment being replaced and locks in a dependency on a fossil fuel. Well-designed R&D and policy strategies should carefully consider the specifics of the technologies being developed or incentivized, recognizing that not all new capital investments at manufacturing facilities will benefit the environment over the long term—even ones that may offer short-term gains in energy productivity or efficiency. New capital investments that offer transformative environmental performance improvements (such as electrification, process intensification, or fuel-switching to renewable or low-carbon fuels or feedstocks) have the greatest long-term impact potential but are also likely to be riskier and more costly to the manufacturer compared to capital investments offering more incremental technology advances.

With regard to the circular economy, analysis of supply/use table input–output data for the United States shows that despite modest improvements in recycling rates since 1998, manufacturers in most industries have not yet made significant shifts toward replacement of virgin material inputs with secondary material. Recycling infrastructure is important because limited scrap supply poses a key barrier to circularity. However, the technical and economic feasibility of material recycling (as measured by cost, energy, and/or emissions intensity compared to incumbent primary production processes) remains low for most materials, limiting uptake even when supply is adequate. Scrap supply and recycling feasibility (α and β respectively in Cullen's circularity index) will need to be improved in tandem to drive further change.

As shown in this article, time-series analysis of (1) material input breakdowns in input–output datasets and (2) capital investment can be used to measure and interpret structural shifts in production systems that may indicate a meaningful industry- or country-level rise in circularity and decarbonization. By combining recent data from several authoritative governmental datasets (EIA, BEA, BLS), we have built a snapshot of trends in material and capital intensity of U.S. manufacturing industries over the last 20 years. Our retrospective analysis highlighted two industries with major technology and policy events influencing their trajectory and demonstrates that the indicators proposed here are sensitive to such changes—even for the very highly aggregated industry definitions considered here. Deployed at higher levels of resolution, similar methods have the potential to enable even more valuable insights and predictions for technology- and product-specific queries.

Author Contributions

Heather P. H. Liddell: conceptualization, methodology, visualization, writing – review and editing, writing – original draft, data curation, formal analysis. **Brian M. Ray:** methodology, data curation, formal analysis, writing – review and editing, visualization. **Joseph W. Cresko:** writing – review and editing, methodology.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that supports the findings of this study are available in the supplementary material of this article.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.