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Method for endogenizing capital in the United States Environmentally-Extended Input-Output model

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Abstract

Each year businesses, governments, and homeowners in the United States invest around one fifth of gross domestic product into the creation of capital assets such as buildings, machinery, and software to enable production and consumption. Use of capital is typically included to some extent in environmental life cycle assessments of goods and services but is not incorporated into most environmentally extended input-output (EEIO) models, including the US Environmental Protection Agency's USEEIO. Capital assets are typically created in years prior to their use, so a challenge lies in distributing the impacts of their creation over time. In this work, a highly detailed capital flow matrix approach is followed to distribute the use of fixed capital assets to consuming industries. Data from the US Bureau of Economic Analysis's Fixed Asset Accounts is merged with its Industry Accounts data by the creation of concordance tables. Public highways and streets are partially reallocated to industries operating vehicles. The resulting capital use matrix is later combined into a modified USEEIO. "Housing" is found to be the largest consumer of fixed assets, followed by general government, fossil fuel extraction, and financial industries involved in leasing. Construction, vehicles, and machinery are mostly used by industries in the form of fixed assets. The types of fixed assets used by industries are consistent with expectations: housing is dominated by structures, transport by equipment, and information industries by intellectual property products.

KEYWORDS

capital flow matrix, capital vintage, environmentally extended input-output, input-output analysis, input-output life cycle assessment, System of National Accounts

1 | INTRODUCTION

1.1 | Significance of capital

Capital enables commercial production of goods and services, facilitates government operations, and shelters and moves the population. This capital is comprised of a diverse set of fixed assets (FAs), from power plants to trucks, pipes to sewing machines, and courthouses to software. Creating capital requires significant investments and produces substantial environmental impacts: 24% both of global final demand and greenhouse gas emissions in 2007 (Södersten, Wood, & Hertwich, 2018).

In the United States during its involvement in WWII (1941–1945), private investment was deferred in favor of military build-up. Since then, the percentage of the gross domestic product (GDP) put toward total investment in FAs has fluctuated around 22% as shown in Figure 1a. The US Bureau of Economic Analysis (BEA) maintains fixed asset accounts (FAA) in addition to GDP accounts. In the time series of fixed asset shares of GDP shown below, private and government investors are distinguished, as well as residential and nonresidential asset categories, and three asset types: intellectual property products (IPP), structures, and equipment (see Figure S1 in the Supporting Information available on the Journal's website for hierarchy).

FAs are used for an extended period and depreciate each year. Some of the new investments effectively maintain the stock of assets by replacing what has depreciated, while the excess investment expands the stock. The net investment measures the difference in annual investment and

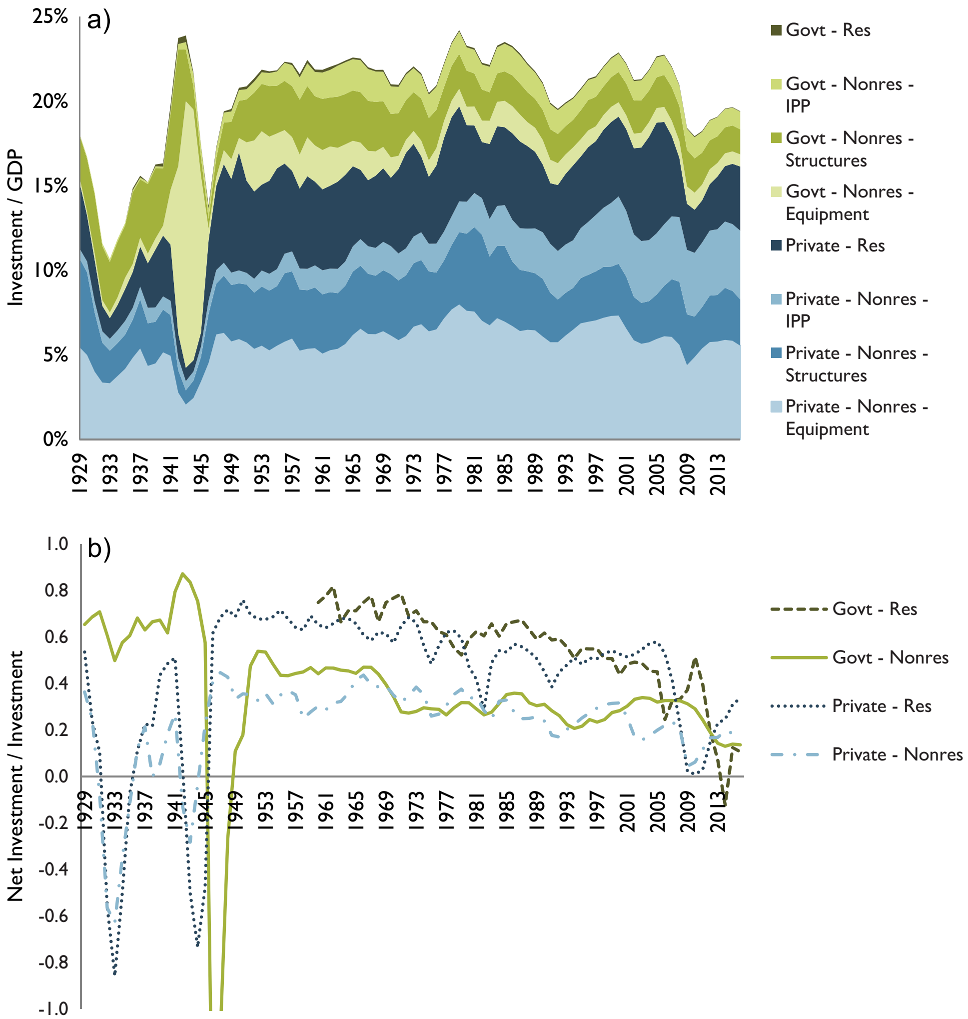

FIGURE 1 (a) US investment in fixed assets (FAs) as a fraction of GDP, both valued in current-cost. Distinguished by government (Govt) versus private investors, residential (Res) versus nonresidential (Nonres) asset categories, and asset types: intellectual property products (IPP), structures, and equipment. (b) Ratio of net investment (investment less depreciation in a given year) to investment, both valued in current-cost. The ratio is negative in years that assets depreciate faster than they are replaced. Some values extend beyond figure limits
Data sources. (US BEA 2018a, 2018b, 2018c). Underlying data used to create this figure can be found in Supporting Information S2.

depreciation. If the ratio of net investment to investment is negative it represents that depreciation is outpacing investment. This was the case for private investment during the Great Depression in the 1930s and WWII (Figure 1). The dip in the government nonresidential ratio after WWII suggests that the government investment in military equipment was not maintained. Post-WWII, the ratio for residential assets tends to exceed that of nonresidential assets, except for the burst of the housing bubble during the 2008 financial crisis.

1.2 | The inclusion of capital in LCA

Environmentally-extended input-output (EEIO) tables have been used to determine the life cycle environmental impacts of average products (Bullard & Herendeen, 1975; Hendrickson, Horvath, Joshi, & Lave, 1998) and the environmental footprints of consumption (Herendeen & Tanaka, 1976). While conventional process-based life cycle assessment (LCA) has been criticized for containing cut-off errors because it does not describe the complete economy, input-output based life cycle assessments often neglect the use of capital and associated environmental impacts (Lenzen, 2000; Lenzen & Treloar, 2004). One popular LCA database, ecoinvent, incorporates infrastructure such as the construction of factories and production of vehicles into downstream activities such as manufacturing and transport (Althaus, Kellenberger, Doka, & Künniger, 2005). This approach is suitable when describing a typical or ongoing process, as it assigns partial responsibility for the environmental impacts associated with the creation of capital assets to the consumers of the downstream goods and services. Frischknecht et al. (2007) argue for the inclusion of capital goods in LCA, finding that their contribution to the environmental impact of ecoinvent processes varies considerably, with processes such as renewable energy being dominated by capital and others like metal processing marginally affected. Chester and Horvath (2009) demonstrate the importance of capturing infrastructure in LCA of passenger transportation. They describe that infrastructure is relatively more important for rail versus air due to more extensive infrastructure requirements and lower operational energy requirements, and that road and highway construction has large energy implications for cars on a per passenger-kilometer basis.

LCAs conducted to inform specific, prospective decisions may elect to exclude impacts of pre-existing capital assets, considering the impacts of their production to be "sunk." For instance, consider a city with only buses wishing to compare environmental impacts in its upcoming public transit investment decision. The road system already exists, and its initial construction could be excluded from the analysis, but the infrastructure for light rail does not and therefore should be included. There may hence be applications of LCA where certain types of capital are selectively included or excluded.

1.3 | Distribution of capital asset impacts

Diewert (2005) states that the fundamental problem of accounting lies in distributing the initial purchase cost of a capital asset over its useful life. We describe several approaches to this problem, substituting initial environmental impact for purchase cost.

In attributional LCAs, datasets are designed to be applicable to a general situation. In ecoinvent, whole units of capital assets are allocated uniformly across their outputs (Althaus et al., 2005). For instance, if a metal working factory is expected to produce 2.18×10^9 kg of products across its 50-year lifetime, then each kilogram of metal product is allocated the inverse, 4.58×10^{-9}, of the impact associated with construction of the metal working factory (Steiner & Frischknecht, 2007).

In EEIO approaches, environmental impacts specific to consumption of products in a particular region and year are assessed. In input-output (IO) tables, investment in capital is included in the final demand categories. Most EEIO analyses exclude the contribution of capital assets created in prior years to production in a given year. When capital is endogenized as an input to production instead, care must be taken during subsequent analyses over a time series to adjust the final demand categories, since continuing to include the gross fixed capital formation (GFCF) within them would upset the economic balances on which an IO table is based.

Previous efforts to endogenize capital used one of two methods discussed by Lenzen and Treloar (2004). Their augmentation method creates a homogenous capital sector consumed according to each industry's GFCF for the given year. Their flow matrix method uses a capital input matrix in the same dimensions of the IO table to assign GFCF of specific types of capital to the appropriate consuming sectors. The latter method requires more data but overcomes the limitations of assuming a homogenous capital product consumed by each industry group. Chen et al. (2018) applied the augmentation approach to the multi-region input-output (MRIO) model the World Input-Output Database (WIOD) but keep track of the year in which capital is formed. Hertwich and Wood (2018) modified the augmentation approach by assigning consumption of a homogenous sector according to consumption of fixed capital (CFC) rather than GFCF. Following the flow matrix method instead, both Suh (2005) and Weber and Matthews (2008) took advantage of the BEA's capital flow tables (CFT) for their analyses. Unfortunately, the most recent BEA CFT is for the year 1997.

While the original flow matrix approach addresses the homogeneity assumption of capital goods, it has two shortcomings. The first is the assumption that the level of GFCF exactly compensates the capital consumption, ignoring annual fluctuations in the formation and net accumulation of capital. If the magnitude and composition of the capital flow matrix are steady over time, using this year's production patterns could be a reasonable approximation. If, however, capital formation is unsteady (see Figure S3), this approach would result in erratically fluctuating environmental impacts. For instance in Figure 2, comparing the computer and electronic products industry's investment in structures to its total industry output demonstrates that with this approach much more capital would be associated with production in 2001 than in 2003 due to the larger relative investment that year; a product made in 2001 would be burdened with more environmental impact than one made in 2003. In reality, production in both years would involve structures created in prior years, and the difference between them should be less stark. Södersten et al. (2018) address this shortcoming by modifying the flow matrix method; they use CFC matrices from a multinational EU KLEMS database (Jäger, 2012) instead of GFCF matrices to endogenize capital in the EXIOBASE MRIO. Key limitations to these KLEMS CFC matrices are their high level of aggregation, with only 8 types of assets and 32 industry categories, and their availability only through the year 2007.

The second shortcoming of existing flow matrix approaches is the use of current year technologies to describe FAs used in the current year but previously formed. The timing of capital production matters since associated environmental impacts trend over time. This work, along with prior studies, assumes that capital used in a given year is created under the technological conditions of that same year. This is akin to a "carbon replacement value" (Müller et al., 2013). Addressing this shortcoming, Pauliuk, Wood, and Hertwich (2014) describe a mathematical framework for dynamic IO, LCA, and material flow analysis (MFA) that can account for the use of specific vintages of capital in a specific year; this framework has not yet been implemented due to the extensive data requirement of such modeling.

2 | OBJECTIVE

In this work, we update and enhance the prior capital flow matrix methods for EEIO in the United States, resulting in capital flow matrices and enabling capital endogenization which is more up-to-date, detailed, and reflective of actual sectoral capital consumption than anything existing in

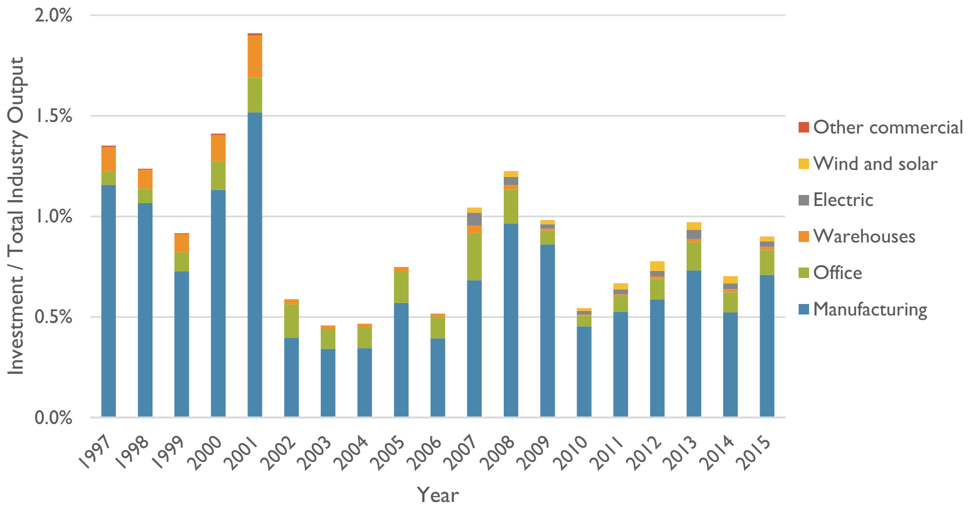

FIGURE 2 US Consumer and Electronic Products industry's investment in key types of structures relative to total industry output, both valued in current-cost. Calculated from US BEA (2018d, 2018g). Underlying data used to create this figure can be found in Supporting Information S2

the literature. We describe the methods developed to endogenize capital consumption in the detailed USEEIO model for the years 2007 and 2012. We enable the distribution of environmental impact of capital formation based on the depreciation of that capital in a given year, rather than the investment in that year, following Södersten et al. (2018). To demonstrate the advantage of using more detailed depreciation data, we compare outcomes using CFC data from BEA with the more aggregated KLEMS matrices. Once this process is complete, the modified USEEIO table can be used to estimate the environmental impacts of consumption, inclusive of the capital assets needed in their production and sale in each year, and to calculate the contribution of capital to total impacts.

3 | METHODS

3.1 | USEEIO

The USEEIO was developed to support the US Environmental Protection Agency's (EPA) sustainable material management goals (Yang, Ingwersen, Hawkins, Srocka, & Meyer, 2017). EPA had evaluated three pre-existing EEIO datasets for the United States but found none satisfied the criteria of transparent, reproducible, open, and temporally relevant. The major complexity lay in creating the satellite tables which associate reported direct environmental impacts with detailed industry groups (DIG). As the USEEIO is a single-region model, it employs the domestic technology assumption, which assumes the same supply chain and environmental impact per dollar for domestic products and imported products. For products such as energy-intensive imports from countries with a relatively more emissions-intensive energy supply systems, this will result in an underestimate of impacts.

The current version of the USEEIO is based on the 2007 benchmark detailed Make and Use tables in producers' value provided by the BEA, which were the most recent detailed tables at the time (Wang & Miller, 2017). As the BEA recently released 2012 benchmark tables and updated the 2007 versions to the new, more detailed, industry group classification, this work incorporates these new tables. To create the IO table, an industry technology construct was used, which assumes that all commodities produced by an industry have the same input structure; we will follow that same assumption here. In Equation (1) from Miller and Blair (2009, p. 207), $\boldsymbol{A}$ is the commodities-by-commodities direct input requirements or technical coefficients matrix, $\boldsymbol{U}$ is the commodities-by-industries use matrix, $\boldsymbol{x}$ is the total industry output vector, $\boldsymbol{V}$ is the industries-by-commodities make matrix, $\boldsymbol{q}$ is the total commodity output vector, $\boldsymbol{B}$ is the normalized use matrix, and $\boldsymbol{D}$ is the normalized make matrix. See Supporting Information for List of Variables.

$$\boldsymbol{A} = \boldsymbol{U}\hat{\boldsymbol{x}}^{-1}\boldsymbol{V}\,\hat{\boldsymbol{q}}^{-1} = \boldsymbol{B}\boldsymbol{D} \tag{1}$$

3.2 | Consumption of fixed capital

In this work, the life cycle impacts of capital assets are distributed based on the value of the service they provide in a given year. The BEA considers CFC to be synonymous with depreciation, and states that as "a cost incurred in the production of GDP, CFC reflects the use of private and

TABLE 1 Final demand investment categories $\boldsymbol{Y}^K$ in the USEEIO Use table

Investor class	#	Final demand investment $\boldsymbol{Y}^K$ categories
Nonresidential private	1	Nonresidential private fixed investment in structures
	2	Nonresidential private fixed investment in equipment
	3	Nonresidential private fixed investment in IPP
Residential private	4	Residential private fixed investment
Government	5	Federal national defense: Gross investment in structures
	6	Federal national defense: Gross investment in equipment
	7	Federal national defense: Gross investment in IPP
	8	Federal nondefense: Gross investment in structures
	9	Federal nondefense: Gross investment in equipment
	10	Federal nondefense: Gross investment in IPP
	11	State and local: Gross investment in structures
	12	State and local: Gross investment in equipment
	13	State and local: Gross investment in IPP

Note. $\boldsymbol{Y}^K$ = final demand investment; USEEIO = US Environmentally Extended Input-Output.

government FAs located in the United States, and is defined as the decline in the value of the stock of assets due to wear and tear, obsolescence, accidental damage, and aging" (US BEA, 2003).

Geometric depreciation rates estimated by Hulten and Wykoff form the basis of BEA estimates (US BEA, 2003). Hulten and Wykoff (1981) note that the depreciation profile often does not align with the decline in the physical efficiency of an asset. They relate the value of capital services to the present value of returns obtained by "renting" the capital to other users or oneself. They also describe that economic depreciation is the difference in value between an asset of age a and a year younger, age $a - 1$, accounting for inflation. Therefore, we assume that the value of capital services to the owner is equivalent to the asset's depreciation for a given year.

3.3 | Preparation of CFC matrix

These methods will primarily describe the approach using CFC data from BEA and later return to a related approach using KLEMS matrices. There are two main steps in the process to endogenize capital in the USEEIO for a given year. The first and most intensive step is the preparation of the CFC use matrix, $\boldsymbol{U}^K$. The second step simply converts the $\boldsymbol{U}^K$ matrix into the $\boldsymbol{A}^K$ direct inputs requirements matrix, by replacing $\boldsymbol{U}$ with $\boldsymbol{U}^K$ in Equation (1). $\boldsymbol{A}^K$ is then added to the original $\boldsymbol{A}$ matrix and used for environmental impact calculations, as described in Berrill, Miller, Wolfram, and Hertwich (2019).

The $\boldsymbol{U}^K$ matrix will allocate some of an industry's investment in a capital asset from prior years i to the year of interest θ (see Figure S2). Here, θ is either 2007 or 2012, since the tables are based on detailed benchmark data. The dimensions of $\boldsymbol{U}^K$ align with the detailed $\boldsymbol{U}$: 405 commodity DIGs χ by 405 industry DIGs ι in producers' value. Two versions of the matrix are created. The intermediate $\boldsymbol{U}^{K^*}$ matrix allocates FAs based on the depreciation of the assets that an industry invested in. The $\boldsymbol{U}^{K^*}$ is then modified to create the final $\boldsymbol{U}^K$ matrix which re-allocates some government-owned assets to the industries which use them.

3.3.1 | BEA data

To create the CFC matrices, we rely heavily on BEA data. The ideal dataset would provide annual CFTs with the annual investment by each ι into FAs represented by χ. Combining that time series with depreciation rates would allow for estimation of CFC of each of the FAs owned by each of the industries. As mentioned in section 1.3, the seventh and latest BEA CFT was published in 1997; it contains 123 industries and 180 FAs, both of which use an outdated classification system. We sought to use more recent and relevant time series data. The BEA maintains several interdependent accounts relevant to this work (US BEA 2018e, 2003, 2016):

- Industry accounts
  - Periodic detailed benchmark and annual aggregated IO tables in producers' value since 1947, with several changes in industry aggregation and classification over time.
  - Margins tables $\boldsymbol{P}$ with details on trade and transport margins for benchmark years.
  - Investment in FAs is provided in several final demand categories $\boldsymbol{Y}^K$ of the IO Use table, as shown in Table 1.

- Fixed asset accounts (FAA)
  - Detailed (underlying) annual data since 1901 for investment $\boldsymbol{H}$, CFC $\boldsymbol{H}^K$, and net stocks of FAs h in purchasers' value. The investment data tables are CFTs.
  - FA general categories of structures, equipment, and IPP.
  - Separate tables for each investor class: Nonresidential private, residential private, and government.
  - FA types within general categories vary by investor class table.
- National income and product accounts (NIPA)
  - Data available since 1929 on the "value and composition of national output and the types of incomes generated in its production."
  - NIPA investment totals tend to align with IO investment totals in purchasers' values.
  - Due to accounting choices, the estimate of FA investment by NIPA and IO sometimes differs from the FAA, so the BEA provides explanatory relationship tables.

The categorization of FA types differs between BEA accounts. For instance, the IO DIG commodity "Electronic computer manufacturing" is one of five that fall under the NIPA "Computers and peripheral equipment" equipment category, which is split into eight FAA categories. Fortunately, the BEA provides an IO/NIPA concordance table for private equipment ("PEQ Bridge") which is a helpful start in this case (US BEA, 2018f). For all other cases, the IO/FAA concordances must be approximated. In another example, the IO DIG commodity "Scientific research and development services" covers 17 FAA categories, but is spread over only 11 NIPA categories. Therefore, the bulk of the effort in creating the CFC matrices is spent on creating and applying concordance tables between IO DIGs and FAs and adjusting for valuation as described in the next section.

3.3.2 | Calculation approach

The process of combining BEA data to create the CFC matrices is diagrammed in Figure 3. The structure of the FAA tables differs by investor class, and the FA types differ within each FA general category (IPP, equipment, and structures).

Therefore, in step (a) CFC tables are created for each of the 13 final demand investment $\boldsymbol{Y}^K$ categories in the format of the detailed $\boldsymbol{U}$ in producers' value. Next in step (b), these 13 tables are combined to create the $\boldsymbol{U}^{K*}$ matrix. Then in step (c), modifications to the highway and streets allocation are made to create the final $\boldsymbol{U}^K$ matrix. This is lastly converted into a technical coefficient matrix. Since detailed IO data is now available for 2007 and 2012, the approach is followed for both years.

(a) Create a detailed CFC table for each final demand investment category

In Figure 3a, sub-steps (i) and (ii) focus on the rows of the $\boldsymbol{U}^{K*}$ matrix by associating assets with detailed commodities and converting from purchasers' to producers' value. The next sub-step (iii) applies CFC data, and the last sub-step (iv) addresses the columns of $\boldsymbol{U}^{K*}$ by spreading the CFC to detailed investors. While the specific BEA tables used for each of the investor classes vary, the basic approach described below is followed for each of the three classes across the 13 $\boldsymbol{Y}^K$ categories.

i. Create IO-FAA commodity concordance in purchasers' value

In order to utilize industry-specific FA data in the FAA, concordances are needed as a bridge to commodities in the IO data. Ideally, a concordance could be built directly between IO and FAA CFC data. CFC is not explicit in IO data; it is only included as a component of gross operating surplus (GOS) in the value added matrix. Therefore, we approximate concordances between the total investment in IO DIG commodities χ and the total investment in FAA FAs h as described below. We assume the concordances apply to total CFC as well, which is a limitation to the method since CFC is influenced by prior investments; it would only be precisely correct if the investment concordance was the same for all prior years. Still, we think it is a reasonable approximation for these years since the structure of the economy changes slowly (Yang et al., 2017) and recent investments influence CFC more than older ones due to use of geometric depreciation rates.

The manual creation of IO-FAA concordance tables $\bar{\boldsymbol{C}}^{\alpha}_{\chi \times h}$ involved comparing investment in IO DIG commodities χ to relevant FA investment h in purchasers' value α for the same year. We assume that "Scrap," "Used and secondhand goods," "Noncomparable imports," and "Rest of world adjustment" commodities do not produce any FA; Yang et al. (2017) removed these four from their model. For a straightforward example with 2012 data, in the $\boldsymbol{Y}^K$ category *Nonresidential private fixed investment in structures*, the χ "Health care structures" ($35.4B) is linked to three h: "Hospitals" ($23.9B), "Special care" ($4.3B), and "Medical buildings" ($7.2B). However, the BEA "PEQ Bridge" for *Nonresidential private fixed investment in equipment* indicates that there is often a many-to-many IO–FAA relationship. For instance, the χ "Irradiation apparatus manufacturing" is linked to two h, "Medical equipment and instruments" and "Nonmedical instruments," which are both comprised of additional commodities χ as well.

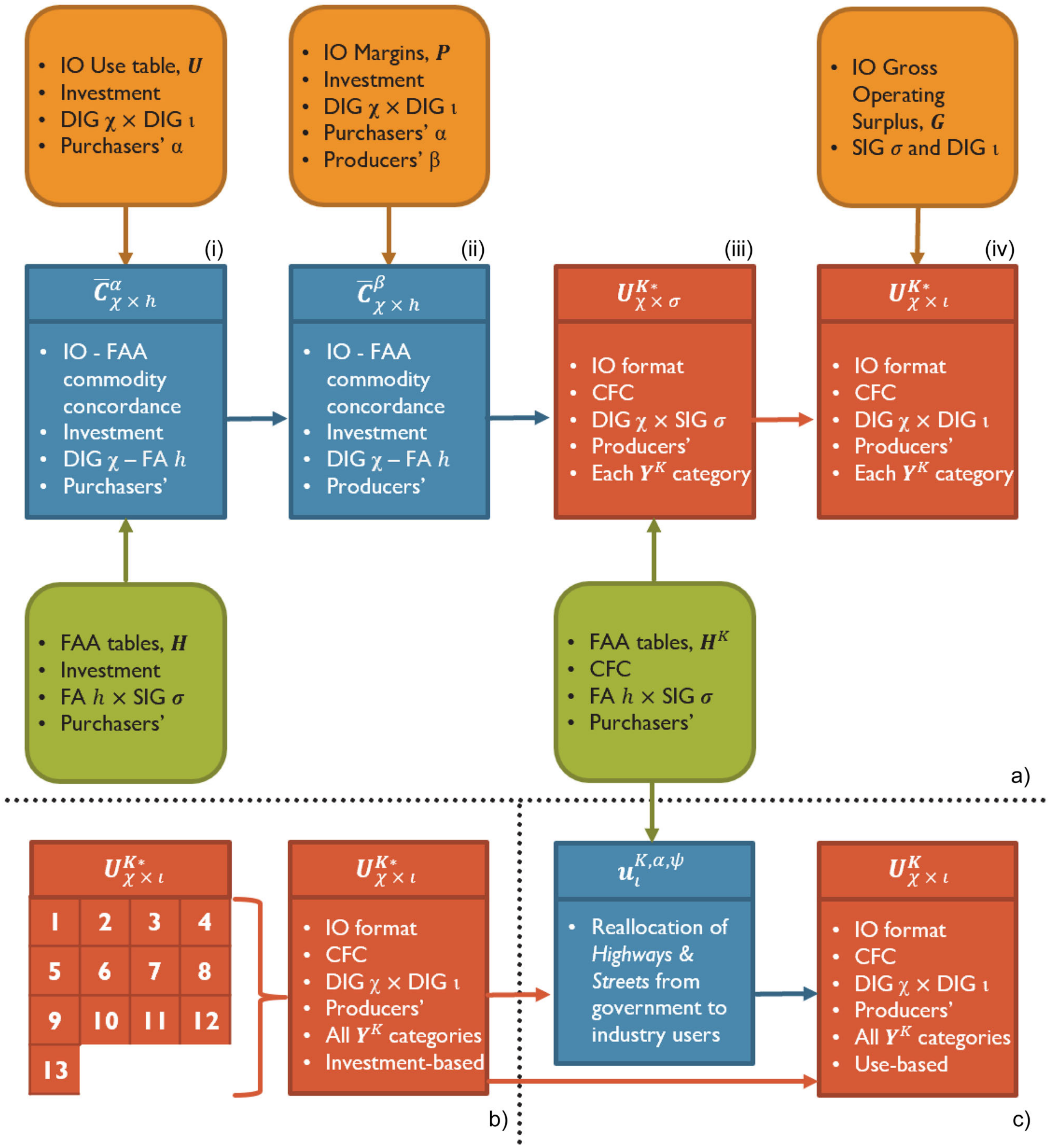

FIGURE 3 Overall approach for construction of the U^K matrix in three steps. (a) Construction of IO CFC table in producers' value for each of the 13 final demand investment categories in Table 1. Rectangles indicate created tables, while rounded rectangles indicate BEA tables. (b) Combination of the 13 tables into the U^{K*} matrix (c) Conversion of U^{K*} to U^K by reallocating highways and streets

Note. IO = Input-Output; CFC = Consumption of Fixed Capital; DIG = Detailed Industry Group; SIG = Summary Industry Group; FAA = Fixed Asset Accounts; BEA = US Bureau of Economic Analysis; U = commodities-by-industries use matrix; U^{K*} = intermediate CFC use matrix; U^K = final CFC use matrix.

It is not always possible to create an exact many-to-many concordance for the other $\boldsymbol{Y}^K$ categories, so several matches required judgment and estimation.

ii. Convert from purchasers' to producers' value

Matrices in producers' value are preferred over purchasers' for EEIO because they distinguish the impact of trade and transport margins from production. A $\boldsymbol{U}$ matrix in purchasers' value α captures the industry inputs based on payment by the industry for the commodity, while a $\boldsymbol{U}$ matrix in producers' value β disaggregates this payment into the revenue earned by the producer of the commodity and the revenue earned by the transport, wholesale, and retail margin services between production and sale. The difference in valuations is most pronounced for equipment as margins are almost negligible for structures and IPP due to the nature of the assets. Details on the calculation approach using transformation matrices are provided in the Supporting Information. The result is $\bar{\boldsymbol{C}}^{\beta}_{\chi\times h}$, an intermediate concordance matrix in producers' value that assigns the fraction of each FA h that goes to each commodity χ.

iii. Apply commodity concordance to CFC data

Having created concordance tables based on investment data, they are now applied to CFC data. In Equation (2), the IO-FAA concordance tables created in producers' value are multiplied by FAA CFC data; $\boldsymbol{H}^K_{h\times\sigma}$ represents the use of different FA h by each industry. The aggregation of the detailed investor industries ι to summary industry groups (SIGs) σ in these tables varies by investor class: there are 63 σ in the nonresidential private class, the only σ in the residential private class is equivalent to the "Housing" ι, and there are three hierarchical categories of the government investor class (see Table 1).

$$\boldsymbol{U}^{K*}_{\chi\times\sigma} = \bar{\boldsymbol{C}}^{\beta}_{\chi\times h} \cdot \boldsymbol{H}^K_{h\times\sigma} \tag{2}$$

iv. Allocate CFC from aggregate investors to DIGs

To arrive at the desired $\chi \times \iota$ matrix, the final task before combining the CFC matrices is to allocate the CFC from the aggregate summary investors σ to the detailed investors ι. This is straightforward for the residential private investor class with its sole investor. Separate procedures are followed for the nonresidential private and government classes.

For the nonresidential private investor class, a proxy for detailed CFC data is used. As mentioned in the preceding step, IO CFC data per industry is only available at the more aggregated SIG level. In the detailed value added matrix, the GOS vector $\boldsymbol{g}_{\iota}$ is the sum of CFC and net operating surplus, which is a profits-like measure (US BEA, 2018h). The GOS is used here as a proxy to proportionally allocate CFC from SIG industries to DIG industries. First, the GOS vector is transformed into a SIG x DIG matrix $\boldsymbol{G}_{\sigma\times\iota}$ using the hierarchical classification of DIGs within SIGs. Sums per SIG are taken in Equation (3), and the GOS matrix is then normalized by these sums, as shown in Equation (4). The normalized matrix determines how much of each SIG's CFC will be allocated to each DIG industry. Applying this matrix to the aggregated intermediate CFC matrix arrives at the intermediate CFC matrix in the proper dimensions in Equation (5).

$$\boldsymbol{g}_{\sigma} = \sum_{\iota} \boldsymbol{G}_{\sigma\times\iota} \tag{3}$$

$$\overline{\boldsymbol{G}_{\sigma\times\iota}} = \widehat{\boldsymbol{g}_{\sigma}}^{-1} \cdot \boldsymbol{g}_{\sigma\times\iota} \tag{4}$$

$$\boldsymbol{U}^{K*}_{\chi\times\iota} = \boldsymbol{U}^{K*}_{\chi\times\sigma} \cdot \overline{\boldsymbol{G}_{\sigma\times\iota}} \tag{5}$$

Allocating CFC to DIGs in the government investor class is not as clear-cut due to complex classifications. There are nine DIGs representing government investors, and three aggregated government investors in the FAA tables. The DIG "Federal general government (defense)" maps directly to "Federal: National defense" in the FAA. Of the eight remaining DIGs, four map to "Federal: Nondefense" and four map to "State and Local" in the FAA. In each group of four DIGs, one pertains to general government, and the other three pertain to government enterprises. The BEA graciously provided us a custom classification of each line of the FAA table as "general government," "government enterprise," or "mix of both" (Miller & Bennett, 2017). Addenda to the government FAA tables provide overall totals of general government and government enterprise per asset type. The lines classified as "mix of both" were allocated proportionally using the addenda totals. To further allocate the government enterprise CFC to DIGs, a modified GOS approach (see Equations (3) and (5)) was used in combination with best judgment. For instance, 100% of the federal nondefense power structures was first assigned to the DIG "Federal electric utilities" before allocating the remaining CFC proportional to GOS.

(b) Create an intermediate detailed CFC combining all $\boldsymbol{Y}^{K}$ categories

This step simply involves summing the 13 $\boldsymbol{U}^{K*}_{\chi\times\iota}$ matrices created for each $\boldsymbol{Y}^{K}$ category. The resulting matrix approximately allocates CFC in producers' prices based on investment. This could be the final matrix, but we chose to address a further issue of asset use versus investment, described in the next section.

(c) Create the final detailed CFC by re-allocating highways and streets

State and Local governments are the predominant investors in, but not the predominant users of, the DIG "Transportation structures and highways and streets" (TSHS, denoted by ψ). Some industries also invest in private roads and parking lots. In the Use table $\boldsymbol{U}$, the only consumer of "State and local general government" is the final demand category "State and local government consumption expenditures." Therefore, although public TSHS have many users, most users are not burdened by the impact of creating them. The final $\boldsymbol{U}^{K}_{\chi\times\iota}$ matrix differs from the intermediate $\boldsymbol{U}^{K*}_{\chi\times\iota}$ matrix in that public TSHS are partially allocated to industries driving vehicles and using the roads. Households also use public TSHS; here, the household share is allocated to State and Local governments, lacking a clear mechanism to allocate it to personal consumption expenditure (PCE) and recognizing that there are other government-owned assets intended for household use such as educational and healthcare structures.

For methodological consistency, the proportion of CFC from vehicle assets, denoted by γ, across industries in purchasers' value α is used to allocate the industrial CFC for TSHS. The five vehicle χ^{γ} are marked in a binary concordance vector $\bar{\boldsymbol{c}}^{\gamma}_{\chi}$: "Automobile manufacturing," "Light truck and utility vehicle manufacturing," "Heavy duty truck manufacturing," "Motor vehicle body manufacturing," and "Truck trailer manufacturing." For each of the four equipment $\boldsymbol{Y}^{K}$ categories (#2, #6, #9, and #12 in Table 1), the FAA data in purchasers' value is converted to commodity DIGs using $\bar{\boldsymbol{C}}^{\alpha}_{\chi\times h}$ in Equation (6), which parallels Equation (2). The CFC is then allocated from aggregate investor industries to DIGs ι following the same approach described for CFC in producers' value in Equation (5), as Equation (7) demonstrates for the nonresidential private class. The sum of vehicle CFC for each industry $\boldsymbol{u}^{K,\alpha,\gamma}_{\iota}$ is found in Equation (8) by applying the binary concordance.

$$\boldsymbol{U}^{K,\alpha}_{\chi\times\sigma} = \bar{\boldsymbol{C}}^{\alpha}_{\chi\times h}\cdot\boldsymbol{H}^{K}_{h\times\sigma} \tag{6}$$

$$\boldsymbol{U}^{K,\alpha}_{\chi\times\iota} = \boldsymbol{U}^{K\alpha}_{\chi\times\sigma}\cdot\overline{\boldsymbol{G}_{\sigma\times\iota}} \tag{7}$$

$$\boldsymbol{u}^{K,\alpha,\gamma}_{\iota} = \bar{\boldsymbol{c}}^{\gamma}_{\chi}\cdot\boldsymbol{U}^{K,\alpha}_{\chi\times\iota} \tag{8}$$

To capture the household, λ, share of vehicle CFC, the vector $\boldsymbol{h}^{K}$ of consumer durable goods (CDG) data within the FAA $\boldsymbol{H}^{K}$ is used (US BEA, 2017). Note that in final demand, household vehicle and other CDG purchasers are part of PCE rather than *Residential private fixed investment* which solely pertains to housing. To find the total industry and household vehicle CFC $u^{K,\alpha,\gamma}$, the sum of household CFC for FAs h "Autos" and "Light trucks" is found in Equation (9), and added to the sum of industry CFC in Equation (10).

$$u^{K,\alpha,\gamma,\lambda} = \sum_{h}\boldsymbol{h}^{K,\alpha,\gamma,\lambda}_{1\times h} \tag{9}$$

$$u^{K,\alpha,\gamma} = u^{K,\alpha,\gamma,\lambda} + \sum_{\iota}\boldsymbol{u}^{K,\alpha,\gamma}_{\iota} \tag{10}$$

The CFC for "State and local general government" TSHS $u^{K,\alpha,\psi}$ is then re-allocated across industries using the ratio between it and total vehicle CFC in Equation (11) to form the intermediate vector $\boldsymbol{u}^{K,\alpha,\psi*}_{\iota}$. The household share $u^{K,\alpha,\psi,\lambda}$ is determined similarly in Equation (12), and then added to the "State and local general government" ι in $\boldsymbol{u}^{K,\alpha,\psi*}_{\iota}$ to arrive at the final "State and local general government" TSHS vector $\boldsymbol{u}^{K,\alpha,\psi}_{\iota}$. This final vector $\boldsymbol{u}^{K,\alpha,\psi}_{\iota}$ is combined with the CFC row vector for privately owned TSHS in $\boldsymbol{U}^{K*}_{\chi\times\iota}$ to represent industrial uses of public and private TSHS in the desired matrix $\boldsymbol{U}^{K}_{\chi\times\iota}$.

$$\boldsymbol{u}^{K,\alpha,\psi*}_{\iota} = \left(\frac{u^{K,\alpha,\psi}}{u^{K,\alpha,\gamma}}\right)\cdot\boldsymbol{u}^{K,\alpha,\gamma}_{\iota} \tag{11}$$

$$u^{K,\alpha,\psi,\lambda} = \left(\frac{u^{K,\alpha,\psi}}{u^{K,\alpha,\gamma}}\right)\cdot u^{K,\alpha,\gamma,\lambda} \tag{12}$$

Alternative approach for creating $\boldsymbol{U}^K$

To compare the impacts of creating $\boldsymbol{U}^K$ from a more aggregated CFC dataset, we adapt the approach developed in Södersten et al. (2018) for many countries in an MRIO to the USEEIO, aided by communication with the lead author (Miller, Södersten, Berrill, & Hertwich, 2018). We prepare the comparison matrix $\boldsymbol{U}^{KLEMS}$ for the year 2007 since the CFC data is not available for 2012. Step (a) is somewhat similar in both approaches, step (b) is unnecessary in the alternative approach, and step (c) is unique to this work; details of the alternative approach are in the Supporting Information. The key differences between the method to make $\boldsymbol{U}^{KLEMS}$ and $\boldsymbol{U}^{K*}$ are: eight asset types and associated depreciation rates in KLEMS data versus 96, 51, and 35 asset types for nonresidential private, residential private, and government classes, respectively in BEA data; 32 investor industries in KLEMS data versus nearly 70 SIGs; GFCF proportions for asset allocation to DIGs based on the sum of investment $\boldsymbol{Y}^K$ rather than separate $\boldsymbol{Y}^K$ matched to investor class and asset category; and differences in GFCF totals despite both datasets deriving from BEA sources.

Create technical coefficient matrix for capital formation

Returning to Equation (1), we can now create the technical coefficient matrix for capital formation $\boldsymbol{A}^K$ with a very similar approach, shown in Equation (13). Since the same total industry output vector $\boldsymbol{x}$ used to normalize $\boldsymbol{U}$ does so for $\boldsymbol{U}^K$, we can combine the two matrices to create a total capital-inclusive use matrix $\boldsymbol{U}^\tau$ and define the capital-inclusive technical coefficient matrix $\boldsymbol{A}^\tau$ in Equations (14) and (15), respectively. We apply these equations to $\boldsymbol{U}^{KLEMS}$ as well. This commodities-by-commodities matrix can now be used to perform comparative environmental impact analyses, described in Berrill et al. (2019).

$$\boldsymbol{A}^K = \boldsymbol{U}^K \hat{\boldsymbol{x}}^{-1} \boldsymbol{V} \hat{\boldsymbol{q}}^{-1} \tag{13}$$

$$\boldsymbol{U}^\tau = \boldsymbol{U}^K + \boldsymbol{U} \tag{14}$$

$$\boldsymbol{A}^\tau = \boldsymbol{U}^\tau \hat{\boldsymbol{x}}^{-1} \boldsymbol{V} \hat{\boldsymbol{q}}^{-1} \tag{15}$$

Aggregate product categories for comparison

To simplify the presentation and analysis of the resulting structure of the CFC matrices, we created a common set of 23 aggregated commodities X and industries I with common characteristics, based on the first two digits of the BEA code. The results are therefore shown either in: $\boldsymbol{U}^K_{\chi \times \iota}$, $\boldsymbol{U}^K_{\chi \times \mathrm{I}}$, $\boldsymbol{U}^K_{\mathrm{X} \times \iota}$, or $\boldsymbol{U}^K_{\mathrm{X} \times \mathrm{I}}$. Note that not all commodities, such as farming, create capital products. A table classifying DIG capital commodities χ into aggregated commodities X is in the Supporting Information.

4 | RESULTS

4.1 | Analysis of CFC matrix

Housing is far and away the top consumer of capital commodities in 2012 (combining owner- and tenant-occupied housing DIGs ι), consuming predominantly the aggregated commodities X "Construction" and "Housing, Real Estate" as shown in Figure 4 for $\boldsymbol{U}^K_{\mathrm{X} \times \iota}$. Branches of federal government are among the top consumers of capital, primarily equipment and research products, while "State and local general government" consumes plenty of construction products (mainly TSHS). The "Oil and gas extraction" ι is high on the list with its obvious consumption of "Mining, Fossil Extraction" capital. Interestingly, the financial ι "Monetary authorities and depository credit intermediation" consumes a sizable quantity of equipment products. This is likely due to the structure of the IO tables, wherein businesses and households pay to use equipment owned by financial institutions; unfortunately for analyses, this creates an average, homogenous financial capital asset. Note that trade and transport margins are combined here as "Margins" among the aggregated capital products. These are not capital products themselves, but the businesses needed to bring the capital products to the purchaser.

Comparing the contribution of capital in $\boldsymbol{U}^K_{\mathrm{X} \times \mathrm{I}}$ to the capital-inclusive Use table $\boldsymbol{U}^\tau_{\mathrm{X} \times \mathrm{I}}$, we gain a sense of the relative importance of types of capital products for production. Figure 5 shows that across almost all industries using the aggregated commodity "23, construction" as an input to production, most of this input is in the form of capital rather than nondurable goods or services. This highlights the fact that the bulk of construction inputs each year are used to create new assets rather than to maintain or upgrade existing assets. The use of commodities "Metals, Vehicles, Machinery," "Science, Prof. Services," and to a lesser extent "Information Industries," as inputs to production is also to a large degree in the form of capital assets, or they are an input to the production of capital assets by the respective industries, such as their use in construction. "Commodities" 42, 4X, and 48 are margins, so their $\boldsymbol{U}^K$ value pertains to margins to facilitate capital creation. In contrast, "Bio, Chemical, Mineral Products" are rarely used directly as capital products; products such as cement are inputs to capital products though and are observable in the $\boldsymbol{U}$ matrix.

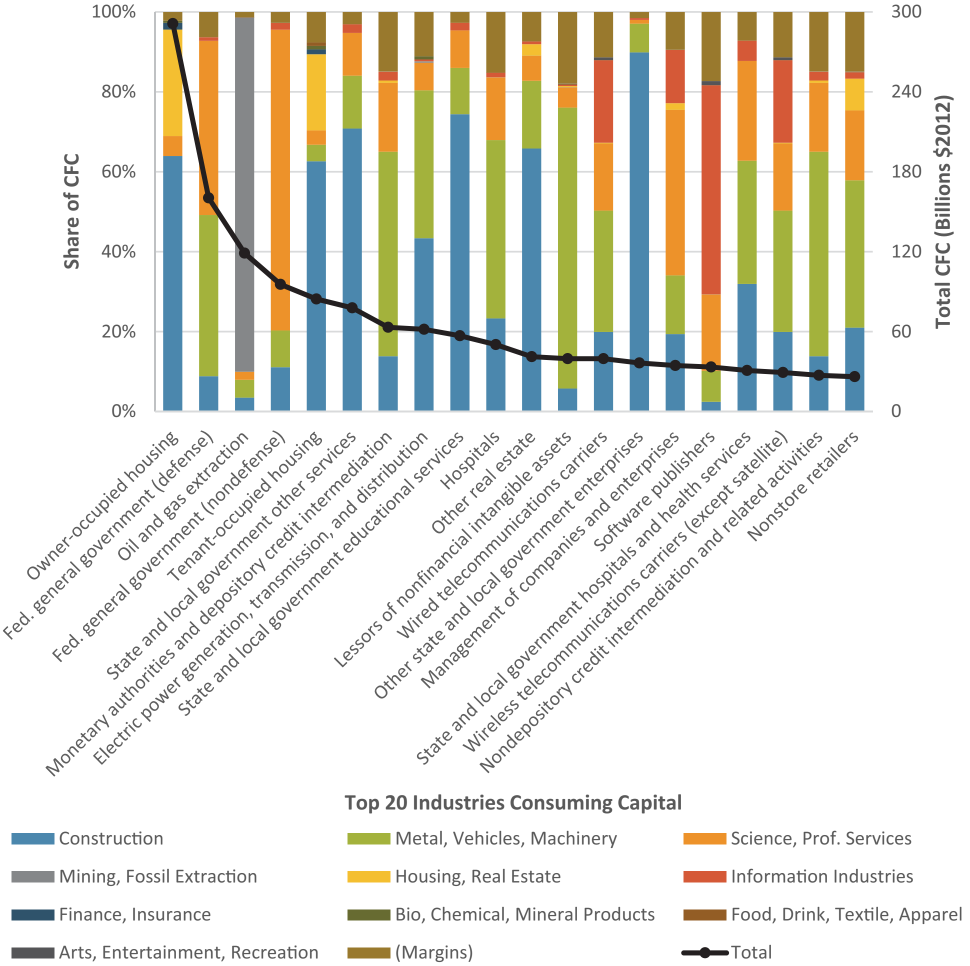

FIGURE 4 Consumption of aggregated capital commodities **X** by the top 20 detailed industries ι in 2012 U^K. Underlying data used to create this figure can be found in Supporting Information S2
Note. CFC = Consumption of Fixed Capital.

Since the CFC matrices were developed by combining 13 Y^K categories differentiated by three asset types, we can assess the use of each asset type toward production. The exception is *Residential private fixed investment* which combines structures and equipment, so the FA concordance tables are used to distinguish the types. Figure 6 presents the share of IPP, equipment, and structures consumed by aggregate industry I (ignoring margins). Ward hierarchical clustering (Murtagh & Legendre, 2014) was used to identify six clusters (see Figure S6), outlined by boxes. The results are often as expected: IPP comprise a large share of information and arts industries; structures dominate housing and extraction industries; and equipment makes up the majority of construction, transport, and delivery industries. Other industries require a greater mixture of capital inputs, such as science and professional services which is more evenly split.

4.2 | Allocation of highways and streets

Despite a 29% decrease in asset use after allocating a portion of the use of TSHS to the industrial users, *State and local general government* remain the largest user of the asset, as shown in Table S4. This is due to the massive personal use of TSHS by households, which is accounted here as *State and local general government* consumption. *Truck* and *Transit transportation* are predictably allocated significant use of TSHS since driving is a primary function of the industries. Notably, firms involved in credit and leasing have the highest increase in TSHS use, presumably due to their ownership of vehicles which are leased and rented to other users.

4.3 | Comparison with alternative approach

The elements of the detailed $\boldsymbol{A}^K$ created through our approach and the detailed $\boldsymbol{A}^K$ created following the most comparable approach found in existing literature (Södersten et al., 2018) are compared in Figure 7. Viewed at any resolution we see considerable differences in coefficients of $\boldsymbol{A}^K$

Aggregated Capital Commodities X	Aggregated Industries I																						
	11 Agri, Forestry, Fishing	21 Mining, Fossil Extraction	22 Electricity, Water	23 Construction	31 Food, Drink, Textile, Apparel	32 Bio, Chemical, Mineral Products	33 Metal, Vehicles, Machinery	42 Wholesale Trade	4X Retail Trade	48 Transport	49 Delivery, Warehousing	51 Information Industries	52 Finance, Insurance	53 Housing, Real Estate	54 Science, Prof. Services	55 Management	56 Admin, Support, Waste Services	61 Education	62 Healthcare, Social assistance	71 Arts, Entertainment, Recreation	72 Accommodation, Restaurants	81 Repair, Personal services	S0 Govt., Reuse, Trade Adjustments
21	*	68%	*	*	1%	*	*	36%	51%	79%	35%	*	100%	88%	5%	1%	3%	*	*	*	1%	*	
23	80%	53%	82%	94%	80%	49%	85%	75%	83%	75%	51%	89%	79%	70%	83%	93%	89%	92%	91%	91%	83%	70%	69%
31	*	78%	90%	1%	*	*	*	1%	1%	6%	20%	3%	100%	70%	*	4%	7%	*	*	1%	*	*	*
32	*	*	2%	*	*	*	*	*	*	*	*	*	*	8%	*	*	*	*	*	*	*	*	*
33	76%	33%	95%	14%	29%	38%	6%	52%	60%	63%	36%	46%	96%	82%	39%	40%	34%	56%	45%	60%	71%	25%	55%
42	15%	25%	54%	9%	4%	7%	7%	13%	30%	17%	16%	52%	74%	44%	32%	43%	32%	43%	23%	36%	18%	21%	25%
4X	58%	62%	29%	3%	16%	20%	27%	71%	36%	13%	35%	85%	92%	71%	60%	100%	37%	80%	53%	64%	11%	12%	
48	7%	3%	6%	2%	*	2%	4%	3%	12%	*	1%	8%	13%	14%	3%	17%	4%	11%	5%	7%	11%	10%	4%
51	1%	6%	11%	3%	6%	11%	29%	14%	7%	7%	12%	30%	15%	3%	35%	31%	17%	20%	5%	76%	*	4%	9%
52														3%									
53	*	*	*	*	*	*	*	*	6%	1%	*	*	2%	44%	*	2%	*	*	*	*	1%	2%	
54	34%	15%	24%	11%	38%	68%	69%	12%	16%	22%	20%	25%	23%	22%	24%	18%	19%	47%	11%	7%	5%	23%	46%
71												5%			22%					9%			

FIGURE 5 Contribution of capital to the capital-inclusive use table. $\boldsymbol{U}^{K}/\boldsymbol{U}^{\tau}$ in 2012. 0% blank, 0% < * < 1%. Underlying data used to create this figure can be found in Supporting Information S2

Note. $\boldsymbol{U}^{K}$ = consumption of fixed capital use matrix; $\boldsymbol{U}^{\tau}$ = total capital-inclusive use matrix.

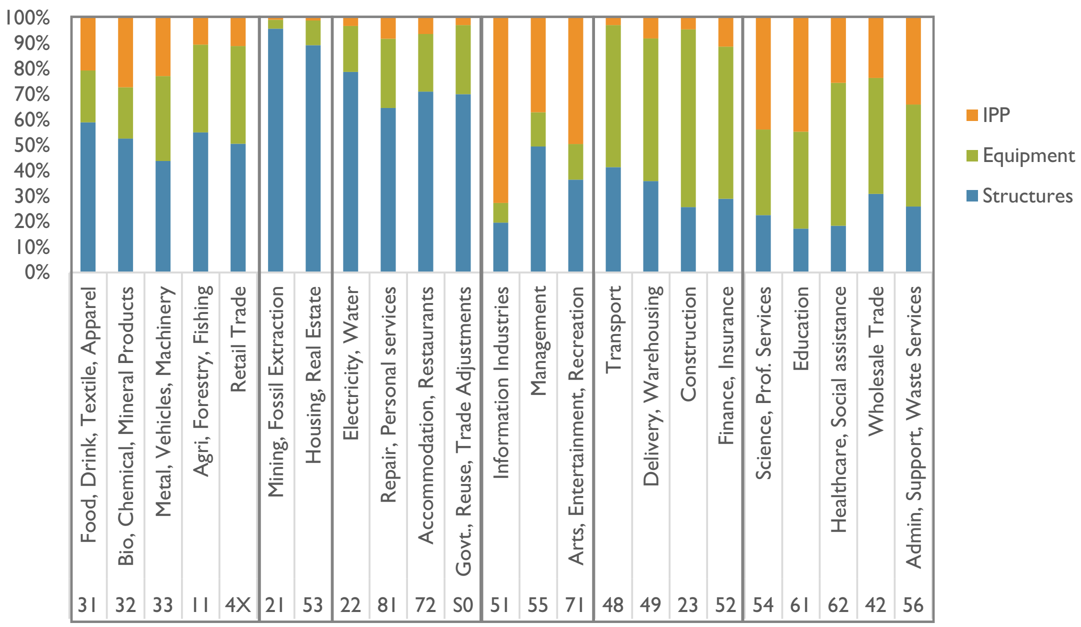

FIGURE 6 Share of intellectual property products (IPP), equipment, and structures in 2012 $\boldsymbol{U}^{K}$ by aggregated industry **I**. Boxes indicate clusters of main types of fixed assets (FAs) used. Underlying data used to create this figure can be found in Supporting Information S2

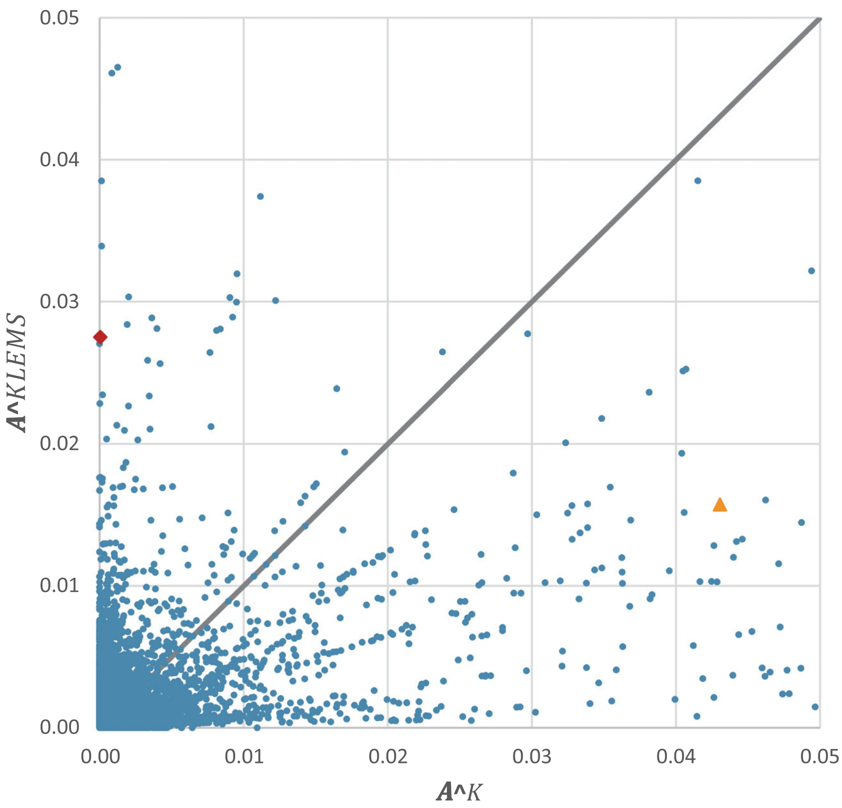

FIGURE 7 Comparison of technical coefficients of the 2007 $\boldsymbol{A}^{K}$ matrix based on BEA data and the alternative $\boldsymbol{A}^{KLEMS}$ based on KLEMS data. Bounds of chart do not encompass all elements (see Figure S5); magnified to show detail. Red diamond indicates use of "Single-family residential structures" in "Tenant-Occupied Housing," and orange triangle indicates use of "Multifamily residential structures" in "Owner-Occupied Housing"
Note. $\boldsymbol{A}^{K}$ = capital technical coefficients matrix based on BEA data, $\boldsymbol{A}^{KLEMS}$ = capital technical coefficients matrix based on KLEMS data. Underlying data used to create this figure can be found in Supporting Information S2.

and $\boldsymbol{A}^{KLEMS}$ (Figure 7 is magnified and excludes some elements); this is perhaps to be expected considering several key differences in approaches described above and detailed in the Supporting Information. To give some examples, the eight assets in the KLEMS data only distinguish software in IPP capital, so elements pertaining to scientific research or computer programming commodities show considerable scatter. Distinction between owner-occupied and tenant-occupied residential investments is possible with BEA FA data but not KLEMS data partially explaining the disagreement for elements in these categories (see representative data points indicated in Figure 7).

5 | DISCUSSION

For EEIO analyses, incorporation of the capital layer substantially enhances the representation of the inputs required for production from a life cycle perspective (see Berrill et al., 2019) and allows a more comprehensive analysis. The methods described here for the detailed USEEIO are one means of doing so. By invoking the FAA, we create a set of heterogeneous capital products attributed to their original investors, which joins the existing flow matrix methods as a major improvement on the augmentation method. By allocating capital based on CFC rather than capital formation, capital consumption is more reasonably allocated and trends more smoothly over time, representing a significant improvement over most existing flow matrix methods. With our approach, fluctuations of CFC is now based on investment in previous years, and large changes in CFC, or $\boldsymbol{A}^{K}$ coefficients, for a given investing industry will only happen when there is a sustained increase or decrease in capital investment over consecutive years (see for example Figure 1 Private residential investments pre- and post-2008).

Our approach is subject to a set of limitations based on data availability and the structure of IO analyses. Many concordance tables were manually estimated with some level of judgment. Were the BEA to publish all underlying concordance tables in the future, it would considerably expedite this process. Also, although capital assets were distributed proportionally to CFC, we acknowledge that monetary depreciation does not always mimic physical deterioration or use (OECD, 2009), and therefore other forms of distribution may be considered for this step. Another choice was that TSHS be allocated proportional to vehicle CFC, and that government would be burdened with the household share. Further, the USEEIO is for a single region, and therefore uses the domestic technology assumption.

We envision future steps to address some of these limitations and extend this work. While we relied on the geometric depreciation rates provided and applied by the BEA, we are not tied to them. Since we have annual FA investment data, any set of depreciation rates can be applied to arrive at the cumulative CFC in a given year. These rates could also be dynamic, trending over time to reflect shifts in lifespans. The USEEIO could also be embedded in an MRIO to overcome the domestic technology assumption.

The allocation of TSHS brought to light a normative question not often addressed in EEIO or LCA: *who should be burdened with general government expenditure?* In the current EEIO framework, government operations are isolated and generally not considered as inputs for production or household wellbeing. Business taxes are a component of the value added matrix and form a basis for government expenditure. Most governments are founded and operated to support the population and the economy. Households and businesses pay taxes and fees to various government bodies, but those payments do not necessarily directly correlate to the benefit received from tangible and intangible government services. An argument can be made to endogenize general government in EEIO analyses, which would involve some restructuring of the Use and Make tables along with subjective allocation decisions. Having done so, impacts of government operations like defense, public health and education, and other major public investments such as transport infrastructure would be shared in some fashion by actors in the economy, and could result in pronounced differences when making environmental comparisons between countries, or estimating the true economic, social, and environmental costs of production of resources, and final products.

The capital flow matrices produced in this work achieve the objective of endogenizing capital in a manner which is most up-to-date, detailed, and reflective of actual sectoral capital consumption. While the limitations listed above can be addressed in future work, the open-source matrices created can be used by researchers to explore the impacts of capital consumption in the United States on a variety of metrics, such as environmental impact as demonstrated in Berrill et al. (2019).

CONFLICT OF INTEREST

The authors have no conflict to declare.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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