Fine particulate matter damages and value added in the US economy

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Emissions of most pollutants that result in fine particulate matter ($PM_{2.5}$) formation have been decreasing in the United States. However, this trend has not been uniform across all sectors or regions of the economy. We use integrated assessment models (IAMs) to compute marginal damages for $PM_{2.5}$-related emissions for each county in the contiguous United States and match location-specific emissions with these marginal damages to compute economy-wide gross external damage (GED) due to premature mortality. We note 4 key findings: First, economy-wide, GED has decreased by more than 20% from 2008 to 2014. Second, while much of the air pollution policies have focused to date on the electricity sector, damages from farms are now larger than those from utilities. Indeed, farms have become the largest contributor to air pollution damages from $PM_{2.5}$-related emissions. Third, 4 sectors, comprising less than 20% of the national gross domestic product (GDP), are responsible for ∼75% of GED attributable to economic activities. Fourth, uncertainty in GED estimates tends to be high for sectors with predominantly ground-level emissions because these emissions are usually estimated and not measured. These findings suggest that policymakers should target further emissions reductions from such sectors, particularly in transportation and agriculture.

externalities | air pollution | environmental accounting | value added | environmental policy

Air pollution is a major contributor to premature mortality in the United States. The Global Burden of Disease reports that it is the ninth largest risk factor contributing to deaths in the United States, responsible for more than 100,000 fatalities in 2016 (1). Epidemiological studies suggest that there exist no safe levels for many local air pollutants. Among these are fine particulate matter (2–4), or $PM_{2.5}$, which the Environmental Protection Agency (EPA) estimates is responsible for over 90% of air pollution-related health damages (5). Exposure to $PM_{2.5}$ has been linked to numerous fatal health consequences, among them ischemic heart disease, stroke, chronic obstructive pulmonary disease, and lung cancer (6). Therefore, despite recent reductions in the average concentration of pollution, risks remain.

This paper has 2 policy-relevant objectives. First, we provide a more comprehensive measure of the contribution of each economic sector to total national output than traditional accounts do and how these contributions evolved over time. Second, the paper guides environmental policymakers' continued efforts to manage risks posed by exposure to $PM_{2.5}$. To do so, we employ integrated assessment models (IAMs), which combine insights from multiple scientific disciplines to tabulate source-specific damages for 5 such pollutants that contribute to ambient levels of $PM_{2.5}$. Since the harm induced by discharges varies not just according to the toxicity of the pollutant but also according to where emissions occur, modeling damages by source is essential for accurate damage estimates and efficient regulatory decision-making.

We make 3 contributions to the literature. First, we update existing damage estimates (7–9) with the most recent available comprehensive national emissions data: EPA's 2014 National Emissions Inventory (NEI) (10). We focus on air pollution damages from premature mortality due to outdoor $PM_{2.5}$ exposure since it constitutes the vast majority of air pollution-related health damages (5). We do not include damages from morbidity or other pollutants such as exposure to nitrogen oxides (NO_x) or ozone. Second, the analysis tracks damages by economic sector over 3 NEI years, 2008, 2011, and 2014. In doing so, we relate monetized pollution damage to conventional measures of the value of production by sector, such as value added (VA). This critical normalization of pollution damage facilitates comparisons of the pollution intensity of output across time within sector and across the economy within a time period. This framework also enables comparisons of each sector's contribution to gross domestic product (GDP) relative to its share of gross external damage (GED) as we illustrate in Fig. 1 (8). Third, this work delves deeply into various sources of uncertainty in the damage estimates. We explore model uncertainty by employing the following IAMs: Air Pollution Emission Experiments and Policy model (AP3) (11), Estimating Air pollution Social Impact Using Regression (EASIUR) (12), and Intervention Model for Air Pollution (InMAP) (13). The paper also conducts sensitivity analyses over critical model parameters. We qualitatively treat data (or input) uncertainty with a focus on the emissions data provided by the EPA. Our concentration differs from other recent studies (14) by employing a more traditional mapping between air pollution external costs and the real economy, in our treatment of uncertainty, and in the intertemporal accounting comparisons.

Significance

In 1999, the National Research Council published a report calling for the integration of externality costs from air pollution into the national accounts. So far, this call for action has not materialized. This study provides updated estimates to these externality costs for the United States for the most recently available data, within the appropriate economic framework, and does so comprehensively through the use of multiple integrated assessment models and for several years. We show that damages in the agriculture sector are very high when compared to sectoral value added. This study provides a basis for further investigations on multiple fronts, such as a more detailed look at particular industries or on a smaller geographical scale.

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Data deposition: Data and code reported in this paper have been deposited at GitHub, https://github.com/ptschofen/PNAS_SectoralMortality.git.

See Commentary on page 19768.

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Results

National Trends in GED. Nationwide GED attributable to production within economic sectors has decreased by 22% from \$1,010 billion to \$790 billion (\$2018) from 2008 to 2014. These damages comprised 5.9% of GDP in 2008, 4.6% in 2011, and 4.2% in 2014. Hence, through 2014, the US economy continues on its path to become less pollution intensive.

Sectoral Trends in GED. Crucial for future pollution control efforts is the fact that nearly 75% of attributable GED occurs in just 4 sectors of the economy: agriculture, utilities, manufacturing, and transportation. Each of these 4 major contributors to GED exhibit falling damages over this time period. For utilities and manufacturing, the decline was most precipitous spanning the Great Recession. Utility sector GED fell by more than 50% over this 6 y time period (see *SI Appendix*, Table S5 for data on all sectors).

The decomposition of GED by emitted pollutant highlights the unique makeup of industrial sectors and how they contribute to air pollution externality costs, as well as the different trajectories of the sectors as the economy becomes less polluting. Agricultural GED is driven by ammonia and primary particulate matter damages, which are caused primarily by livestock emissions and fertilizer application (NH_3), and field burning, as well as combustion emissions from agricultural equipment and other crop-related activities (primary $PM_{2.5}$). Utility emissions and GED are dominated by sulfur dioxide (SO_2) from coal-fired power plants, but recent closures of coal plants and fuel-switching to natural gas (15)[†] have drastically reduced damages from that sector. Fig. 2 shows that the rate of reduction in utility GED is uniquely rapid. As such, as of 2014, agriculture generates the largest sectoral GED. In manufacturing, damages are distributed much more evenly across all precursor pollutants, given the variety of very different subsectors and industries. The biggest sources of both NO_x and primary $PM_{2.5}$ damages within the transportation sector are from trucks and diesel combustion in marine and rail transportation. Primary particulate matter in the "other" category in Fig. 2, consisting of the remaining 16 sectors of the economy, is the predominant contributor to GED, and a large portion of that occurs in the construction subsector.

Two changes in approach produce differences with respect to earlier work in this space (8, 9). The much higher damages in absolute terms for agriculture, utilities, and transportation in this analysis are due to a reworked mapping of area source damages to economic sectors and to model updates and refinements that have been made to the original Air Pollution Emission Experiments and Policy (APEEP) model as described in Clay et al. (11). Another prior study computes GED for energy production-related emissions (16). While the taxonomy of sectors is different for the studies, it is possible to compare electricity generation with our utility damages for both 2008 and 2011. We find that GED is similar for 2011 but observe a considerable difference for 2008, with our current estimate being nearly 60% larger.

Changes in Pollution Intensities. Pollution intensities, which we measure by comparing GED to VA, have declined across all major sectors in the economy. By indexing the GED/VA ratios we provide a sense of relative changes. Once again, the steep decline in pollution intensity for the utility sector stands out. Damages per unit VA fell by over 50%. Our estimates also highlight considerable reductions in this indicator in the transportation sector. GED/VA fell by almost 70% from 2008 to 2014. For manufacturing and agriculture, the ratio relative to 2008 has also declined but by less than 20%. For the rest of the economy, encapsulated in the "all others" category, the pollution intensity has decreased rapidly from 2008 to 2011 but then increased from 2011 to 2014.

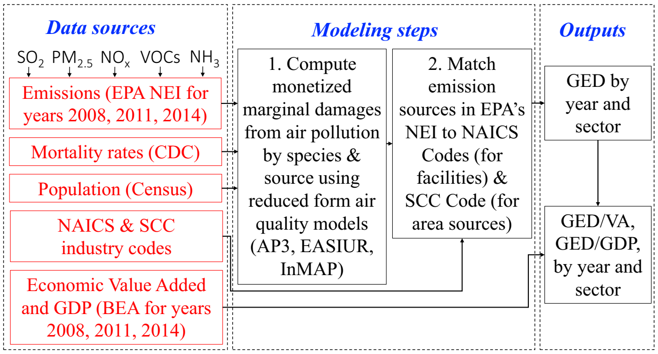

Fig. 1. Method chart for modeling framework.

GED Trends at Subsectoral Levels. Among the 47 subsectors for which we have tabulated GED, several stand out because they show either high GED or GED/VA ratios, and we highlight them in Fig. 3.

The largest changes in the time period observed took place for utilities, where a significant decrease in GED occurred despite essentially constant real VA. Farm damages have declined slightly while the subsector has expanded in real terms. Both truck transportation and water transportation damages have decreased, reducing the GED/VA ratio for both subsectors. Along with chemical products, petroleum products are the only subsector from manufacturing with GED higher than \$15 billion (\$2018), yet there exist other subsectors such as paper and metal products manufacturing that also elicit GED higher than \$5 billion. GED in petroleum products have stayed fairly constant, whereas real VA for this subsector appears to have changed in accord with the business cycle: contracting between 2008 and 2011 and then expanding slightly from 2011 to 2014.

Fig. 3 also provides insights on the subsectors' GED/VA ratios. Any subsector below the 45° line exhibits a GED/VA ratio less than unity. Similarly, those above the line have a ratio greater than unity. Subsectors are displayed if they showed either GED of \$30 billion or higher (the exception for this is "other services, except government," which includes emissions attributed to private households), a GED/VA ratio of 0.4 or higher, or both. Another important consideration is that most subsectors in the economy are below the 45° line since they produce greater VA than GED. Table 1 shows the industry groups with the highest GED/VA ratios in the North American Industry Classification System (NAICS). It further reinforces the considerable reduction in pollution damage intensity in the US economy from 2008 to 2014. In 2008, 4 industries produced GED in excess of reported VA. In 2014, there was just one. Digging more deeply into the environmental accounts yields insights into the significant variation in pollution intensity within sectors. The sectoral analysis revealed that the transportation sector GED was well below VA. Table 1, however, shows that water transport GED is nearly twice as large as VA in 2008. Similarly, the manufacturing sector VA far exceeds GED. However, both "nonmetallic minerals products" and "iron and steel mills" are still responsible for GED equivalent to more than 20% of their VA. Within the agricultural sector, crop production has become considerably cleaner over time, while just the opposite holds for livestock and animal production.

In summary, we find that the overall pollution intensity of the US economy fell from 2008 to 2014. GED is remarkably concentrated in just 4 sectors. Within these sectors, considerable heterogeneity across subsectors in GED and GED/VA ratios exist. While most subsectors and industries evince falling GED/VA ratios, some such as livestock production remain stubbornly high.

[†]S. Holland, E. Mansur, N. Muller, A. Yates, Decompositions and policy consequences of an extraordinary decline in air pollution from electricity generation. (NBER Working Paper 25339, National Bureau of Economic Research, Cambridge, MA, 2018).

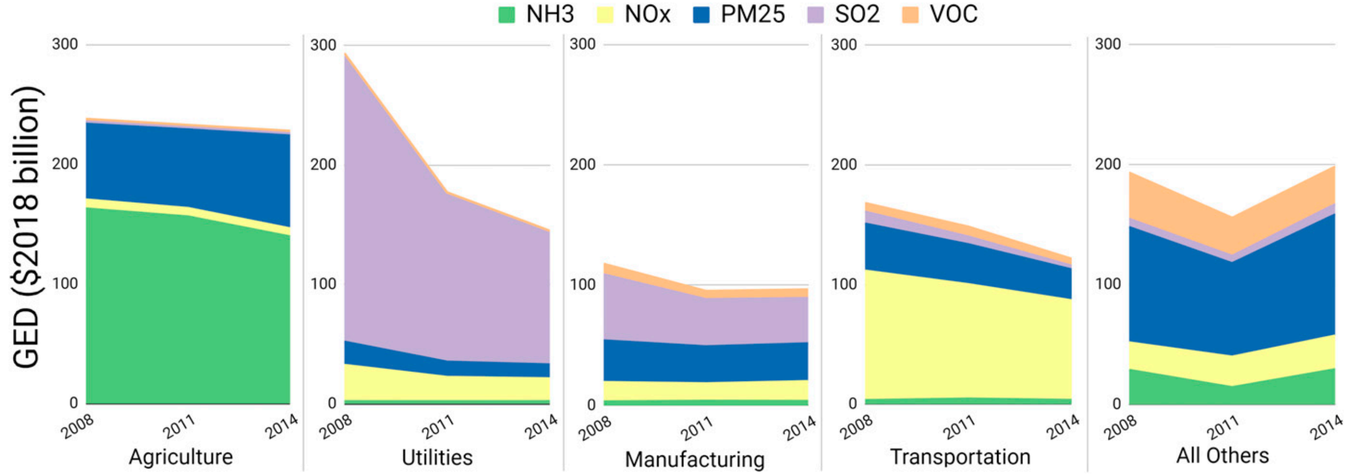

Fig. 2. GED (in $2018) attributable to economic sectors and their respective precursor pollutants (NH_3, NO_x, primary $PM_{2.5}$, SO_2, and VOCs). GED was calculated for the 3 most recent NEI years: 2008, 2011, and 2014.

Sensitivity and uncertainty analysis. Previous work with IAMs for fine particulate matter reports that marginal damages are most sensitive to the parameters chosen for the value of mortality risk (VMR; commonly referred to as the value of a statistical life (17, 18)) and the dose–response (DR) function for adult mortality selected from the epidemiological literature (19). As an alternative, we report here GED calculations for 2014 with the DR function provided by the most recent published estimate from the Harvard Six Cities cohort study (4). This is the most commonly used alternative DR function in the literature (20). For 2014, our estimates for economy-wide attributable GED more than double (an increase of 106%) from $790 billion to $1,600 billion in 2018 prices. *SI Appendix*, Table S6 contains various combinations of different DR functions and VMR for 2014.

Model Comparison. In addition to the sensitivity analysis focusing on the aforementioned parameters, we also explore model uncertainty. As alternatives to AP3, we use EASIUR and InMAP (12, 13). All 3 models differ significantly in the methods they employ to derive marginal damages from emissions of $PM_{2.5}$ and its precursors. Whereas AP3 uses source–receptor matrices that are derived from Gaussian dispersion modeling, EASIUR computes marginal damages based on regressions fit to output from Comprehensive Air Quality Model with Extensions (CAMx) (21), a computationally intense chemical transport model. InMAP, on the other hand, is essentially a temporally averaged chemical transport model with parameters derived from a more traditional chemical transport model, Weather Research Forecasting model coupled with Chemistry (WRF-Chem) (22).

For this comparison, we use the same model DR function and VMR across all 3 models. Since EASIUR and InMAP are calibrated to 2005, we adjusted the marginal damages for changes to population and mortality rates as suggested by the authors of each model, yet we multiply the marginal damages with the same emission inputs for the 3 NEI years. Aside from these caveats, the differences we report stem from the underlying air quality models themselves.

A recent review of these models (23) reports that the national emission-weighted averages of marginal damages computed with the 3 IAMs vary by less than 30%. Nonetheless, there do exist considerable regional differences for the precursor pollutants NO_x and sulfur dioxide (SO_2) (23). Table 2 reports damages and GED/VA ratios from the top 4 sectors across the 3 IAMs. In *SI Appendix*, we provide maps and further summary statistics on regional and emission-weighted differences of marginal damages across the 3 models.

The largest differences in GED/VA ratios manifest in sectors where NO_x and SO_2 are the predominant contributor to GED: transportation and utilities (Fig. 2). Both transportation and utility damages are highest in the AP3 model, at $120 and $150 billion, respectively. For the economy as a whole, damages computed with EASIUR and InMAP are ∼30 to 40% lower than in AP3.

The 3 IAMs differ in how dispersion and atmospheric chemistry are modeled. The spatial implications of these differences, both from individual sources and from particular sectors, is an important area for future research. We cannot resolve this source of the disparities in model predictions because the extent of published research on such model comparisons only encompasses marginal damages (5). Nonetheless, our work is illustrative in that it highlights the differences in GED estimates from the models, and we attempt to shed light on these divergences by providing maps to visualize regional differences in marginal damages estimated by each model in *SI Appendix*. In addition, our multimodel

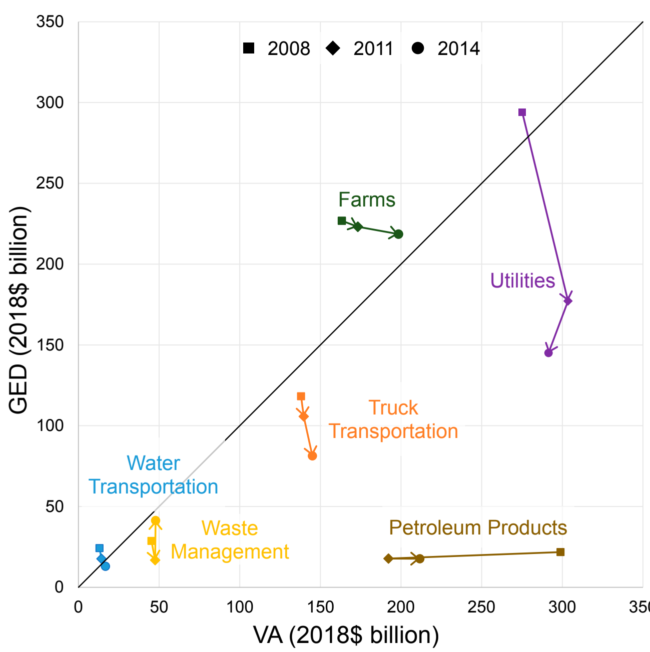

Fig. 3. GED versus VA for 2008, 2011, and 2014 for select subsectors in $2018 billion. The dividing line signifies a ratio of 1 between damages and VA.

Table 1. GED to VA ratios for 4-digit NAICS industries from 2008 to 2011 for the 10 highest-ranked industry groups

Industry group (2008)	GED/VA	Industry group (2011)	GED/VA	Industry group (2014)	GED/VA
Water transportation	1.9	Animal production and aquaculture	1.7	Animal production and aquaculture	2.0
Animal production and aquaculture	1.6	Water transportation	1.2	Waste management and remediation services	0.87
Electric power generation, transmission, and distribution	1.4	Crop production	1.1	Water transportation	0.78
Crop production	1.2	Electric power generation, transmission, and distribution	0.76	Crop production	0.72
Truck transportation	0.86	Truck transportation	0.76	Electric power generation, transmission, and distribution	0.63
Waste management and remediation services	0.63	Rail transportation	0.37	Truck transportation	0.56
Nonmetallic mineral products	0.35	Waste management and remediation services	0.35	Rail transportation	0.35
Rail transportation	0.32	Nonmetallic mineral products	0.29	Nonmetallic mineral products	0.28
Iron and steel mills and manufacturing from purchased steel	0.32	Iron and steel mills and manufacturing from purchased steel	0.28	Transit and ground passenger transportation	0.28
Transit and ground passenger transportation	0.27	Transportation structures and highways and streets	0.26	Iron and steel mills and manufacturing from purchased steel	0.23

Our taxonomy for the economic classification system of the BEA is sectors (2-digit NAICS) > subsectors (3-digit NAICS) > industry groups (4-digit NAICS) > industries (6-digit NAICS).

GED estimates suggest that future research should explore how these 3 IAMs differ in the way they deal with chemistry and transportation of pollutants with a particular focus on exposures and GED. We would like to stress that for the atmospheric science community to continue performing comparative modeling analysis and deepening the understanding of the different model results is of utmost importance for decision analysis in this space.

Data uncertainty. An additional form of uncertainty stems from the underlying data used in the IAMs. While there is uncertainty in the validity and accuracy on all types of data we use (for vital statistics such as population and mortality data and for emission data), we find that the biggest source of uncertainty among them stems from emissions produced by ground-level sources. Emissions from point sources that emit large quantities of pollutants are often regulated directly by EPA. As such, for sources such as large power plants, the pollution content of the flue gas is measured directly. Emissions from ground-level sources, on the other hand, are rarely measured, and many of EPA's estimates for them are derived from estimated activity levels and emission factors provided from the literature (24). Besides uncertainty associated with the level of emissions, EPA's classification system (source classification codes or SCCs) does not align with the NAICS system. This complicates attribution of emissions to the NAICS. The present analysis attributes emission sources only to industries with a clear mapping between SCCs and NAICS codes (accessible in *SI Appendix*). As such, many emissions (in addition to biogenic emissions) drop out of the accounting exercise. Future work will revisit both the SCC codes and how they can be mapped more precisely, as well as other methods to attribute the remaining emissions that do not clearly map to a sector [see GitHub, https://github.com/ptschofen/PNAS_SectoralMortality.git (10), for a table with our SCC to NAICS mapping].

Discussion

Many authors have previously argued for the extension of the national income and product accounts to include damages from environmental pollution (8, 25, 26). The present paper contributes to that literature by developing pollution damage estimates from the most recent available nationally comprehensive emissions data and by computing damages using 3 distinct IAMs. Presenting results across multiple models facilitates the development by the US Bureau of Economic Analysis of an official set of environmental accounts, and we provide an important step in that direction.

Importantly, this analysis relates GED to VA. This normalization recognizes that economic activity is productive. As such, meaningful comparisons of pollution damage either across different sectors in a given year or within sectors across years requires comparisons to productivity within the market boundary. If a sector (or the entire economy) generates the same VA in real terms over time, while reducing its GED, it is actually providing more net value to society. Conversely, if damages rise relative to market output, net value declines. Furthermore, GED larger than VA indicates that due to the effect of air pollution alone, there is a net loss to society from that sector or industry. This has clear implications for the appropriate measurement of growth.[‡]

Beyond our economy-wide damage estimates, we report GED by sector and, where possible, at the subsector level. This approach provides several clear benefits. While air pollution in the United States as a whole has been decreasing over the last decade, this is not a uniform process across the economy. Damages from electricity generators have decreased more rapidly than damages in the agriculture sector. This insight should provide some guidance for policymakers as to where to focus their resources as we strive to further reduce the adverse effects of air pollution. Also, our work beneath the sectoral level shows that there is considerable variability even within different sectors in how damage-intensive different activities are. This applies not just for sectors but also on a geographical scale. Sectors such as agriculture are not only diverse in their composition of industries but also in where their operations are located. This study's goal is to provide an overview at the national level. A next step analyzes damages at different spatial scales. While this paper focuses solely on local air pollutants, it bears mentioning that some sectors are also responsible for large quantities of carbon dioxide emissions which are also damaging to the economy (27).

We offer 3 concluding considerations. First, VA is not the only way to measure the contribution of economic activity to national

[‡]N. Z. Muller, *Long-Run Environmental Accounting in the U.S. Economy* (NBER Working Paper 25910, National Bureau of Economic Research, Cambridge, MA, 2019).

Table 2. GED and GED to VA ratios for 2014, expressed in 2018 prices for 3 different IAMs: AP3, EASIUR, and InMAP

Sector	GED AP3 ($ billion)	GED/VA	GED EASIUR ($ billion)	GED/VA	GED InMAP ($ billion)	GED/VA
Agriculture	230	0.98	180	0.77	160	0.70
Utilities	150	0.50	91	0.31	92	0.31
Manufacturing	96	0.04	54	0.02	44	0.02
Transportation	120	0.22	52	0.10	81	0.15
All others	200	0.01	120	0.01	170	0.01
No attribution	570	NA	420	NA	480	NA

output. Thus, if a sector contributes value to (nonair pollution) public goods that are outside the scope of VA, our GED/VA will overestimate the pollution intensity of that sector's output. In addition, we argue that the deduction of the GED from GDP is warranted because mortality risks in particular are an unpriced externality. Recent research tabulates considerable expenditures related to air pollution-induced morbidity (28). However, such expenditures are reflected in the national accounts (as are other costs of illness estimates), and so deduction would be conceptually inappropriate.

Second, we urge caution when interpreting GED/VA ratios larger than unity. We certainly do not advocate for closing industries in such cases. Rather, this is an indication, within the context of macroeconomic aggregate statistics, that damages are likely inefficiently high. In such cases, regulators should consider making sensible changes to emission controls at the margin.

Third, the evolution of the US economy toward a service-based economy could degrade our ability to precisely attribute damages to economic sectors. That is, as more economic activity (VA) takes place in sectors that produce ground-level emissions, relative to heavy manufacturing or fossil fuel-fired power plants, that cannot be reliably connected to specific NAICS codes, the fraction of measured GED relative to unattributable GED will fall. Similarly, many modern-day activities, such as personal transportation via ride hailing services or package deliveries in small vehicles, are less easy to track either in an economic sense or from the standpoint of emissions. In addition to the challenges that this evolution poses for traditional economic accounting, it necessitates further efforts by EPA to develop approaches to link ground-level emissions to NAICS sectors.

Materials and Methods

We calculate GED as the product of marginal damages times emissions by pollutant and source location for all emissions of ammonia (NH_3), nitrogen oxides (NO_x), primary fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), and volatile organic compounds (VOCs) as they contribute to the formation of atmospheric $PM_{2.5}$ in the contiguous United States. We adopt this computational framework based on guidance from the environmental accounting literature (29).

In mathematical terms,

$$GED_l = \sum_{i,j,k} \left(MD_{i,j,k} {}^* E_{i,j,k,l} \right)_{\forall i,j,k,l},$$

where *GED* is GED in economic unit *l* (sectors, subsectors, or more detailed), *MD* is marginal damage in county *i* for pollutant *j* at effective height *k*, and *E* is emission in county *i* for pollutant *j* at effective height *k* in economic unit *l*.

Computing Marginal Damages with IAMs. The IAMs used in this study are AP3, EASIUR, and InMAP (11–13, 30). These models need several data inputs: emissions by county and stack height, and vital statistics such as mortality rates and population by county and age group. The models use the spatially resolved emissions data and employ a simplified air quality model (reduced complexity model [RCM]) to compute baseline concentrations of particulate matter for each location *i*. Following the baseline run, the model is run again but with a perturbation in emissions for a given source to compute the difference in concentrations of $PM_{2.5}$ across the country. Population data are used to assess the exposure of vulnerable people to the pollutants. DR functions coupled with mortality rate data are used to estimate the number of premature mortality cases caused by the perturbation in emissions. Our default DR function is from the American Cancer Society cohort study (3).

Monetary damage is then calculated by multiplying the estimate for premature mortality due to the emission perturbation with the VMR (17). We use the value suggested by the EPA for this valuation and adjust it to account for changes to per capita incomes as recommended by EPA (20, 31).

Emissions (*E*) Data by County, Source, and Effective Height. Emissions data are obtained from EPA's NEI for 2008, 2011, and 2014. The 2014 NEI data that were used are from the 2014v2 revision (10, 24). We assigned emissions by county for all ground-level sources and according to the effective height of release for facilities, which we calculated based on EPA data of stack parameters where available (see *SI Appendix* for more detailed explanation). All 3 IAMs separately model emissions according to whether discharges are made at ground level or are elevated.

Economic Data and Inflating to Current Prices. The economic data were obtained from the Bureau of Economic Analysis (BEA). Tables for VA for all economic units and for 2008, 2011, and 2014 were downloaded from the BEA

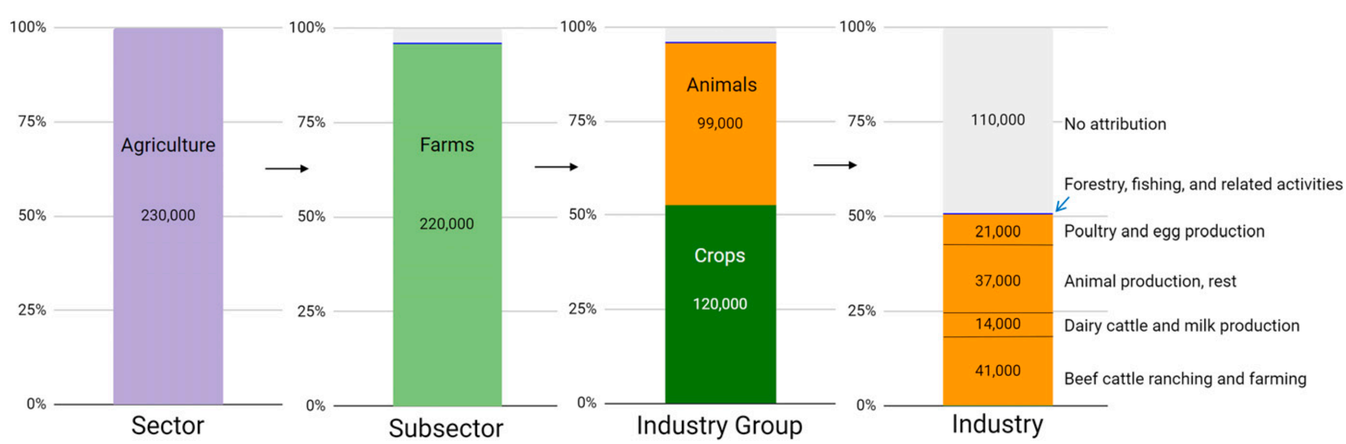

Fig. 4. Attribution of agricultural GED to economic units. At the industry level, attribution to individual crops is impossible with EPA data alone, so most damages from the crops industry group drop out.

website. The values were taken from the spreadsheet expressed in chained 2012 dollars and then inflated with the Bureau of Labor Statistics' consumer price index calculator to convert to 2018 dollars.

Additional Details on the IAMs. The AP3 model uses population and mortality data corresponding to each year of analysis. The data are from postcensal and intercensal estimates for population data and from the CDC's Wide-Ranging Online Data for Epidemiologic Research database (32) for mortality rates. For age groups in counties where the total number of deaths falls below the reporting thresholds of the CDC, we imputed rates based on state, regional, or national averages.

For the EASIUR model, we used marginal damages from the model's website and adjusted them for changes to population and mortality rates, as suggested in the SI of ref. 12. These adjustments are derived from projections for these 2 parameters from the EPA's Environmental Benefits Mapping and Analysis Program user guide. EASIUR marginal damages are reported for ground-level emissions, at 150 m elevation, and at 300 m elevation.

We obtained the InMAP marginal damages via download from the Center for Air, Climate, and Energy Solutions (CACES) website (www.caces.us) and inflated them to current prices but did not make any adjustments for population or mortality changes. The data downloaded from the CACES center also only come in 2 source types: ground level or elevated. We assigned each facility in the dataset to the "elevated" marginal damage for its respective county.

Both EASIUR and InMAP damages are computed based on emissions data from 2005. Since both of these models use more complicated chemical transport models to compute $PM_{2.5}$ concentrations, it is much more difficult to update them with current emissions data (*SI Appendix*, Table S4 is comparing estimated air pollution deaths from all 3 models).

Details on Attribution of GED. After running the IAMs to compute marginal damages ($/ton), we matched emissions with the corresponding marginal damage based on pollutant, location, and release height to compute GED. We then assigned GED to economic sectors, subsectors, industry groups, and industries. A sizable portion of GED in all 3 IAMs could not be attributed to any economic unit either because they could not be clearly mapped to a specific sector or because they were biogenic or caused by wildlife and therefore not associated with any kind of economic activity. Overall, we were able to attribute around 60% of total GED to industrial sectors for the years 2008, 2011, and 2014.

Linking damages to the economic accounts at subsectoral levels. We analyze damages not just at the sectoral level but also in more detail at the subsector and industry group and partially at the industry level for select sectors. The sparsity of information contained in the EPA's reporting of area source emissions means that more and more emissions drop out (i.e., cannot be attributed to an economic unit) the deeper the detail level of the economic accounts. Fig. 4 illustrates this with the agriculture sector.

Nearly all GED that we attributed at the sector level (2-digit NAICS) could also be mapped to the subsector (3-digit) and industry group (4-digit) level. Going one level deeper, though, comes at a cost of not being able to attribute most of the emissions to industries relating to the production of crops based on EPA information alone. Nevertheless, accepting this tradeoff still often reveals the heterogeneity of damage intensities within a sector. Comparing GED to VA, an indicator of an economic unit's contribution to the GDP, the agriculture sector (as a whole in 2014) GED/VA ratio was 0.98, suggesting that the damages from air pollution in the sector are on par with the value the sector generates to the economy. Looking at the subsectors instead reveals that these damages occur predominantly in the farms subsector, yet even within farms the GED/VA ratios vary considerably. Whereas the GED/VA ratio was 0.72 for the group of crop-producing industries in 2014, it was 2.0 for animal production in that year. Analyzing particular industries within that sector is difficult due to the fact that BEA only publishes data at that granularity every 5 y, and these benchmark years do not line up with EPA's releases of the emission inventories. However, preliminary calculations indicate that the GED/VA ratio within this group is highest for the poultry industry with an estimated range of 3 to 7.

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