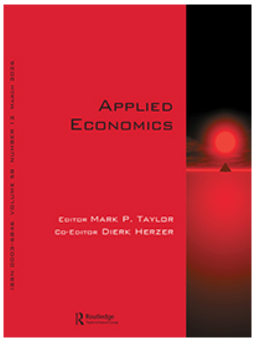

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The marginal cost of carbon emissions abatement across sectors

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ABSTRACT
The marginal cost of carbon emission reduction is a crucial metric for assessing the economic and environmental implications of climate change mitigation policies. This study provides a comprehensive analysis of the marginal cost of carbon emissions reductions across 546 sectors of the U.S. economy, employing a structural decomposition analysis and a partial hypothetical extraction method. The results reveal substantial heterogeneity in the marginal abatement costs across sectors, with estimates ranging from \$27.52 to \$16,899 per ton of CO_2 emission averted. The distribution of marginal abatement costs is found to be right-skewed, with many sectors exhibiting costs below \$500 per ton, while a few sectors exceed \$5,000 per ton. This finding suggests that a carbon price between \$50 and \$500 per ton could lead to significant abatement across a wide range of sectors, covering approximately 52% of total emissions. However, the presence of a long tail of high-cost sectors highlights the challenges and potential economic disruptions associated with a uniform carbon pricing approach. Our analysis highlights the importance of designing climate policies that consider the unique characteristics and abatement opportunities of each sector.

KEYWORDS
Carbon price; input-output model; partial hypothetical extraction; carbon intensity

JEL CLASSIFICATION
Q54; D57; Q58; C67

I. Introduction

Climate change poses an increasing threat to the global economy, human health, and the environment. The urgent need to reduce greenhouse gas emissions and limit warming to below 2°C above pre-industrial levels is widely recognized (IPCC 2018). Carbon pricing, which puts a price on emissions, is regarded as one of the efficient and cost-effective tools for driving decarbonization (Stiglitz et al. 2017). However, designing optimal carbon pricing policies involves complex economic, social, and political considerations.

A central debate is whether to adopt a uniform carbon price across all sectors or differentiate carbon prices based on sector-specific characteristics. Advocates of a uniform price argue it is economically efficient, equalizing marginal abatement costs (MAC) to ensure least-cost emissions reductions (Hoel 1996; Tirole 2012). Others argue that due to cross-industry variation in MAC (e.g. Gamtessa and Çule 2023), a uniform price would be economically disruptive, disproportionately burden emissions-intensive industries and risk carbon leakage through trade, and therefore requires sector-specific approaches (Böhringer and Rutherford 2002; Markusen, Morey, and Olewiler 1993). Sector-specific carbon pricing aims to address these efficiency and competitiveness concerns, tailoring prices to each industry's abatement potential and technological readiness. By setting differentiated tax rates or caps, policymakers can potentially achieve similar environmental benefits with lower economic disruption compared to a one-size-fits-all approach (Abrell, Rausch, and Schwarz 2018; Böhringer, Rosendahl, and Storrøsten 2017). However, differential tax rate-setting requires accurate assessment of heterogeneous abatement costs across all sectors, which is a significant empirical challenge.

Existing research shows that estimates of sector-level abatement costs vary widely, partly due to differences in methodologies, assumptions, and data sources (Huang, Corbett, and Jin 2015; Kesicki and Ekins 2012). Among the approaches, distance function (DF) models have emerged as an especially prominent tool for estimating MAC because they rely on historical production data to

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construct efficiency frontiers, measuring how far an industry's current combination of inputs and outputs lies from the theoretical best-practice frontier. DF approaches typically posit trade-offs between desirable outputs (e.g. economic goods) and undesirable outputs (e.g. greenhouse gases), but can diverge substantially in their theoretical and empirical specifications. Some research focuses on input distance functions (IDF), in which the maximum proportional reduction in emissions is measured under fixed output (Tang et al. 2016). Others adopt directional distance functions (DDF) that allow simultaneous adjustments to inputs, outputs, and emissions according to a chosen vector (Tang, Wang, and Zhou 2021; Wu, Ma, and Tang 2019), though the results are often highly sensitive to that vector's specification (Kuosmanen and Zhou 2022). Still another variant is the non-radial distance function (NRDF), which relaxes assumptions of proportional scaling in emissions abatement and thereby permits asymmetric adjustments to individual pollutants (L. Yang et al. 2017; Zhang et al. 2022). These DF-based methods can provide rich insights into the marginal abatement opportunities in agriculture, manufacturing industries, or energy production; however, their estimates depend critically on assumptions such as parametric versus nonparametric specification, joint production of multiple greenhouse gases, and whether abatement is conditional or unconditional on production (Ma, Hailu, and You 2019). Even within DDF approaches, for instance, the conventional specification may inflate MAC estimates by an order of magnitude when compared to nonparametric alternatives (Kuosmanen and Zhou 2022), thereby complicating efforts to translate such findings directly into policy targets.

Other modelling frameworks also address sector-level abatement costs. CGE models capture trade-induced emissions leakage and cross-industry spillovers but can lack the technological detail needed for sector-specific policies (Antimiani et al. 2016; Böhringer, Carbone, and Rutherford 2018). Partial equilibrium models offer richer sector-level detail yet often miss economy-wide linkages (Hirst and Keep 2018; Rootzén and Johnsson 2013). Input – output methods reveal interdependencies but rely on fixed-coefficient assumptions and null-jointness of desirable and undesirable outputs (Kay and Jolley 2023; Z. Yang et al. 2015). IAMs project long-run trajectories and capture climate – system interactions but are highly aggregated (Nordhaus 2017; Rogelj et al. 2018). Further complications include dynamic, path-dependent abatement investments (Vogt-Schilb, Meunier, and Hallegatte 2018), region-specific constraints (Böhringer, Rosendahl, and Storrøsten 2017; Duan et al. 2019), and non-CO_2 mitigation challenges (Harmsen et al. 2019, 2023). Beyond these core methodologies, the Slacks-Based Measure (SBM) approaches (Wu, Ma, and Tang 2019) have assessed static and dynamic heterogeneity in abatement costs, and bioeconomic modelling has addressed agriculture and related sectors. Tang (2024) examined adaptation in North Xinjiang, Tang et al. (2019) evaluated carbon farming's cost-effectiveness, and Tang and Hailu (2020) explored smallholder farms' adaptation in the Loess Plateau. However, these methods also face data-intensity issues, may struggle with dynamic feedbacks, and can be difficult to generalize beyond specific regions or production systems.

In an effort to alleviate some noted weaknesses of other methods of abatement cost estimation, we propose a novel method that combines structural decomposition analysis (SDA) and partial extraction techniques. Building on input-output foundations (Dietzenbacher and Los 1998), we attribute economy-wide emissions changes to sectoral drivers, isolating the roles of carbon intensity, production structure, and final demand. Extending hypothetical extraction logic (Dietzenbacher and Lahr 2013; Duarte, Mainar-Causapé, and Sanchez Choliz 2017), we estimate potential emissions reductions and economic costs of sector-specific abatement action. Applying this SDA-extraction framework, we generate transparent, consistent MAC estimates for carbon across each of 546 disaggregated sectors in the United States. Key findings reveal striking variability in MAC across sectors, ranging from $27.52/ton in utilities to nearly $16,899/ton (in 2022 U.S. dollars)[1] for the Greeting Card Publishing industry. While some primary/manufacturing industries show MAC

[1]All currency values in this article are in constant 2022 U.S. dollars, and a ton refers to a metric ton (1,000 kg).

under \$500/ton, many service sectors exceed \$2,000/ton.

This paper makes several key contributions to the marginal abatement cost and carbon pricing literature. First, our novel application of SDA-extraction methods generates uniquely detailed and consistent estimates of sector-specific MAC's that account for cross-industry spillovers, providing a transparent basis for tailoring carbon tax levels. Second, we identify sectors with the greatest potential for cost-effective emissions reductions, such as renewable electricity generation, manufacturing, and mining. Third, we apply machine learning tools to identify how industry output, carbon intensity, and carbon emission factors can predict the MAC of an industry, offering potentially valuable information for policy makers on how to most efficiently achieve carbon emissions reduction targets. The rest of the paper is structured as follows. Section II presents our analytic framework, detailing the integration of SDA and hypothetical extraction techniques, followed by data sources. Section III presents the main results. Section IV discusses the implications of our findings, limitations, and Section V concludes with a summary of our key findings and their potential implications for carbon pricing and climate policy.

II. Model

Our methodology combines structural decomposition analysis (SDA) with partial extraction methods to estimate sector-specific marginal abatement costs. Following Miller and Blair (2022), Let **L** be a nxn Leontief Inverse Matrix, **f** a n×1vector of final demands, **x** an n×1vector of output, and 0 and 1 representing starting and ending time periods. Additive structural decomposition can be defined as:

$$\Delta x = \left(\tfrac{1}{2}\right)(\Delta L)\left(f^0 + f^1\right) + \left(\tfrac{1}{2}\right)\left(L^0 + L^1\right)(\Delta f) \quad (1)$$

In Equation 1, the first term on the right-hand side refers to the technology change contribution to output change and the second term output change due to the final demand change. We extend the additive concept of structural decomposition to a third variable, carbon emissions, using the approach highlighted by Miller and Blair (2022) for constructing additive decompositions of three or more terms. We decompose a change in carbon emissions by extending Equation 1. Let **e** be a n×1vector of carbon emissions (CO_2) per dollar of output for n sectors. By following Miller and Blair (2022), we obtain the following:

$$\begin{aligned}\Delta E = & \left[\frac{1}{2}\Delta e\left(L^0 f^0 + L^1 f^1\right)\right] \\ & + \frac{1}{2}\left[e^0(\Delta L)f^1 + e^1(\Delta L)f^0\right] \\ & + \left[\frac{1}{2}\left(e^0 L^0 + e^1 L^1\right)\Delta f\right]\end{aligned} \quad (2)$$

In this three-variable decomposition, the first term on the right-hand side of the equation represents the change in total emissions (***E***) due to the change in carbon emission intensity between time periods zero and one. The second term is the change in total emissions due to the change in technology, and the last term shows changes in emissions due to changes in final demand.

In partial extraction analysis, we follow Dietzenbacher and Lahr (2013) and their collection of efforts for expanding hypothetical extraction techniques. They developed a partial extraction technique based on Henderson and Searle (1981) that can be applied to the Leontief Inverse matrix in Equation 3:

$$\bar{L} = L - \frac{\alpha L e_k b_k^{'} L}{1 + \alpha b_k^{'} L e_k} \quad (3)$$

In Equation 3, $\bar{\boldsymbol{L}}$ represents the constrained Leontief Inverse function, α represents a constraint parameter (0 = full extraction, 1 = no extraction), and e_k is a unit vector of the constrained sector k which has zeros along the n×1vector except for the value of one on the kth row of that vector. The row vector, $b_k^{'}$, is the kth row vector of the direct requirements matrix (A) corresponding to **L** that includes all coefficients of the direct requirements matrix in the kth row except for being replaced by a zero in the kth column of the kth row. Dietzenbacher and Lahr (2013) also show that the n×1vector of final demands, $\boldsymbol{f}$ can similarly be constrained in Equation 4.

$$\bar{f} = (1 - \alpha) f_k \quad (4)$$

Here, $\bar{f}$ represents the constrained final demand vector and f_k is the final demand of the kth sector that is being constrained.

The constrained form of the Leontief Inverse matrix ($\bar{L}$) and final demand ($\bar{f}$) represent a generalization of the complete hypothetical backward extraction described by Dietzenbacher and Lahr (2013) as partial extraction. In complete hypothetical extraction, a sector is removed from the economy by zeroing out its row and column. Partial extraction constrains the output produced from a sector by α to meet intermediate and final demand. We rearrange Equations 3 and 4 to get:

$$\Delta L = L^0 - \bar{L} \tag{5}$$

$$\Delta f = f^0 - \bar{f} \tag{6}$$

In Equations 5 and 6 we reinterpret **L** as L^0 and f as f^0. Now, we incorporate our partial extraction analysis into our structural decomposition formula such that Equation 2 now transforms into an equation not decomposing the total emissions change between two points in time but becomes a projection equation that can be used to identify the constraining level α of a given sector necessary to reduce total emissions, E, by a given amount.

We identify the abatement, cost to the economy of reducing E by a given amount by converting Equation 2 into the following equation.

$$\begin{aligned}\Delta V = &\left[\frac{1}{2}\Delta v\left(L^0 f^0 + L^1 f^1\right)\right] \\ &+ \frac{1}{2}\left[v^0(\Delta L) f^1 + v^1(\Delta L) f^0\right] \\ &+ \left[\frac{1}{2}\left(v^0 L^0 + v^1 L^1\right)\Delta f\right]\end{aligned} \tag{7}$$

In Equation 7, **v** refers a vector of value-added coefficients (value-added per dollar of output) and ΔV refers to the total change in value added for the entire regional economy. To integrate Structural Decomposition Analysis (SDA) and Extraction, we first substitute Equations 5 and 6 into Equation 2 to compute the emissions reduction, $\Delta E_k(\alpha)$. We then solve for the value of αthat achieves a certain reduction in emissions. Substituting this αinto the value-added equation allows us to compute $\Delta V_k(\alpha)$. By calibrating the extraction proportion to achieve a one-unit reduction in total CO_2 ($\Delta E = 1$), our model yields the ratio of lost value added to abated CO_2. This ratio is interpreted as the marginal abatement cost:

$$MAC_k = \frac{\Delta V_k(\alpha)}{\Delta E_k(\alpha)} \tag{8}$$

For industry-level analysis, we then aggregate these sector-specific MACs into weighted averages that reflect the relative importance of different sectors within each industry group. This weighting is necessary because sectors within the same industry can vary substantially in their emissions levels and economic characteristics. For any sector $k$within a given industry group G, its weight w_k is defined as the ratio of its CO_2 emissions to the total emissions from all sectors in that group. Mathematically, this is expressed as:

$$w_k = \frac{CO_2 Emissions_k}{\sum_{j\in G} CO_2 Emissions_j} \tag{9}$$

$CO_2\text{Emissions}_k$ is the total CO_2 emissions (measured in million metric tons, for example) from sector k.

$\sum_{j\in G} CO_2\text{Emissions}_j$ represents the sum of CO_2 emissions from all sectors $j$within the group G.[2] Once each sector's weight is determined, the next step is to compute the weighted average MAC for the industry group. This is done by taking each sector's MAC (the cost associated with reducing one ton of CO_2) and multiplying it by its corresponding weight. The results are then summed over all sectors in the group. The formula is:

$$\text{MAC}_G = \sum_{k\in G}\left(w_k \times \text{MAC}_k\right) \tag{10}$$

MAC_k is the marginal abatement cost for sector k; MAC_G is the weighted average MAC for the entire industry group G. This procedure determines how much value added is lost across the economy when constraining economic activity to reduce emissions at both sector and industry levels. In essence, the SDA approach decomposes emissions changes into distinct channels (technology, structure, final demand), while partial extraction provides the mechanism for selectively constraining individual

[2]The 546 sectors in the IMPLAN database were aggregated into 11 industry groups, G: https://support.implan.com/hc/en-us/articles/115009674428-IMPLAN-Industry-Schemes.

sectors. This integration enables us to compute sector-specific MAC that capture both direct effects and indirect impacts through input-output linkages. To enhance the replicability of our study, we have updated the original GAMS code (version 42.4.0) and made it available on GitHub.[3] This repository will be made publicly accessible upon publication. Please note that, due to the proprietary nature of the IMPLAN dataset, the original data cannot be shared.

The primary data source used in this research is the IMPLAN (Impact Analysis for Planning) database (IMPLAN (2022)), which provides a detailed representation of the U.S. economy. We extract the IxI Social Accounting Matrix, final demand, and value-added data from the IMPLAN online portal for 2022. The 546-aggregation scheme is used in IMPLAN to capture the sectoral detail.

III. Results

Our analysis of the marginal abatement costs across 546 sectors of the U.S. economy reveals striking heterogeneity in MAC and carbon emissions abatement opportunities. Figure 1 illustrates the right-skewed distribution of sectors at different MAC levels, with a high concentration of sectors below \$500 per ton of CO_2. About 52% of total emissions are covered by sectors with estimated MAC between \$50 and \$500 per ton, suggesting substantial cost-effective abatement potential within this price range. However, the frequency of sectors declines rapidly beyond \$500/ton, indicating increasing MAC. The long tail extending past \$3,000/ton, with some sectors exceeding \$5,000/ton, represents the most challenging and expensive cases for emissions reductions.

Figure 2 shows the MAC at the sector level. The 'Utilities' sector has the lowest weighted MAC at approximately \$266/ton, followed by the 'Manufacturing' sector at around \$500/ton. In utilities, many emission sources are relatively centralized – such as coal- or gas-fired power plants – and there exist well-established, cost-competitive options for switching to lower-carbon technologies. For instance, efficiency upgrades, fuel switching (e.g. coal to natural gas), and substitution of renewable energy sources (e.g. wind or solar) can yield comparatively large and low-cost emissions reductions. Consequently, the potential for energy efficiency improvements and economies of scale helps keep MAC in this sector lower than in others. By contrast, the 'Government Enterprises' and 'Services' sectors have the highest MAC, at roughly \$3,000/ton and \$2,000/ton, respectively. For these sectors, which have limited flexibility in adjusting operations and likely only uneconomical options for investments in low-carbon infrastructure and technologies, a carbon tax would be less effective, operating only through price increases and output reductions. The sectors with the highest MAC share common characteristics: very low carbon

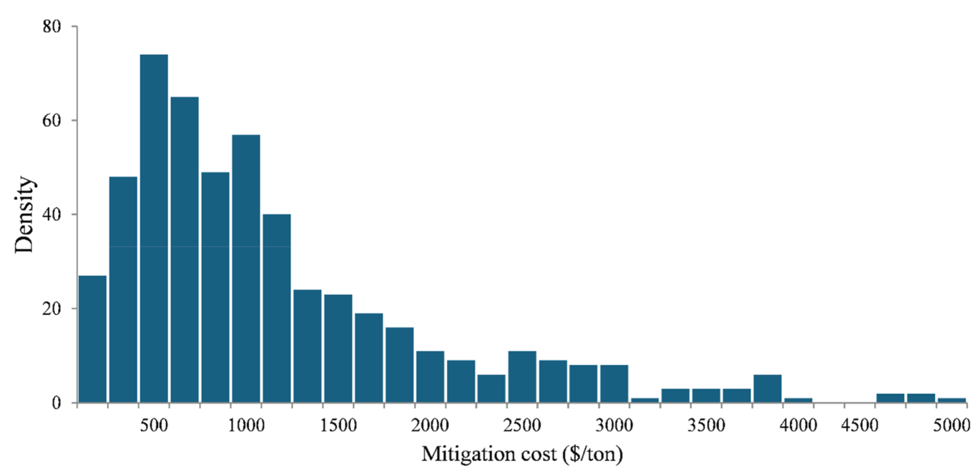

Figure 1. Distribution of U.S. economic sectors by marginal abatement cost for CO_2 emissions mitigation.

[3]The code is archived in a GitHub repository: https://github.com/jinggangguo/MACs.

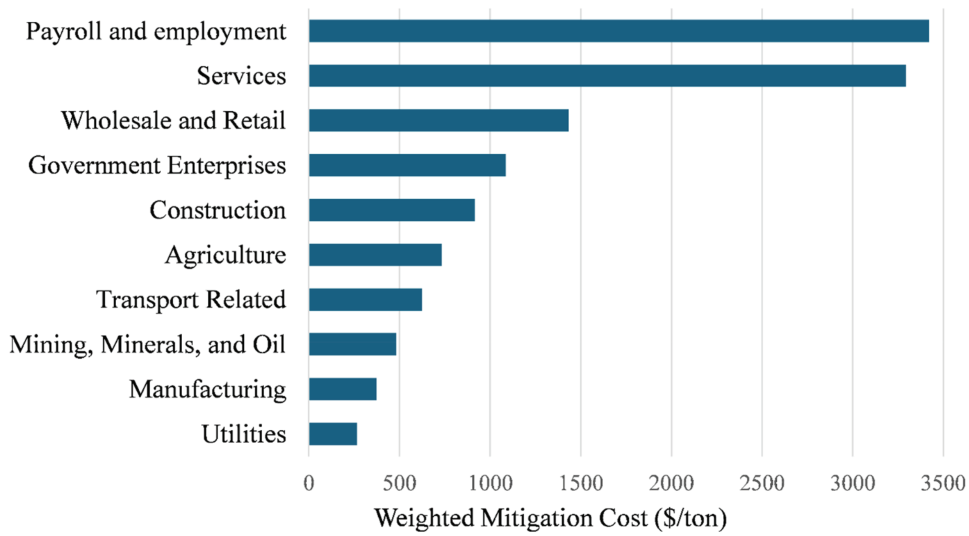

Figure 2. Sector-level weighted average marginal mitigation abatement costs for CO_2 emissions in the U.S. economy.

intensities (0.001–0.038 kg/$) but significant indirect emissions through complex supply chains, making immediate emission reductions particularly costly. For example, greeting card publishing (NAICS 511,191) has a carbon intensity of just 0.02 kg/$, but depends extensively on carbon-heavy inputs such as chemicals and transportation. Our analysis indicates that fully eliminating these indirect emissions could cost as much as $16,899 per ton of CO_2. Eliminating these indirect emissions would entail a thorough restructuring of supply chains, resulting in high economic disruption per ton abated. Given these constraints, relying on carbon pricing alone would likely present steep challenges for sectors whose MAC exceed $1,000 per ton. Alternative policies for these high-cost sectors might merit deeper exploration, including innovation incentives, such as R&D tax credits for low-carbon alternatives in paper-based publishing or chemicals, and demand-side measures, including those facilitating increased rates of recycling or use of higher shares of renewable materials in production.

Table 1 shows the 30 sectors with the lowest MAC. We can find the dominance of the utilities sector among the lowest-cost sectors, with eight industries related to electric power generation having MAC ranging from $27.5/ton to $34.9/ton. Despite its relatively low MAC, this sector is the one of the largest contributors to carbon emissions, emitting 895 million tons of carbon. Several Manufacturing sub-sectors, such as Glass Product Manufacturing made of purchased glass ($33/ton) and Other Concrete Product manufacturing ($70.7/ton), also demonstrate low marginal abatement costs, indicating the potential for cost-effective emissions abatement in certain manufacturing processes and materials. The Mining, Minerals, and Oil sector, represented by Other Nonmetallic Minerals Services ($34.8/ton), and the Government Enterprises sector, with sub-sectors such as Other State Government Enterprises ($42.6/ton) and Postal Service ($67.4/ton), also present opportunities for cost-effective emissions reductions. It is important to note that while these 30 sectors collectively account for only 1.86% of the total economic output, they contribute a disproportionately high 23.84% of the total carbon emissions. The results indicate there is a potential to achieve substantial emissions reductions without placing a heavy burden on the overall economy.

Table 1 also reveals complex relationships between marginal abatement costs, carbon intensity, carbon emissions, and economic output, motivating more in-depth exploration. To investigate these relationships more rigorously, we apply two machine learning techniques – Gradient Boosting (GB) and Random Forest (RF) – to determine the relative importance of three variables (total output, carbon intensity, and carbon emissions) in predicting MAC across different sectors of the economy.

Table 1. The sectors in the United States with the lowest marginal abatement cost for CO_2 emissions (2022 U.S. dollars).

Industry name	Sector	Output (M $)	Marginal abatement cost ($/ton)	Carbon intensity (kg/$)	Carbon emission (M ton)
Electric Power Generation- All Other	U	684.9	27.5	6.19	4.23
Electric Power Generation - Biomass	U	3114.7	30.2	6.19	20.47
Electric Power Generation - Geothermal	U	916.1	31.3	6.19	6.51
Glass Product Manufacturing	M	13752.3	33.0	0.33	5.42
Electric Power Generation - Fossil Fuel	U	130000.0	33.6	6.19	895.00
Electric Power Generation - Solar	U	6464.5	33.9	6.19	55.70
Electric Power Generation - Hydroelectric	U	6564.2	34.0	6.19	46.45
Electric Power Generation - Nuclear	U	41567.5	34.5	6.19	280.00
Other Nonmetallic Minerals Services	M	34486.7	34.8	0.12	6.18
Electric Power Generation - Wind	U	21356.6	34.9	6.19	166.00
Other State Government Enterprises	G	18385.1	42.6	0.01	0.20
Private Households	S	24158.4	52.5	0.00	0.00
Postal Service	G	66141.7	67.4	0.04	2.25
Other Concrete Product Manufacturing	M	15526.8	70.7	0.05	0.86
Lime Manufacturing	M	2480.6	72.3	3.16	8.90
Other Federal Government Enterprises	G	16752.8	82.0	0.04	0.61
Steel Wire Drawing	M	5022.7	92.4	0.06	0.40
Petrochemical Manufacturing	M	101000.0	112.2	0.23	48.38
Local Government Passenger Transit	G	15485.7	129.4	0.13	1.15
Malt Manufacturing	M	1428.7	137.3	0.09	0.13
Artificial and Synthetic Fibers and Filaments Manufacturing	M	17167.1	154.1	0.29	6.23
Nitrogenous Fertilizer Manufacturing	M	12677.9	164.6	1.01	22.10
Phosphatic Fertilizer Manufacturing	M	5235.7	167.0	1.01	8.22
State Government Passenger Transit	G	1896.1	172.5	0.13	0.15
Miscellaneous Nonmetallic Mineral Products Manufacturing	M	5265.9	172.7	0.14	0.78
Water Transportation	T	46892.0	182.3	0.43	26.57
Synthetic Dye and Pigment Manufacturing	M	7539.8	183.9	0.83	6.97
Cement Manufacturing	M	9758.4	185.1	7.24	74.70
Industrial Gas Manufacturing	M	20649.0	186.7	0.63	16.87
Iron and Steel Mills and Ferroalloy Manufacturing	M	92541.8	187.9	0.71	122.00
Share of the Total Economy		1.86%			23.84%

Sector U represents Utilities, M represents Mining, Minerals, and Oil, T represents Transport Related, G represents Government Enterprises, S represents Services.

Figure 3 shows that the importance scores for these variables vary significantly by sector. In particular, the Random Forest model identifies carbon intensity as the most important predictor for several industries, most notably Manufacturing (0.67) and Agriculture (0.26). Meanwhile, total output dominates Mining, Minerals, and Oil (0.42), although carbon emissions also play a noteworthy role (0.24). The Utilities sector stands out for its emphasis on carbon emissions (0.45) over carbon intensity (0.33), reflecting a tendency for large-scale emission sources in that sector to drive overall abatement costs. The Gradient Boosting results generally align with these findings, while uncovering some distinct sectoral variations. In Manufacturing, carbon intensity remains a dominant predictor (0.69), and Mining, Minerals, and Oil again shows a strong weighting

	RF: Total output	RF: Carbon intensity	RF: Carbon emission	GB: Total output	GB: Carbon intensity	GB: Carbon emission
Agriculture	0.44	0.26	0.30	0.17	0.11	0.72
Construction	0.33	0.40	0.27	0.31	0.46	0.23
Government Enterprises	0.31	0.31	0.39	0.31	0.34	0.35
Manufacturing	0.15	0.67	0.18	0.13	0.69	0.18
Mining Minerals and Oil	0.42	0.35	0.24	0.65	0.30	0.05
Payroll and employment	0.49	0.07	0.44	0.54	0.00	0.46
Services	0.42	0.35	0.22	0.47	0.39	0.14
Transport Related	0.34	0.35	0.31	0.25	0.42	0.33
Utilities	0.22	0.33	0.45	0.07	0.49	0.44
Wholesale and Retail	0.39	0.13	0.48	0.36	0.14	0.50

Figure 3. Relative importance in predicting sector-level marginal abatement costs. Note: RF represents the random forest method; GB represents the gradient boosting method.

on total output (0.65). However, under Gradient Boosting, Agriculture places a notably high importance on carbon emissions (0.72), contrasting with the more balanced pattern observed in Random Forest. Government Enterprises exhibits a relatively uniform weighting across all three features (RF: 0.31, 0.31, 0.39; GB: 0.31, 0.34, 0.35), indicating that multiple factors contribute comparably to its MAC levels. Despite such differences in specific importance values, both models consistently emphasize that high-intensity sectors often see disproportionate gains from reducing their carbon intensity, whereas industries with large total emissions or extensive indirect emissions may require broader efforts to achieve reductions – ranging from operational optimizations to supply-chain transformations. While it is premature to draw any conclusions about optimal economic policy, our research shows how a broader assessment of alternative abatement strategies could entail varying weights on strategies designed to achieve each of output, intensity, and emissions objectives and evaluating the resulting outcomes with respect to desired policy goals.

IV. Discussion

This study presents a comprehensive analysis of the social costs of carbon across 546 sectors of the U.S. economy, using a novel approach that combines structural decomposition analysis with partial extraction techniques. Our results reveal significant heterogeneity in the distribution of abatement costs, with estimates ranging from \$27.52 to \$16,899 per ton of CO_2 (2022 U.S. dollars). This wide variation underscores the potential relevance of considering sector-specific factors when designing carbon pricing policies, rather than assuming a uniform abatement cost across the economy. This study also provides a roadmap for understanding how carbon policies would differentially affect each industry, allowing policy makers to tailor their policy designs (Zhang et al. 2022).

An important clarification concerns the terminology of 'social cost of carbon' (SCC). In this study, we estimate marginal abatement costs (MAC), which measure the economic cost of avoiding one additional unit of carbon emissions through changes in production or technology. By contrast, the SCC – often derived from integrated assessment models (Nordhaus 2017) – quantifies the monetized damages caused by emitting an additional ton of CO_2, including economic, environmental, and health impacts over a long horizon. Because MAC capture mitigation expenses rather than the full range of climate damages, they can diverge substantially from SCC estimates. Indeed, some of our sector-level MAC exceed typical SCC ranges, reflecting the near-term difficulties of decarbonizing certain industries. To avoid confusion, and to provide further insight, future work could compare our estimated MAC to established SCC values. Such a comparison would help policymakers assess the extent to which specific abatement efforts are cost-effective from a broader societal standpoint, as strategies with MAC below the SCC would represent net gains in welfare if implemented at scale.

Our findings are broadly consistent with those of Gamtessa and Çule (2023), who used a hyperbolic output distance function (HODF) approach and stochastic frontier estimation to estimate the (MAC for 30 industries in Canada, based on detailed data from Statistics Canada. Both studies emphasize the heterogeneity in abatement costs across sectors and identify the utilities sector as having low abatement costs. Gamtessa and Çule (2023) conclude that sectors with higher greenhouse gas (GHG) intensities generally have lower MAC, suggesting more cost-effective abatement opportunities. Our analysis also shows that the Utilities and Manufacturing sectors exhibit a strong negative correlation between abatement costs and carbon intensity, supporting this conclusion. However, our study extends the analysis to a much larger set of sectors, providing a more comprehensive picture of the distribution of MAC across the U.S. economy. While directly comparing our results to previous studies is challenging, given the different methods, data, and assumptions used, the consistency in key findings strengthens the reliability of our conclusions.

We employed both Gradient Boosting and Random Forest algorithms to evaluate how carbon intensity, total emissions, and economic output influence marginal abatement costs. Although the two ensemble methods yielded broadly consistent findings – highlighting carbon intensity as a dominant predictor in most sectors – some differences emerged in the relative ranking of variables, reflecting each algorithm's distinct way of combining individual decision trees. Rather than selecting one approach over the other, we used both to cross-validate the robustness of our results. Where their outcomes converge, we gain confidence in the overarching conclusion that carbon intensity strongly explains variation in MAC; where they diverge, we obtain a deeper view of the complex interactions among variables in different industries. Thus, the combination of GB and RF offers complementary perspectives, allowing us to present a more comprehensive analysis of the key drivers behind sector-level abatement costs.

It is important to acknowledge the limitations inherent in our analysis. One key limitation is the inclusion of only three variables – total output, carbon intensity, and carbon emissions – in the machine learning analysis. While these variables provide important insights into some of the influencing factors of MAC, they may not capture the full complexity of the variables affecting abatement costs. Future research could expand the set of variables considered in the machine learning models to provide a more comprehensive understanding of the drivers of abatement costs. Another limitation of the study lies in the aggregation of carbon emission coefficients across sectors. The electricity sector, in particular, is affected by this limitation, as the same emission coefficient is applied regardless of the specific energy source (e.g. solar, biomass, or fossil fuels). This aggregation may obscure important differences in the carbon intensities of different electricity generation technologies, potentially leading to less precise estimates of MAC. In future research, using technology-specific carbon intensity values for each type of power generation would provide a much more accurate representation of the emissions landscape in the electric power sector. This approach would account for the differences in emissions per unit of output for various energy sources, such as nuclear, wind, solar, or fossil fuels, and would enable more precise analysis and comparison of emissions across different power generation technologies.

Despite these limitations, our results provide a valuable foundation for further analysis and policy design. The MAC estimates can serve as the backbone for cost minimization analysis, which seeks to identify the least-cost pathways for achieving specific emissions reduction targets. By combining our sector-specific MAC estimates with data on abatement potentials and other relevant factors, policymakers can be provided with the empirical tools needed to design the most effective and efficient strategies for reducing greenhouse gas emissions.

V. Conclusion

This study provides a detailed analysis of the marginal abatement costs of carbon emissions across 546 sectors of the U.S. economy, using a novel method that integrates structural decomposition analysis with partial hypothetical extraction techniques. The results reveal substantial heterogeneity in MAC, ranging from 27.52 to 16,899 per ton of CO_2. The key contributions of this study are threefold. First, the application of SDA-extraction methods provides a transparent and consistent framework for estimating sector-specific MAC, capturing the complex interdependencies and spillover effects across industries. This approach offers policymakers a detailed roadmap for tailoring carbon pricing policies to minimize economic disruption while maximizing emissions reductions. Second, the identification of sectors with low MAC, such as utilities and certain manufacturing industries, highlights opportunities for cost-effective abatement, particularly through investments in energy efficiency and low-carbon technologies. Third, the use of machine learning techniques to analyse the drivers of MAC provides valuable insights into the relative importance of carbon intensity, emissions, and economic output, enabling more targeted and efficient policy interventions. Moreover, the reliance on widely available IO tables and emissions data, rather than data-intensive alternatives like distance function analyses, ensures transparency and replicability while enabling regular updates. The partial extraction component ensures sector-specific MAC estimates while preserving interindustry linkages, avoiding the conflation of effects that can arise in computable general equilibrium models. The policy implications of this study are significant too. A carbon price in the range of 50 to 500 per ton could drive substantial emissions reductions across a wide range of sectors, covering approximately 52% of total emissions. However, the presence of high-cost sectors implies that decision makers could productively consider policies, such as targeted subsidies, technology incentives, or sectoral exemptions, to mitigate economic disruptions and ensure a smooth transition.

In summary, this study offers a detailed, sector-level blueprint for understanding and exploring options for reducing carbon emissions in the U.S. economy. In light of increasing pressures to accelerate decarbonization and the ongoing debate over uniform versus differentiated carbon taxes, our findings provide critical insights for designing effective and economically efficient climate policies. Future research could build on these results by exploring dynamic policy adjustments and further refining the predictive capabilities of our machine learning models.

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