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Decarbonization or Carbon Outsourcing? The Effect of Commodity Price Movements Across Industries

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Abstract

Using a panel of nine manufacturing industries in 43 economies over the period 1990-2015, we examine how international commodity price movements affect carbon emissions across industries. We find that commodity price movements are associated with larger reductions in emissions intensity in physical-capital-intensive industries, whereas the emissions response does not vary systematically with human capital intensity. The results are economically meaningful and robust. The evidence points to cross-industry reallocation as the dominant adjustment channel, with commodity price movements associated with lower value-added growth in physical-capital-intensive industries, whereas the evidence for within-industry emissions-efficiency improvements is weaker. We further show that industries experiencing larger declines in domestic emissions intensity also exhibit larger increases in emissions embodied in imports, suggesting some relocation of emissions-intensive production across borders. Overall, commodity price movements appear to support domestic decarbonization while raising concerns about carbon outsourcing.

Keywords: Commodity prices, Carbon emissions, Physical capital intensity, Industrial reallocation, Decarbonization, Carbon outsourcing
JEL: F18, L60, O13, Q43, Q56

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1. Introduction

Climate change is one of the defining economic and environmental challenges of the twenty-first century. While a large literature examines the determinants of environmental quality, much less is known about how international commodity price movements affect carbon emissions across industries. This is surprising given the central role that commodity markets play in shaping production, investment, and structural transformation across both developed and developing economies (Deaton and Miller, 1996; Arezki and Brückner, 2012; Collier and Goderis, 2012; Lee, 2023).

This paper examines whether the environmental consequences of commodity price movements differ systematically across industries according to their production structures. In particular, we ask three related questions. First, do commodity price movements affect carbon emissions across industries? Second, do these effects vary according to industries' dependence on human and physical capital? Third, through which economic channels do these effects operate?

To address these questions, we exploit variation in industries' human and physical capital intensity. Following the empirical approach of Rajan and Zingales (1998), we examine whether commodity price movements have differential effects on emissions intensity across industries with different production structures. We combine industry-level measures of human capital intensity (HCI) and physical capital intensity (PCI) from Erman and te Kaat (2019) with data on carbon emissions, economic activity, and environmental policies from De Haas and Popov (2023), and merge these with international commodity prices from Gruss and Kebhaj (2021). Our final dataset covers nine manufacturing industries in 43 developed and developing economies over the period 1990-2015.

Industries differ substantially in their production technologies. Some rely heavily on installed physical capital, while others depend more strongly on skilled labor. These differences may shape how industries respond to commodity price movements because the costs and opportunities for adjusting production, investment, and emissions vary across production technologies. Therefore, understanding whether commodity price movements generate heterogeneous environmental effects across industries can shed light on how production structure shapes environmental outcomes.

The empirical analysis yields three main findings. First, commodity price movements are associated with larger reductions in emissions intensity in industries that depend more heavily on physical capital. By contrast, we find little evidence that industries with different levels of human capital intensity respond differently to commodity price movements. These results are economically meaningful and robust across a wide range of alternative specifications, samples, and commodity price measures.

Second, we investigate the channels through which commodity price movements are associated with changes in emissions intensity. Following De Haas and Popov (2023), we consider two potential adjustment pathways: cross-industry reallocation and improvements in emissions efficiency within industries. The evidence points to cross-industry reallocation. Commodity price movements are associated with lower value-added growth in physical-capital-intensive industries, consistent with a relative contraction of activities that rely more heavily on installed capital. In contrast, we find weaker and less consistent evidence that the relationship reflects improvements in emissions efficiency within industries.

Third, we examine whether reductions in domestic emissions intensity reflect genuine decarbonization or the relocation of carbon-intensive production abroad. Using emissions embodied in imports as an outcome variable, we find that industries experiencing larger declines in domestic emissions intensity also exhibit larger increases in imported emissions. The increase is concentrated in imported intermediate inputs and goods associated with gross fixed capital formation. These findings suggest that part of the observed reduction in domestic emissions may reflect carbon outsourcing rather than solely domestic environmental improvement.

In sum, the results support two complementary interpretations. On the one hand, commodity price movements are associated with lower domestic emissions intensity, particularly in physical-capital-intensive industries. On the other hand, part of this reduction appears to be offset by increases in emissions embodied in imports. Therefore, evaluating the environmental consequences of commodity price movements requires distinguishing between domestic emissions reductions and the global distribution of emissions. For policymakers, the results suggest that domestic emissions reductions should be evaluated alongside emissions embodied in trade. For firms and investors, the findings underscore the importance of accounting for production structure and supply chain exposure when assessing the environmental and economic consequences of commodity price movements.

This paper contributes to three strands of literature. First, it contributes to research on the determinants of environmental quality and carbon emissions (Grossman and Krueger, 1995; Li and Reuveny, 2006; Managi et al., 2009; Acheampong, 2019; De Haas and Popov, 2023). While previous studies have examined the environmental implications of factors such as economic growth, finance, institutions, trade, and inequality, little attention has been paid to the role of international commodity price movements in shaping emissions across industries with different production structures.

Second, the paper contributes to the growing literature on commodity prices and their socioeconomic and political consequences (Brückner and Ciccone, 2010; Arezki and Brückner, 2012; Caselli and Tesei, 2016; Naeem et al., 2024). Whereas existing research has primarily focused on macroeconomic, political, and financial outcomes, we provide new evidence on the environmental consequences of commodity price movements using a cross-country industry-level identification strategy.

Third, our paper contributes to the emerging literature on decarbonization, carbon leakage, and emissions embodied in trade (Davis and Caldeira, 2010; Peters et al., 2011; Baumert et al., 2019). By jointly examining domestic emissions intensity and emissions embodied in imports, we show that reductions in domestic emissions need not imply equivalent reductions in global emissions. This distinction is particularly important in economies where production is concentrated in physical-capital-intensive industries.

The remainder of the paper is structured as follows. Section 2 elaborates on the literature and builds the hypotheses. Section 3 describes the data and outlines the identification strategy. Section 4 presents the main results, robustness checks, and analysis of adjustment channels. Section 5 concludes the paper.

2. Theoretical framework and hypotheses

Commodity price movements are an important determinant of production and investment decisions across both developed and developing economies. Changes in international commodity prices affect input costs, profitability, factor returns, and investment incentives, thereby influencing the allocation of resources across industries (Deaton and Miller, 1996; Brückner and Ciccone, 2010; Caselli and Tesei, 2016; Lee, 2023). Because industries differ substantially in their production technologies, the environmental consequences of commodity price movements are unlikely to be uniform across industries. Thus, understanding how production structure shapes these responses is central to explaining the relationship between commodity prices and carbon emissions.

2.1. Commodity price movements and production structure

Industries differ in their dependence on production factors. Some rely heavily on installed physical capital, while others depend more strongly on skilled labor and intangible assets. These differences may influence how industries respond to commodity price movements because the costs and opportunities for adjusting production, investment, and emissions vary across production technologies.

For instance, physical-capital-intensive industries typically operate with large fixed capital stocks and substantial expenditures on intermediate inputs. As a result, changes in commodity prices can have important implications for operating costs, capacity utilization, and investment decisions. Previous research shows that commodity price fluctuations can alter the allocation of resources across industries, affect industrial competitiveness, and influence structural transformation (Harding and Venables, 2016; Van Der Ploeg and Poelhekke, 2017; Lee, 2023). To the extent that physical-capital-intensive industries face greater adjustment costs and stronger exposure to changes in input prices, commodity price movements may generate larger adjustments in production and investment, and therefore larger changes in emissions intensity.

By contrast, human-capital-intensive industries depend primarily on skilled labor and intangible assets rather than on installed physical capital. Because their production processes are less dependent on large fixed capital stocks, commodity price movements may affect their production and emissions decisions differently from those of physical-capital-intensive industries. These differences in factor dependence provide a natural source of heterogeneity through which commodity price movements may generate heterogeneous environmental responses across industries.

These arguments lead to the production structure hypothesis:

Hypothesis 1. The relationship between commodity price movements and emissions intensity differs across industries according to their production structures. In particular, physical-capital-intensive industries are expected to exhibit stronger emissions-intensity responses than industries that rely less heavily on physical capital.

2.2. Potential adjustment channels

If commodity price movements affect emissions intensity differentially across industries, an important question concerns the underlying adjustment process. Following De Haas and Popov (2023), we consider two potential channels: cross-industry reallocation and within-industry emissions efficiency.

The first channel operates through changes in the allocation of economic activity across industries. Commodity price movements alter relative profitability and investment incentives, encouraging resources to move between industries. A large literature shows that commodity-price cycles can reshape industrial composition through changes in competitiveness, investment patterns, and structural transformation (Deaton and Miller, 1996; Harding and Venables, 2016; Van Der Ploeg and Poelhekke, 2017; Lee, 2023). If more emissions-intensive industries experience relatively weaker growth following commodity price movements, aggregate emissions intensity may decline even in the absence of technological change. Under this mechanism, emissions fall because the composition of production changes rather than because individual firms become cleaner.

A second possibility is that commodity price movements induce firms to improve emissions efficiency within industries. Higher input costs may encourage energy conservation, cleaner production methods, or investment in more efficient technologies (Popp, 2002; Blazquez et al., 2017). However, the empirical relevance of this channel is less clear. Technological upgrading often requires substantial investment and may be constrained by financing conditions, institutional quality, or uncertainty regarding future commodity prices (Havranek et al., 2016; Badeeb et al., 2017). Consequently, the relative importance of improvements in emissions efficiency compared with cross-industry reallocation remains an empirical question.

These considerations motivate the cross-industry reallocation hypothesis:

Hypothesis 2. Commodity price movements affect emissions intensity through changes in the allocation of economic activity across industries, with physical-capital-intensive industries experiencing relatively weaker growth.

2.3. Carbon outsourcing

Reductions in domestic emissions do not necessarily imply equivalent reductions in global emissions. If commodity price movements reduce domestic production in emissions-intensive industries, firms may increasingly rely on imported intermediate inputs or capital goods produced abroad. In this case, part of the decline in domestic emissions may reflect the relocation of emissions-intensive activities rather than a genuine reduction in global emissions.

This possibility is closely related to the literature on carbon leakage and emissions embodied in trade (Davis and Caldeira, 2010; Peters et al., 2011; Branger and Quirion, 2014; Baumert et al., 2019). Consumption-based measures of emissions attribute carbon emissions to final demand rather than production location and therefore capture emissions embodied in international trade. Previous studies show that declines in territorial emissions can be partly offset by increases in emissions embodied in imports, particularly when production shifts toward foreign suppliers with carbon-intensive technologies (Davis and Caldeira, 2010; Peters et al., 2011; Wang and Kuusi, 2024).

Commodity price movements may reinforce these dynamics by altering the relative costs of domestic and foreign production and by changing firms' sourcing decisions for intermediate and capital goods. If industries respond to changing commodity prices by substituting toward imported intermediate goods or imported capital equipment, domestic emissions may fall while imported emissions rise. The environmental consequences of commodity price movements, therefore, depend not only on domestic production responses but also on how production is distributed across international supply chains.

This discussion underpins the carbon outsourcing hypothesis:

Hypothesis 3. If commodity price movements induce the relocation of emissions-intensive activities across borders, reductions in domestic emissions intensity will be accompanied by increases in emissions embodied in imports.

3. Data and identification strategy

This section describes the construction of the main variables and the identification strategy used to examine how commodity price movements affect emissions intensity across industries.

3.1. Data

Our environmental outcome measures are based on the industry-level CO_2 emissions data constructed by De Haas and Popov (2023), who combines information from the International Energy Agency (IEA) on CO_2 emissions from fuel combustion with value added data from the United Nations Industrial Development Organization (UNIDO) and the Organization for Economic Co-operation and Development Structural Analysis (OECD-STAN) databases. Our primary outcome is industry-level CO_2 emissions intensity, measured as combustion-based CO_2 emissions divided by GDP. This measure captures variation in emissions intensity across industries while accounting for differences in economic scale. Since combustion-based emissions do not capture embodied or full lifecycle emissions, reductions in measured domestic emissions may reflect improvements in emissions efficiency, changes in the allocation of production across industries, or shifts in production activity across locations. Therefore, we interpret emissions responses with this distinction in mind and assess robustness to alternative specifications.

Using a scaled measure facilitates comparisons across industries and focuses attention on emissions intensity rather than emissions levels alone. At the same time, ratio-based measures may be sensitive to scaling choices (Aswani et al., 2024), reflecting changes in either the numerator or the denominator, implying that reductions in emissions intensity can arise through lower emissions, higher output, or both. Therefore, we complement the baseline analysis with additional outcomes that separately examine industry value added growth and CO_2 emissions per unit of value added, allowing us to distinguish between cross-industry reallocation and within-industry emissions-efficiency channels.

Our measure of country-specific commodity price exposure is based on the database of Gruss and Kebhaj (2021), who employ commodity prices and trade information from the International Monetary Fund (IMF) Primary Commodity Prices, the World Bank's Global Economic Monitor, the United States Energy Information Administration (EIA), and the United Nations Comtrade databases for 40 commodities. Specifically, the index combines internationally determined commodity prices with fixed country-specific export weights, thereby capturing changes in the external commodity price environment faced by each country. Formally, the index is defined as $CommodityPrice_{c,t} = \sum_{k=1}^{K} P_{k,t}\ \Omega_{c,k}$, where $P_{k,t}$ denotes the international price of commodity k in year t, and $\Omega_{c,k} = \omega_{c,k,\tau}/\sum_{k=1}^{K}\omega_{c,k,\tau}$ is the fixed export-share weight of commodity k in country c's export basket in year $t = \tau$, with ω denoting the value of exports of a representative commodity. Our baseline specification uses the three-year moving average of the logarithm of this index, $CommodityPrice_{c,t,3MA}$, to smooth short-term volatility and mitigate measurement error (Fenske and Zurimendi, 2017; Caselli and Tesei, 2016). As a robustness check, we consider alternative moving-average windows and lag structures.

Following Erman and te Kaat (2019), our empirical analysis exploits two industry benchmarks. The first benchmark is the human capital intensity (HCI), constructed as the share of workers in a U.S. industry with at least a high school diploma, based on the Current Population Survey (CPS). HCI reflects the skill composition of production, which may affect an industry's ability to reorganize production processes or adopt efficiency-enhancing responses when relative input costs change. The second benchmark, physical capital intensity (PCI), is defined as the ratio of real capital stock to value added, using NBER manufacturing data. PCI captures dependence on installed capital, which may constrain short- to medium-run adjustment because production technologies are less easily reconfigured.[1] In essence, these benchmarks capture persistent differences in industrial production structures.

We remove the United States from the analysis because it serves as an industry benchmark. The resulting panel covers nine manufacturing industries in 43 countries over the period 1990–2015. Table B.1, panel A presents descriptive statistics for the baseline variables, while panel B reports descriptive statistics by industry. The data show substantial variation in emissions intensity across industries, motivating the industry-level identification strategy described below.

3.2. Identification strategy

Our empirical strategy follows the cross-country, cross-industry framework pioneered by Rajan and Zingales (1998) and applied in related contexts by Erman and te Kaat (2019), De Haas and Popov (2023), and Lee (2023). The key idea is that industries within the same country-year are exposed to the same aggregate commodity price environment but may respond differently, depending on their production structures, as captured by HCI and PCI. To do this, we estimate the following model:

$$y_{c,i,t} = \alpha_{c,i} + \beta_{c,t} + \theta_{i,t} + \gamma(CommodityPrice_{c,t,3MA} \times IB_i) + \varepsilon_{c,i,t} \qquad (1)$$

where $y_{c,i,t}$ denotes CO_2 emissions intensity of industry i in country c for year t, $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of

[1]Both HCI and PCI are mapped to the 3-digit ISIC classification.

international commodity export prices, and IB_i represents the relevant time-invariant industry benchmarks (i.e., either HCI or PCI). The specification includes country $\times$ industry fixed effects ($\alpha_{c,i}$), country $\times$ year fixed effects ($\beta_{c,t}$), and industry $\times$ year fixed effects ($\theta_{i,t}$). $\varepsilon_{c,i,t}$ is the error term. Standard errors are clustered at the country-industry level.

A potential concern is reverse causality, whereby changes in industry-level emissions influence commodity price movements. This concern is mitigated by the construction of the commodity price index, which is based on internationally determined commodity prices and predetermined country-specific export weights, making it unlikely to be driven by developments within any particular industry. Given the small size of individual industries relative to global commodity markets, it is unlikely that changes in industry-level emissions systematically influence international commodity prices. Accordingly, the identifying variation runs from commodity price movements to industry-level emissions outcomes rather than the reverse. Moreover, because HCI and PCI are predetermined industry characteristics measured independently of the sample countries, identification relies on differential responses across industries rather than on aggregate correlations between commodity price movements and emissions outcomes.

The fixed effects structure absorbs all country-level shocks common to industries within a country-year, global industry-specific shocks common across countries, and time-invariant differences in industrial structure within countries.[2] Consequently, identification comes from differential responses of industries with different production structures to the same commodity price movement within a given country-year. This framework helps mitigate concerns that the estimated relationships are driven by omitted country-level confounders or aggregate global trends that jointly affect commodity prices and emissions. Finally, the identifying assumption is not that the levels of HCI or PCI are identical across countries, but that industries that are relatively more skill- or capital-intensive in the benchmark economy remain relatively more skill- or capital-intensive elsewhere.

[2]Note that commodity prices and the industry benchmarks enter only through their interaction, as their main effects are absorbed by the fixed effects.

4. Econometric results

4.1. Main results

Table 1 reports estimates of equation (1), which examines whether the emissions-intensity consequences of commodity price movements differ systematically across industries according to their production structures. Columns (1) and (2) introduce our two industry benchmarks separately. Using OLS, we find no evidence that commodity price movements affect emissions intensity differently across industries with varying levels of HCI. By contrast, the interaction between commodity prices and PCI is negative and statistically significant, indicating that the relationship between commodity price movements and emissions intensity becomes increasingly negative as industries become more physical-capital-intensive.

Column (3) presents our benchmark specification, which includes both interaction terms simultaneously. The results are largely unchanged. The coefficient on the commodity price–HCI interaction remains statistically indistinguishable from zero, while the coefficient on the commodity price–PCI interaction remains negative and statistically significant. The similarity of the estimates across specifications suggests that the PCI result is not driven by the omission of human capital intensity and instead reflects a distinct role for physical capital intensity in shaping industries' emissions-intensity responses. These findings imply that commodity price movements do not affect all industries uniformly. Rather, the response of emissions intensity to commodity price movements appears to be concentrated in physical-capital-intensive industries. This pattern suggests that physical-capital-intensive industries exhibit stronger emissions-intensity responses to commodity price movements than less capital-intensive industries.

The estimated relationship is also economically meaningful. Using the benchmark estimate in column (3), a one-standard-deviation increase in commodity prices is associated with a differential emissions-intensity response of approximately 0.0018 units between industries at the 75th and 25th percentiles of the PCI distribution. Relative to the sample mean emissions intensity of 0.007, this represents approximately 26% of the average level of emissions intensity in the sample. The implied difference is even larger when comparing industries at the extremes of the PCI distribution. For example, the estimated response of Basic Metals (PCI=3.35) exceeds that of Textiles, Textile Products, Leather, and Footwear (PCI=1.02) by approximately 0.0044 units following a one-standard-deviation increase in commod-

Table 1: Commodity price movements and emissions intensity

	CO_2 emissions/GDP			
	OLS	OLS	OLS	GMM
	(1)	(2)	(3)	(4)
$CommodityPrice_{c,t,3MA}$ × HCI	-0.0014		0.0004	-0.0029
	(0.0132)		(0.0138)	(0.0120)
$CommodityPrice_{c,t,3MA}$ × PCI		-0.0053*	-0.0053*	-0.0069***
		(0.0030)	(0.0030)	(0.0013)
Industrial share	0.0212***	0.0211***	0.0211***	0.0067**
	(0.0057)	(0.0058)	(0.0057)	(0.0030)
Country × industry fixed effects	Yes	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.92	0.93	0.93	
Number of observations	7924	7924	7924	7257

Note. The table reports OLS estimates in columns (1)-(3) and GMM estimates in column (4) of the relationship between commodity price movements and industry-level CO_2 emissions intensity, allowing the response to vary according to human capital intensity (HCI) and physical capital intensity (PCI). The dependent variable is CO_2 emissions/GDP, measured as aggregate industry-level CO_2 emissions (kilograms) divided by GDP (million US dollars). $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of international commodity export prices. HCI is the share of employees with at least a high school diploma. PCI is the amount of total real capital stock divided by value added. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.

ity prices, equivalent to roughly 63% of the sample mean emissions intensity. These magnitudes suggest that the emissions-intensity consequences of commodity price movements are substantially larger in industries that rely more heavily on installed capital.

Column (4) examines the robustness of the benchmark results using a dynamic specification that includes a lagged dependent variable and is estimated using GMM. The results closely mirror the OLS estimates. The interaction between commodity prices and HCI remains statistically insignificant, whereas the PCI interaction continues to be negative and statistically significant. Moreover, the magnitude of the PCI coefficient increases relative to the benchmark specification, suggesting that the estimated relationship is not driven by persistence in emissions intensity. The consistency of the results across estimation methods strengthens confidence in the benchmark findings.

In sum, the results provide consistent evidence that the emissions-intensity consequences of commodity price movements depend on industries' production structures. However, this heterogeneity operates primarily through differences in physical capital intensity rather than differences in human capital intensity. Across all specifications, industries that depend more heavily on installed capital exhibit stronger emissions-intensity responses to commodity price movements than less capital-intensive industries. These findings are consistent with the production structure hypothesis, which predicted that the emissions-intensity consequences of commodity price movements would vary systematically across industries according to their dependence on physical capital.

4.2. Robustness checks

Before examining the mechanisms underlying these findings, we first assess the robustness of the baseline results. We begin by considering alternative measures of commodity prices. The baseline analysis employs a three-year moving average of commodity prices. Table 2 re-estimates the model using two-, four-, and five-year moving averages in columns (1)-(3), and uses lagged commodity prices in column (4). Across all specifications, the interaction between commodity prices and PCI remains negative and statistically significant, with coefficient magnitudes remarkably similar to those reported in Table 1. By contrast, the interaction between commodity prices and HCI remains statistically indistinguishable from zero. These results indicate that the baseline findings are not sensitive to the particular construction of the commodity price measure.

We further augment the baseline specification with a range of additional macroeconomic controls. Table B.2 introduces interactions involving GDP per capita, population, environmental legislation, and carbon taxation. The coefficient on the commodity price–PCI interaction remains negative, statistically significant, and quantitatively similar to the baseline estimate in all cases. The stability of the PCI coefficient across specifications suggests that the baseline findings are not driven by omitted macroeconomic factors correlated with commodity price movements.

We then investigate whether the results depend on sample composition and institutional characteristics. Columns (1)-(3) of Table B.3 replicate the

Table 2: Commodity price movements and emissions intensity: Alternative measures

	CO_2 emissions/GDP			
Z	2MA (1)	4MA (2)	5MA (3)	$t-1$ (4)
$CommodityPrice_{c,t,Z}$ × HCI	0.0015	-0.0080	-0.0033	-0.0058
	(0.0114)	(0.0127)	(0.0129)	(0.0104)
$CommodityPrice_{c,t,Z}$ × PCI	-0.0067***	-0.0086***	-0.0095***	-0.0066***
	(0.0013)	(0.0014)	(0.0014)	(0.0012)
Industrial share	0.0067**	0.0067**	0.0071**	0.0068**
	(0.0030)	(0.0030)	(0.0029)	(0.0030)
Country × industry fixed effects	Yes	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
Number of observations	7274	7184	7220	7274

Note. The table reports GMM estimates of the relationship between commodity price movements and industry-level CO_2 emissions intensity using alternative constructions of the commodity price measure. Columns (1)-(3) use two-, four-, and five-year moving averages of international commodity export prices, respectively, while column (4) uses the one-year lag of commodity prices. The dependent variable is CO_2 emissions/GDP, measured as aggregate industry-level CO_2 emissions (kilograms) divided by GDP (million US dollars). HCI is the share of employees with at least a high school diploma. PCI is total real capital stock divided by value added. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.

analysis using the OECD-STAN sample and alternative outcome measures, including value added growth and emissions per unit of value added. The estimated PCI interaction remains negative and statistically significant across all specifications, indicating that the main findings are not specific to the UNIDO sample or to the use of emissions per GDP as the outcome variable. Columns (4)-(6) further divide the sample into advanced economies, emerging markets, and low-income countries. While the negative PCI effect is strongest among advanced economies and remains statistically significant for low-income countries, it is weaker and statistically insignificant for emerging markets. Figure B.1 further examines whether the baseline relationship differs across institutional environments. The negative PCI interaction remains evident across countries with differing levels of financial development, democracy, and legal quality. In sum, these results indicate that the baseline relationship is not confined to a particular subset of countries or institutional settings. These conclusions are further supported by a series of leave-one-out exercises in which countries and industries are sequentially excluded from the estimation sample. The resulting coefficients remain qualitatively similar to the baseline estimates.

Finally, we examine whether the decline in domestic emissions intensity is accompanied by changes in emissions embodied in imports, as suggested by the carbon outsourcing hypothesis. Table 3 reports estimates using imported emissions as the outcome variable, finding that the interaction between commodity prices and PCI is positive and statistically significant. Moreover, the increase in imported emissions is concentrated in intermediate goods purchased by firms within the same industry and in goods associated with gross fixed capital formation. These findings suggest that part of the reduction in domestic emissions observed in Table 1 is offset by higher emissions embodied in imported production, providing evidence consistent with a degree of carbon outsourcing.

Table 3: Commodity price movements and emissions embodied in imports

	Total imports (1)	Households (2)	Same industry (3)	Other industries (4)	GFCF (5)	Government (6)
$CommodityPrice_{c,t,3MA}$ × HCI	-0.0015	-0.0014**	0.0029*	-0.0003	-0.0013***	-0.0000
	(0.0033)	(0.0007)	(0.0016)	(0.0019)	(0.0004)	(0.0000)
$CommodityPrice_{c,t,3MA}$ × PCI	0.0011***	-0.0000	0.0010***	0.0000	0.0001**	0.0000
	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0000)
Industry share	0.0018**	-0.0006***	0.0028***	-0.0007	-0.0000	0.0000
	(0.0009)	(0.0002)	(0.0004)	(0.0005)	(0.0001)	(0.0000)
Country × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2851	2851	2851	2851	2851	2851

Note. The table reports GMM estimates of the relationship between commodity price movements and emissions embodied in imports, allowing the response to vary according to human capital intensity (HCI) and physical capital intensity (PCI). The estimates are used to examine the carbon outsourcing hypothesis. The dependent variable is CO_2 emissions embodied in imports divided by GDP for six importer categories: total imports, households, firms in the same industry, firms in other industries, gross fixed capital formation (GFCF), and government. $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of international commodity export prices. HCI is the share of employees with at least a high school diploma. PCI is total real capital stock divided by value added. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.

In sum, the robustness exercises provide strong support for the baseline results. Across a wide range of alternative commodity price measures, samples, outcome measures, and additional controls, the relationship between commodity prices and emissions intensity remains strongest in physical-capital-intensive industries. At the same time, the carbon-leakage analysis suggests that part of the observed decline in domestic emissions reflects a reallocation of emissions-intensive production across borders, highlighting the importance of distinguishing between domestic decarbonization and carbon outsourcing.

4.3. Potential adjustment channels

Having established the robustness of the baseline finding that commodity price movements are associated with larger reductions in emissions intensity in physical-capital-intensive industries, we next investigate the channels through which commodity price movements affect emissions intensity, focusing on two potential channels. Following De Haas and Popov (2023), we consider: (i) changes in the allocation of production across industries, captured by changes in value added; and (ii) improvements in emissions efficiency within industries, captured by CO_2 emissions per unit of value added.

We begin by adopting an indirect approach. Specifically, we augment the baseline specification with interactions between the proposed channel variables and the industry benchmark measures. This allows us to assess whether the baseline relationship between commodity prices and emissions intensity weakens once the channel variables are taken into account. We estimate:

$$\begin{aligned} y_{c,i,t} = \alpha_{c,i} + \beta_{c,t} + \theta_{i,t} + \gamma(CommodityPrice_{c,t,3MA} \times IB_i) \\ + \delta(m_{c,i,t} \times IB_i) + \varepsilon_{c,i,t} \end{aligned} \tag{2}$$

where $m_{c,i,t}$ denotes the proposed channel variable, namely either ΔValue added or CO_2 emissions/value added, and all other variables are as previously described. If these variables account for the relationship between commodity prices and emissions intensity, the estimated coefficient on the commodity price interaction should become weaker once they are included in the specification.

Tables 4 and 5 report the results. The evidence provides little indication that value-added growth accounts for the baseline findings. Across specifications, the interaction between commodity prices and PCI remains negative and statistically significant after controlling for interactions involving value-

Table 4: Commodity price movements, value added growth, and emissions intensity

	CO_2 emissions/GDP			
	OLS	OLS	OLS	GMM
	(1)	(2)	(3)	(4)
$CommodityPrice_{c,t,3MA}$ × HCI	0.0007	0.0009	0.0002	-0.0033
	(0.0139)	(0.0139)	(0.0139)	(0.0119)
$CommodityPrice_{c,t,3MA}$ × PCI	-0.0052*	-0.0052*	-0.0051*	-0.0063***
	(0.0030)	(0.0030)	(0.0030)	(0.0013)
ΔValue added × HCI	0.0019***		0.0070**	0.0001
	(0.0007)		(0.0030)	(0.0011)
ΔValue added × PCI		0.0002	-0.0016*	0.0008**
		(0.0003)	(0.0010)	(0.0003)
Industrial share	0.0246***	0.0229***	0.0253***	0.0122***
	(0.0066)	(0.0061)	(0.0068)	(0.0037)
Country × industry fixed effects	Yes	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.93	0.93	0.93	
Number of observations	7827	7827	7827	7158

Note. The table reports OLS estimates in columns (1)-(3) and GMM estimates in column (4) used to assess whether value added growth accounts for the relationship between commodity price movements and industry-level CO_2 emissions intensity. The dependent variable is CO_2 emissions/GDP, measured as aggregate industry-level CO_2 emissions (kilograms) divided by GDP (million US dollars). $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of international commodity export prices. HCI is the share of employees with at least a high school diploma. PCI is total real capital stock divided by value added. ΔValue added is the annual growth rate of industry-level value added. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.

added growth. The inclusion of value-added growth interactions has little effect on the estimated PCI coefficient.

The results are different when emissions per unit of value added are introduced. In this case, the interaction between commodity prices and PCI becomes substantially weaker in the OLS specifications, while the channel variables themselves are strongly associated with emissions intensity. In particular, the interaction between emissions per unit of value added and

Table 5: Commodity price movements, emissions efficiency, and emissions intensity

	CO_2 emissions/GDP			
	OLS	OLS	OLS	GMM
	(1)	(2)	(3)	(4)
$CommodityPrice_{c,t,3MA}$ × HCI	-0.0003	-0.0009	0.0014	0.0099
	(0.0115)	(0.0123)	(0.0104)	(0.0117)
$CommodityPrice_{c,t,3MA}$ × PCI	-0.0038	-0.0038	-0.0041	-0.0077***
	(0.0025)	(0.0025)	(0.0026)	(0.0013)
CO_2 emissions/value added × HCI	0.0027***		0.0089***	0.0045***
	(0.0006)		(0.0027)	(0.0005)
CO_2 emissions/value added × PCI		0.0005***	-0.0013**	-0.0008***
		(0.0001)	(0.0005)	(0.0001)
Industrial share	0.0265***	0.0251***	0.0286***	0.0037
	(0.0059)	(0.0060)	(0.0059)	(0.0030)
Country × industry fixed effects	Yes	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.94	0.93	0.94	
Number of observations	7845	7845	7845	7173

Note. The table reports OLS estimates in columns (1)-(3) and GMM estimates in column (4) used to assess whether differences in emissions efficiency account for the relationship between commodity price movements and industry-level CO_2 emissions intensity. The dependent variable is CO_2 emissions/GDP, measured as aggregate industry-level CO_2 emissions (kilograms) divided by GDP (million US dollars). $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of international commodity export prices. HCI is the share of employees with at least a high school diploma. PCI is total real capital stock divided by value added. CO_2 emissions/value added measures industry-level CO_2 emissions (kilograms) divided by value added (million US dollars). The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.

HCI enters positively, whereas the corresponding interaction with PCI enters negatively. These patterns suggest that differences in emissions efficiency account for part of the relationship between commodity prices and industry-level emissions intensity. The GMM estimates broadly support this interpretation, although the PCI interaction remains statistically significant, indicating that emissions efficiency does not fully explain the baseline findings.

Table 6: Direct evidence on cross-industry reallocation and emissions-efficiency channels

	ΔValue added		CO_2 emissions/value added	
	OLS	GMM	OLS	GMM
	(1)	(2)	(3)	(4)
$CommodityPrice_{c,t,3MA}$ × HCI	-0.0482	-0.3716	1.0142	-3.1057
	(0.2237)	(0.4414)	(2.0354)	(3.6171)
$CommodityPrice_{c,t,3MA}$ × PCI	-0.0550**	-0.1387***	-0.8766*	0.3396
	(0.0247)	(0.0527)	(0.5039)	(0.3516)
Industrial share	-1.7018***	-6.4378***	-2.6751***	6.4870***
	(0.1595)	(0.1354)	(0.9307)	(0.9838)
Country × industry fixed effects	Yes	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.48		0.87	
Number of observations	9123	8313	7878	7199

Note. The table reports OLS estimates in columns (1) and (3) and GMM estimates in columns (2) and (4) used to assess whether commodity price movements affect the proposed adjustment channels: cross-industry reallocation and within-industry emissions efficiency. The dependent variable is ΔValue added, defined as the annual growth rate of industry-level value added, in columns (1)-(2), and CO_2 emissions/value added, defined as industry-level CO_2 emissions (kilograms) divided by value added (million US dollars), in columns (3)-(4). $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of international commodity export prices. HCI is the share of employees with at least a high school diploma. PCI is total real capital stock divided by value added. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.

We next examine these channels directly by estimating whether commodity price movements affect the proposed channel variables themselves. Specifically, we estimate:

$$m_{c,i,t} = \alpha_{c,i} + \beta_{c,t} + \theta_{i,t} + \gamma(CommodityPrice_{c,t,3MA} \times IB_i) + \varepsilon_{c,i,t} \qquad (3)$$

where the outcome of interest is now ΔValue added or CO_2 emissions/value added. The results are reported in Table 6.

The first set of estimates considers changes in value added. Both the OLS and GMM results indicate that commodity price movements are associated with lower growth in industries that are more physical-capital-intensive. This pattern is consistent with a relative contraction of production in industries that depend more heavily on installed capital. Importantly, the relationship operates primarily through PCI rather than HCI, mirroring the baseline results.

The second set of estimates examines emissions per unit of value added. The OLS estimates suggest that commodity price movements are associated with lower emissions intensity within physical-capital-intensive industries, consistent with improvements in emissions efficiency. However, the corresponding GMM estimates are weaker and less precisely estimated. Consequently, the evidence for within-industry efficiency improvements is more tentative than the evidence for production reallocation.

In sum, the results suggest that the decline in emissions intensity documented in the baseline analysis is driven primarily by cross-industry reallocation effects, with weaker and less consistent evidence for within-industry efficiency improvements. Thus, the evidence points to changes in the composition of industrial activity as the primary adjustment channel linking commodity price movements to lower emissions intensity in physical-capital-intensive industries. These findings are consistent with the cross-industry reallocation hypothesis developed in Section 2.

5. Conclusion

This paper provides industry-level evidence on the relationship between international commodity price movements and carbon emissions across countries. Using a panel of nine manufacturing industries in 43 developed and developing economies over the period 1990-2015, we examine whether the environmental consequences of commodity price movements differ according to industries' production structures. We find that physical-capital-intensive industries exhibit larger reductions in emissions intensity in response to commodity price movements. By contrast, we find little evidence that commodity price movements affect emissions intensity differently across industries with varying levels of human capital intensity. The estimated relationships are economically meaningful and robust to a wide range of alternative specifications.

We further examine the channels through which commodity price movements are associated with changes in emissions intensity. The evidence suggests that the relationship operates primarily through cross-industry reallocation effects. Specifically, commodity price movements are associated with lower value-added growth in physical-capital-intensive industries, consistent with a relative contraction of activities that rely more heavily on installed capital. We find weaker and less consistent evidence that the relationship reflects improvements in emissions efficiency within industries. In sum, the results indicate that changes in the composition of industrial activity play a more important role than within-industry efficiency improvements in explaining the observed decline in emissions intensity.

An important implication of our findings is that reductions in domestic emissions do not necessarily imply a corresponding decline in global emissions. Using emissions embodied in imports as an outcome variable, we find that industries experiencing larger reductions in domestic emissions intensity also exhibit larger increases in imported emissions. This pattern suggests that part of the observed decline in domestic emissions may reflect the relocation of emissions-intensive production across borders rather than solely domestic decarbonization. Hence, the results highlight the importance of distinguishing between reductions in domestic emissions and changes in the global distribution of emissions.

More broadly, our findings suggest that industrial structure plays an important role in shaping the environmental consequences of commodity price movements. At the same time, the evidence on emissions embodied in imports indicates that reductions in domestic emissions may partly reflect the international relocation of emissions-intensive production. These findings underscore the importance of evaluating decarbonization from a global rather than a purely domestic perspective, particularly in economies where production is concentrated in physical-capital-intensive industries. For policymakers, the results suggest that domestic emissions reductions should be evaluated alongside emissions embodied in trade. For firms and investors, the findings underscore the importance of accounting for production structure and supply-chain exposure when assessing the environmental and economic consequences of commodity price movements.

Our analysis is subject to limitations. First, while the evidence points to cross-industry reallocation as the primary adjustment channel, the available data do not allow us to fully trace the international relocation of emissions-intensive production. Future work combining industry-level production data with firm- or product-level trade data could provide a more complete assessment of the relationship between domestic decarbonization and carbon outsourcing. Second, our sample ends in 2015 and therefore does not capture more recent developments in commodity markets, climate policy, and global decarbonization efforts. As more recent cross-country industry-level datasets become available, future research may revisit these relationships in evolving economic and environmental contexts. In sum, the findings suggest that commodity price movements can contribute to lower domestic emissions intensity, but such reductions do not necessarily imply comparable declines in global emissions.

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A. Variable definitions

CO_2 emissions/GDP: Country and industry-specific emissions of carbon dioxide, in tons, divided by the country's GDP (millions USD). We extract this from De Haas and Popov (2023). Original data source: International Energy Agency (IEA).

Growth in value added: Annual growth rate of industry-level value added. We extract this from De Haas and Popov (2023). Original data source: United Nations Industrial Development Organization (UNIDO)/Structural Analysis (STAN) database of the Organization for Economic Co-operation and Development (OECD).

CO_2 emissions/value added: Country and industry-specific emissions of carbon dioxide, in kilograms, divided by the industry's value added. We extract this from De Haas and Popov (2023). Original data source: IEA; UNIDO/STAN.

CO_2 emissions embodied in imports: CO_2 emissions embodied in imports, measured separately for six importer categories (total imports, households, firms in the same industry, firms in other industries, gross fixed capital formation (GFCF), and government), divided by GDP. We extract this from De Haas and Popov (2023). Original data source: World Input-Output Database (WIOD).

Industrial share: Industry value added divided by total economy-wide value added. We extract this from De Haas and Popov (2023). Original data source: UNIDO/STAN-OECD.

Human capital intensity: The share of employees with at least a high school diploma. We extract this from Erman and te Kaat (2019). Original data source: Current Population Survey (CPS).

Physical capital intensity: Total real capital stock divided by value added. We extract this from Erman and te Kaat (2019). Original data source: National Bureau of Economic Research (NBER) manufacturing database.

Commodity price movements: Three-year moving average of the logarithm of the international commodity export price index. We obtain the commodity export price index from Gruss and Kebhaj (2021). Original data source: IMF Primary Commodity Prices database; Global Economic Monitor, World Bank; US Energy Information Administration (EIA).

Log GDP per capita: Country's real per capita GDP. We extract this from De Haas and Popov (2023). Original data source: World Development Indicators (WDI).

Population: Country's population, in billions of inhabitants. We extract this from De Haas and Popov (2023). Original data source: WDI.
Environmental laws and policies: Number of environmental laws and policies enacted in a country until the current year. We extract this from De Haas and Popov (2023). Original data source: IEA database for policies.
Carbon tax: Dummy variable equal to 1 if the country has a carbon tax or ETS. We extract this from De Haas and Popov (2023). Original data source: Carbon Tax Center.
Financial development: Sum of private-sector credit and value of all listed stocks (and the value of all issued private corporate bonds), divided by the country's GDP. We extract this from De Haas and Popov (2023). Original data source: Beck et al. (2000).
Equity share: Value of all listed stocks, divided by the sum of credit to the private sector and the value of all listed stocks. We extract this from De Haas and Popov (2023). Original data source: Beck et al. (2000).
Political institutions: The revised combined Polity score (Polity2) capturing each regime authority spectrum on a 21-point scale ranging from -10 (hereditary monarchy) to $+10$ (consolidated democracy). We obtain this from Marshall and Gurr (2018).
Legal origins: Dummy variable equal to 1 if the country in which an industry is located has a common law legal origin, and 0 for civil law countries. We obtain this from La Porta et al. (2008).

B. Additional figures and tables

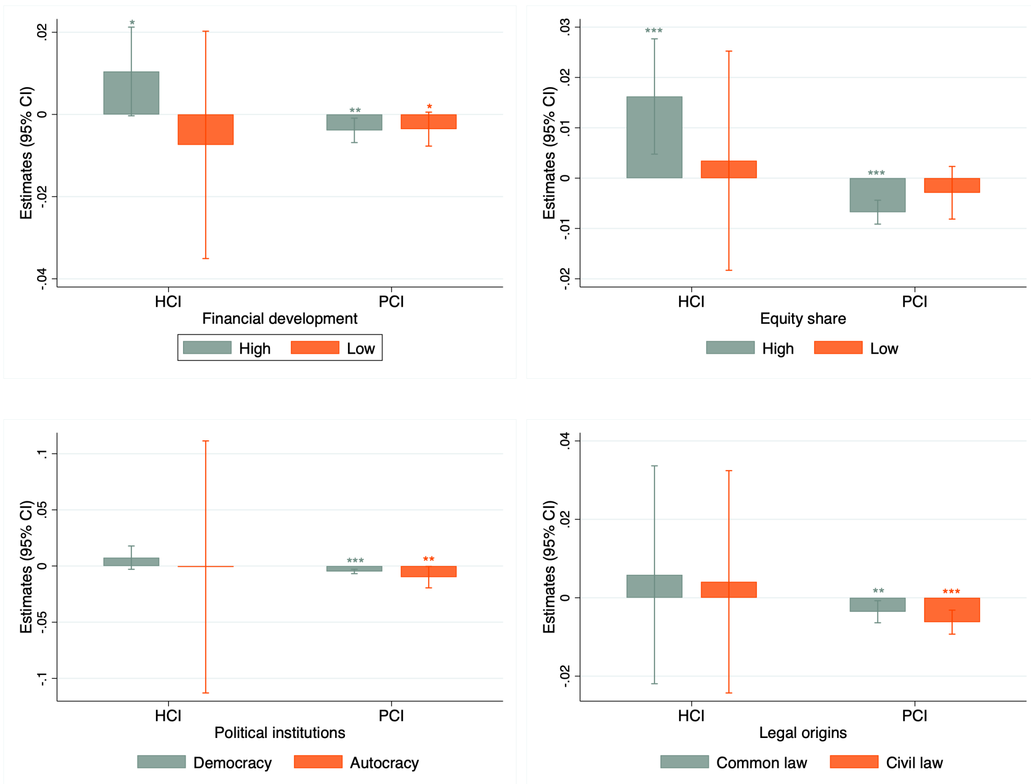

Figure B.1: Heterogeneous effects

Note. The figure shows GMM estimates of the relationship between commodity price movements and industry-level CO_2 emissions intensity, allowing the response to vary according to human capital intensity (HCI) and physical capital intensity (PCI). The dependent variable is CO_2 emissions/GDP, measured as aggregate industry-level CO_2 emissions (kilograms) divided by GDP (million US dollars). HCI is the share of employees with at least a high school diploma. PCI is total real capital stock divided by value added. The displayed coefficients correspond to the interaction between HCI (or PCI) and $CommodityPrice_{c,t,3MA}$, where $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of international commodity export prices. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.

Table B.1: Descriptive statistics

	Panel A: Summary statistics					
	N	Mean	SD	CV	Min	Max
CO_2 emissions/GDP	7,924	0.007	0.017	2.429	0.000	0.254
Δ Value added	7,829	0.002	0.189	94.500	-1.000	1.000
CO_2 emissions/value added	7,849	1.334	2.945	2.208	0.001	43.120
3-year MA of commodity prices	7,924	4.191	0.353	0.084	3.240	4.748
HCI	7,924	0.655	0.091	0.139	0.520	0.790
PCI	7,924	1.894	0.751	0.397	1.020	3.350
Industry value added share	7,919	0.110	0.094	0.855	0.000	0.505

	Panel B: Industry-level averages					
	CO_2 emissions/ GDP	HCI	PCI	Δ Value added	CO_2 emissions/ value added	Industry value added share
Food products, beverages and tobacco	0.006	0.580	1.340	0.009	0.418	0.178
Textiles, textile products, leather and footwear	0.002	0.520	1.020	-0.032	0.321	0.066
Wood and products of wood and cork	0.001	0.550	2.080	0.008	0.494	0.026
Pulp, paper, paper products, printing and publishing	0.003	0.680	1.620	-0.013	0.712	0.070
Chemical, rubber, plastics and fuel products	0.010	0.790	2.290	0.010	0.808	0.181
Other non-metallic mineral products	0.016	0.640	2.630	0.002	3.915	0.051
Basic metals	0.033	0.630	3.350	-0.004	4.587	0.057
Fabricated metal products, machinery and equipment	0.003	0.770	1.020	0.013	0.133	0.233
Transport equipment	0.001	0.740	1.550	0.010	0.135	0.073

Note. Panel A reports summary statistics for the main variables used in the analysis. Panel B reports industry-level averages for the nine manufacturing industries in the sample. SD denotes the standard deviation and CV denotes the coefficient of variation (standard deviation divided by the mean). HCI is human capital intensity and PCI is physical capital intensity. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990–2015. See the text and Appendix A for variable definitions.

Table B.2: Commodity price movements and emissions intensity: Additional macro controls

	CO_2 emissions/GDP			
	GDP	Population	Environmental laws	Carbon taxes
	(1)	(2)	(3)	(4)
$CommodityPrice_{c,t,3MA}$ × HCI	-0.0031	0.0005	-0.0081	-0.0027
	(0.0119)	(0.0118)	(0.0114)	(0.0120)
$CommodityPrice_{c,t,3MA}$ × PCI	-0.0051***	-0.0052***	-0.0069***	-0.0067***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Industry share	0.0077***	0.0084***	0.0067**	0.0067**
	(0.0030)	(0.0029)	(0.0029)	(0.0030)
Country × industry fixed effects	Yes	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
Number of observations	7257	7257	7176	7257

Note. The table reports GMM estimates of the relationship between commodity price movements and industry-level CO_2 emissions intensity after controlling for additional macroeconomic variables. Column (1) controls for log GDP per capita, column (2) for population, column (3) for environmental laws and policies, and column (4) for carbon taxes. The dependent variable is CO_2 emissions/GDP, measured as aggregate industry-level CO_2 emissions (kilograms) divided by GDP (million US dollars). $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of international commodity export prices. HCI is the share of employees with at least a high school diploma. PCI is total real capital stock divided by value added. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.

Table B.3: Commodity price movements and emissions intensity: Alternative samples

	OECD countries			Different country groups		
				Advanced economies	Emerging markets	Low-income countries
	CO_2 emissions/GDP	ΔValue added	CO_2 emissions/ value added	CO_2 emissions/GDP		
	(1)	(2)	(3)	(4)	(5)	(6)
$CommodityPrice_{c,t,3MA}$ × HCI	0.0006	-0.1095	2.2195*	-0.0037	-0.0074	0.0529
	(0.0054)	(0.3544)	(1.2883)	(0.0051)	(0.0303)	(0.0959)
$CommodityPrice_{c,t,3MA}$ × PCI	-0.0016***	-0.1606***	-0.5386***	-0.0015***	-0.0046	-0.0175*
	(0.0006)	(0.0374)	(0.1265)	(0.0006)	(0.0029)	(0.0094)
Industry share	0.0143***	-9.3167***	7.8571***	0.0051***	0.0075	-0.0031
	(0.0039)	(0.2808)	(0.9880)	(0.0015)	(0.0066)	(0.0105)
Country × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	5332	5495	5331	4505	2335	417

Note. The table reports GMM estimates of the relationship between commodity price movements and industry-level emissions intensity, allowing the response to vary according to human capital intensity (HCI) and physical capital intensity (PCI), using alternative country samples. The dependent variable is CO_2 emissions/GDP, measured as aggregate industry-level CO_2 emissions (kilograms) divided by GDP (million US dollars), except in column (2), where the dependent variable is ΔValue added (annual growth rate of industry-level value added), and column (3), where the dependent variable is CO_2 emissions/value added (industry-level CO_2 emissions divided by value added). $CommodityPrice_{c,t,3MA}$ is the three-year moving average of the logarithm of international commodity export prices. HCI is the share of employees with at least a high school diploma. PCI is total real capital stock divided by value added. The sample consists of an annual panel of nine manufacturing industries in 43 countries over the period 1990-2015. Country-industry-clustered standard errors are reported in parentheses. ***, **, and * indicate significantly different from zero at 99%, 95%, and 90%, respectively. See the text and appendix A for variable descriptions.