The Competitiveness Impacts of Climate Change Mitigation Policies

Joseph E. Aldy, William A. Pizer

Abstract: The pollution haven hypothesis suggests that unilateral domestic climate change mitigation policy would impose significant economic costs on carbon-intensive industries, resulting in declining output and increasing net imports. In order to evaluate this hypothesis, we undertake a two-step empirical analysis. First, we estimate how production and net imports change in response to energy prices using a 35-year panel of approximately 450 US manufacturing industries. Second, we use these estimated relationships to simulate the impacts of changes in energy prices resulting from a $15 per ton carbon price. We find that energy-intensive manufacturing industries are more likely to experience decreases in production and increases in net imports than less-intensive industries. Our best estimate is that competitiveness effects—measured by the increase in net imports—are as large as 0.8% for the most energy-intensive industries and represent no more than about one-sixth of the estimated decrease in production.

JEL Codes: F18, Q54, Q52

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THE DEBATE OVER CLIMATE CHANGE policy has largely focused on the design of instruments that will impose a price on the emission of carbon dioxide (CO_2) and other greenhouse gases. In the context of this debate, attention has turned to the prospect that the cost of using fossil fuels could increase under various climate change policy instruments, including economy-wide cap-and-trade and carbon tax policies, as well as state cap-and-trade programs (such as in California and the northeastern

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states), state renewable and alternative energy mandates in the power sector, and greenhouse gas regulatory mandates under the Clean Air Act. The policy-induced higher energy prices could cause adverse competitiveness effects for energy-intensive firms in developed countries, such as in Western Europe and the United States, if they move forward with mitigation efforts while major developing countries postpone action.

The concerns about competitiveness are consistent with the pollution haven hypothesis that suggests that firms relocate economic activity from high regulatory cost to low regulatory cost countries. While sometimes framed as an "economy versus the environment" question with regard to conventional pollution (Morgenstern, Pizer, and Shih 2002), this effect is especially troubling in the context of climate change policy. The relocation of economic activity would increase CO_2 emissions in developing countries, thereby undermining the global environmental benefits of the developed country's emission mitigation policy. That is, it is an "economy *and* the environment" problem.

In this paper, we present evidence that energy price increases due to carbon pricing (\$15/tCO_2) lead to declines in output of as much as 5% for the most energy-intensive manufacturing industries—one-sixth of which is due to competitiveness effects. To draw these conclusions, we begin by defining the competitiveness effect as the change in net imports due to the implementation of a domestic carbon-pricing policy. We employ an empirical strategy that examines the historical relationship between energy prices and production and net imports in the US manufacturing sector. Taking advantage of the fact that market-based CO_2 policy instruments such as cap and trade and emission taxes operate primarily by raising energy prices, as would a carbon performance standard under the Clean Air Act (US EPA 2014), we use this estimation to infer the competitiveness effect of US-only CO_2 regulation.

Our approach uses within-industry energy price variation over time to identify the competitiveness effect, variation that arises from both geographical differences in industry location (and energy prices) and differences in each industry's energy

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mix. This is akin to estimating the various elasticities related to energy prices underlying the computable general equilibrium models that have yielded previous economy-wide competitiveness and emission leakage estimates. However, we generate results in a reduced-form regression framework of equilibrium outcomes at a much more disaggregated level (four-digit industry).[1] In particular, through interaction terms, we allow the estimated effects to vary with the energy intensity of production, allowing us to differentiate impacts among more or less energy-intensive industries. Our analysis employs manufacturing industry data over the 1974–2009 period and employs industry-specific energy prices as a proxy for market-based carbon-pricing regulation. Like much of the literature on estimating energy price elasticities, we estimate output and competitiveness effects in an empirical framework that focuses on short-run responses to a change in energy prices. In practice, a firm may respond to a carbon price—expecting it to be permanent—differently than to an idiosyncratic energy price shock. We note, however, that the volatility in allowance market prices, such as in the EU Emission Trading Scheme for carbon dioxide and other cap-and-trade programs (Aldy and Viscusi 2014), may undermine firms' abilities to predict and plan for carbon prices. In this case, a short-run response through our empirical approach may provide a plausible simulation of firm behavior under climate change regulation characterized by volatile carbon prices.

We use our estimated model to simulate the impacts of a US-only \$15 per ton CO_2 price, translated into the likely changes in energy prices. We focus on \$15 per ton CO_2 because the energy price changes are consistent with the observed variation in our historic energy price data; \$15 per ton is also in line with prices expected under various cap-and-trade and carbon tax legislative proposals in recent years. Moreover, the California cap-and-trade program has had allowance prices in this range in recent years (allowances traded for \$12 per ton on average in 2014) and the proposed electricity price impacts under the Environmental Protection Agency's proposed Clean Power Plan are consistent with this carbon price (Aldy and Pizer 2015).[2] We apply this price to an economy-wide carbon price simulation, consistent with an economy-wide tax or cap-and-trade program.

1. Emission leakage is typically a broader concept than the competitiveness measure we define and estimate in this paper. Emission leakage includes the relocation of emissions associated with a change in net imports, as we describe here, but can also include an increase in emissions in countries without carbon mitigation policy as a result of changes in world energy prices and/or changes in the terms of trade.

2. US EIA (2013) estimates that an economy-wide \$15/tCO_2 price would increase all-sector retail electricity prices by 0.6 ¢/kWh on average nationwide. US EPA (2014) estimates that the proposed Clean Power Plan would increase all-sector retail electricity prices by 0.4–0.7 ¢/kWh across four scenarios.

We find that the higher energy prices associated with this carbon price would lead to a production decline of as much as 5% among key energy-intensive sectors (e.g., iron and steel, aluminum, cement, etc.). We also find, however, that this energy price increase would translate into a smaller-than-one-percent increase in net imports, reflecting either a lack of substitutability with foreign goods or a lack of additional global capacity over the horizon we examine (1–3 years via various lagged models). The approximately eight-tenths of a percent shift in energy-intensive production overseas is our estimated adverse competitiveness effect. Put another way, as a share of the total 5% effect on the most energy-intensive industries, the "competitiveness" component is only about one-sixth.

Quantitatively, the overall results suggest the competitiveness effects associated with a $15 per ton CO_2 price is consistently no more than 1% of production. To put this estimated impact in context, consider that the standard deviation of the annual growth rate in the value of shipments was 12.9% during our sample. Some energy-intensive industries, such as iron and steel and aluminum, experienced variation in growth in excess of the manufacturing sector average. For other energy-intensive industries, including paper, cement, and bulk glass, the variation was in the 10%–12% range, on average.

Our work builds on a substantial literature that has examined the question of whether environmental regulations adversely affect the competitive position of American industry. Numerous theoretical analyses have suggested that environmental policy could create so-called "pollution havens" in developing countries: "The conventional wisdom is that environmental regulations impose significant costs, slow productivity growth, and thereby hinder the ability of US firms to compete in international markets. This loss of competitiveness is believed to be reflected in declining exports, increasing imports, and a long-term movement of manufacturing capacity from the United States to other countries, particularly in 'pollution-intensive' industries" (Jaffe et al. 1995, 133).

Empirically evaluating this conventional wisdom has proven challenging (Jaffe et al. 1995; Levinson and Taylor 2008). A variety of factors may mitigate or dominate the effect of environmental regulatory costs in determining manufacturing location decisions. First, the availability of relevant factors of production, such as appropriately skilled labor, natural resources, and capital, can play a more significant role than pollution control costs (Antweiler, Copeland, and Taylor 2001). Second, transportation costs may discourage relocation to countries far from the major markets for manufactured goods (Ederington, Levinson, and Minier 2005). Third, firms with a significant share of their investments in large, fixed physical structures also appear to move activity less in response to environmental regulations (Ederington et al. 2005). Fourth, proximity to firms that produce inputs or purchase outputs—for example, agglomeration economies—also discourages relocation (Jeppesen, List, and Folmer 2002).

Since the most pollution-intensive industries tend to be relatively immobile by these measures of "footlooseness," the empirical literature typically finds quite limited impacts of environmental regulations on international competitiveness. Levinson and Taylor (2008) show that US pollution abatement costs in the 1970s and 1980s increased net imports in the manufacturing sector from Mexico and Canada. The estimated increase in net imports roughly equaled about 10% of the total increase in bilateral trade for both Mexico and Canada, suggesting that other factors played much more substantial roles in the evolution of trade among the North American trading partners. An extensive literature on the competitiveness effects of variation in environmental policies across the US states has shown more significant impacts on domestic firm relocation resulting from variation in the stringency of environmental regulations (Henderson 1996; Greenstone 2002). Kahn and Mansur (2013) find even larger effects looking at adjacent counties. The larger domestic competitiveness effects may reflect the fact that labor costs and availability of capital do not vary much across the US states and counties, and transportation costs are less important, relative to the international context.

This empirical literature has focused on retrospective analyses of US environmental regulations. The absence of a domestic CO_2 regulatory or taxation regime precludes us from taking exactly the same approach. The popular alternative has been to use applied computable general equilibrium models to simulate potential competitiveness impacts of pricing carbon (IPCC 2001). These CGE models have been useful in quantifying aggregate leakage rates as well as important interaction effects across markets that only a general equilibrium model can capture. A limitation of these models is their focus on aggregate effects that obscures effects on individual industries. While informative, this approach provides little to no differentiation among industries with different energy intensities and elasticities with respect to energy prices. Indeed, it is typical to make a common set of assumptions that yield a common response across the entire manufacturing industry to a carbon-pricing policy. As our analysis shows, this approach can underestimate the impacts on the more energy-intensive manufacturing industries. In this way, our work is a natural complement to this literature.

The next section presents our empirical methods and data. Section 2 presents the results of our empirical analyses of the relationships between energy prices and net imports and production. Section 3 illustrates the results of our simulation of a near-term unilateral US CO_2 mitigation policy on the US manufacturing sector. The final section concludes with comments on future research and implications for policy design.

1. METHODS AND DATA FOR EMPIRICAL ANALYSIS

The pollution haven hypothesis suggests that a climate change policy would impose significant economic costs on carbon-intensive industries, resulting in declining output and increasing net imports. In order to evaluate this hypothesis, we undertake a two-step empirical analysis. First, we use historic energy prices as a proxy for climate change mitigation policy. We estimate how production and net imports change in response to energy prices in the US manufacturing sector. Second, we take these estimated relationships to simulate the impacts of changes in energy prices resulting from a climate change mitigation policy that effectively prices CO_2 emissions.

In evaluating the pollution haven hypothesis, we take two issues into consideration. The costs of climate policy are anticipated to be greater for carbon-intensive industries. With more than 80% of US greenhouse gas emissions occurring as a result of fossil fuel combustion, carbon intensity and energy intensity are effectively the same in the context of domestic mitigation policy. Thus, we test for how energy prices affect production and net imports as a function of industries' energy intensity. Moreover, we explicitly discern impacts on production from impacts on net imports. The change in net imports reflects the adverse competitiveness impacts of a domestic mitigation policy. The change in production could reflect these competitiveness effects—and a one-for-one substitution of net imports for domestic production would suggest that the entire change in production was driven by competitiveness pressures. It is possible, however, that domestic production could decline more than the change in net imports, representing a decline in domestic consumption. For example, customers of energy-intensive manufactured goods could exploit opportunities for economizing on their consumption, such as an auto manufacturer using less steel in response to climate policy induced increases in steel prices. At the same time, frictions in trade and differences between domestic and imported goods may preclude one-for-one substitution by net imports.

As a result, our empirical strategy tests two hypotheses. First, do idiosyncratic energy price changes cause manufacturing production to decline? Second, do idiosyncratic energy price changes cause manufacturing net imports to increase? In investigating these hypotheses empirically, we will allow for energy price impacts to vary with industry energy intensity. We will also assess the ratio of these two effects, the fraction of changes in production resulting from changes in net imports, that is, from competitiveness effects. Understanding these two impacts will provide a better understanding of the likely economic mechanisms driving changes in US manufacturing under a climate change mitigation policy. Discerning international competitiveness effects from reduced domestic consumption effects would also inform very different policy responses, as discussed in our final section.

To estimate production and competitiveness effects, we use a sample of nearly 450 US industries at the four-digit industry (SIC 1987) level of disaggregation over the 1974–2009 period, with a primary sample over 1979–2005 given data limitations. The general reduced-form regression specification takes this form:

$$Y_{it} = \alpha_i + \theta_t + f(\gamma, e_{i,t-1}) + f(\beta, e_{i,t-1}) \ln P_{i,t}^{energy} + \delta' X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where Y_{it} represents the outcome measure—either the natural logarithm of production or the ratio of net imports to lagged production—for four-digit industry i and year t; the α's and θ's are fixed effects for industries and years, respectively; the function $f(\cdot)$ defines the responsiveness of the outcome to energy prices as a flexible function of lagged energy intensity $e_{i,t-1}$ and parameters γ and β; $\ln P_{i,t}^{energy}$ represents the level of US carbon regulation—which we proxy with the natural logarithm of domestic industry-specific energy prices; and X_{it} is a vector of additional determinants of the industry outcome measures. In our preferred model specifications reported below, we estimate (1) as the following:

$$\begin{aligned} Y_{it} = {} & \alpha_i + \theta_{g(i),t} + \gamma_{\ln e} \ln e_{i,t-1} + (\beta_{\ln P} + \beta_{\ln P \times \ln e} \ln e_{i,t-1}) \ln P_{i,t}^{energy} \\ & + \delta_{oil} \ln P_t^{oil} \ln e_{i,t-1} + \delta_{tar} TAR_{i,t} + \delta_{pcs} PCS_{i,t} + \delta_{hcs} HCS_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{1'}$$

where X_{it} includes the interaction of the world oil price and lagged energy intensity, average industry tariffs (TAR) and factor intensity variables (to estimate the returns to physical capital, PCS, and human capital, HCS). The fixed effects $\theta_{g(i),t}$ represent year by two-digit industry group fixed effects (the grouping function $g(i)$ maps each of the 448 four-digit industries into 20 two-digit aggregates).[3] Including the interaction of the world oil price and lagged energy intensity permits us to control for energy price impacts in foreign trade partners that might vary based on energy intensity (versus nonvarying effects picked up by $\theta_{g(i),t}$). In effect, our models attempt to estimate the impact of domestic industry energy prices on industry outcomes conditional on the energy prices faced by foreign manufacturers. Note that the energy intensity function is included alone, as well as interacted with energy prices. The use of lagged energy intensity is designed to limit potential endogeneity, described below. In estimating (1′), we weight each observation by the 1974–2009 average value of shipments for that industry. This solves the empirical problem that industries with very small shipment values can have explosive net import values, an issue we test in our robustness checks. Summary statistics for our data are presented in table 1.We now describe our model specification and variable construction in more detail.

Domestic Production

Our outcome variables are constructed from the NBER-CES manufacturing database (Bartlesman, Becker, and Gray 2000) and from Schott (2008, 2010). We use the value of shipments by industry from the NBER-CES Manufacturing Industry Database (SIC-87 version) as our measure of domestic production. This provides value of shipments data for 459 industries over the 1958–2009 period in millions of

3. We appreciate a referee's suggestion that we should account for aggregated industry-specific trends in our empirical model.

Table 1. Summary Statistics of Raw Data (1974–2009)

	Mean	SD	SD (within)	SD ([Two-Digit SIC-by-Year] and Industry Fixed Effects)	Minimum	Maximum	Observations	Industries	Average Observations per Industry
Value of shipments ($2009 billion)	9.665	22.389	8.121	7.322	.024	738.370	16,415	459	35.76
(logged)	1.476	1.228	.359	.290	−3.722	6.604	16,415	459	35.76
Net imports (share of lagged value of shipments)	.183	1.109	.816	.706	−1.731	40.374	13,034	448	29.09
Total energy price (2009$/MMBTU)	10.717	4.305	2.877	1.655	.795	181.804	16,135	459	35.15
(logged)	2.286	.440	.276	.081	−.229	5.203	16,135	459	35.15
Electricity price (2009$/MMBTU)	23.575	6.818	5.918	4.358	1.702	362.365	16,183	459	35.26
(logged)	3.131	.241	.189	.098	.532	5.893			
Lagged energy intensity (% of value of shipments)	2.314	3.161	.923	.778	.108	34.139	15,964	459	34.78
(logged)	.425	.811	.257	.204	−2.227	3.530	15,964	459	34.78
Tariff (average rate, %)	1.565	3.310	2.722	1.715	.000	100.080	13,388	448	29.88
Physical capital	.615	.121	.067	.051	−1.117	.976	16,415	459	35.76
Human capital	.120	.050	.031	.023	−.240	.635	13,485	459	29.38

Note.—Production data from the NBER-CES database are available for 459 industries from 1974 to 2009. Trade data from Schott (2008, 2010) are only available for a subset of 405 industries from 1974 to 2005 and another 43 industries from 1974 to 1989. The disappearance of these 43 industries after 1989 arises from a change in the data source and concordance. Human capital data are only available from 1979 to 2009.

dollars. Given the significant variation in size of US manufacturing industries, we estimate all production models with the natural logarithm of value of shipments.[4]

Net Imports

For net imports, we use Peter Schott's public database (2008, 2010) on SIC-87-level trade data. This provides gross imports and gross exports data for 405 industries over the 1972–2005 period and 446 industries over the 1972–1989 period measured in millions of dollars. We constructed net imports as the difference between the gross imports and gross exports variables and then scaled this value by the lagged value of shipments measure (we examine these variables separately in our robustness checks). Scaling by production addresses the significant variation in size of US manufacturing industries and is the norm in this literature (e.g., Ederington et al. 2005). We use lagged, rather than current, value of shipments because of the endogeneity of domestic production and net imports.

Energy Prices

We use energy prices as a proxy for regulation under a hypothetical carbon-pricing regime because both cap-and-trade programs, including the EPA Clean Power Plan, and carbon taxes affect behavior by raising energy prices. While historic price changes were not caused by carbon pricing, we hypothesize that future carbon pricing would have a similar effect. We construct an energy price index, P_{it}, that varies by four-digit industry and year:

$$P_{it} = \left(P_{it}^{Elec}\right)\left(\frac{Q_{j(i)t}^{Elec}}{\sum_{f'}^{F} Q_{j(i)t}^{f'}}\right) + \sum_{f \neq Elec}^{F} \left\{ \underbrace{\left[\sum_{s}^{S} \left(P_{st}^{f}\right) \left(\frac{GSP_{sj(i)t-1}}{\sum_{s'}^{S} GSP_{s'j(i)t-1}} \right) \right]}_{P_{j(i)t}^{f}} \left(\frac{Q_{j(i)t}^{f}}{\sum_{f'}^{F} Q_{j(i)t}^{f'}} \right) \right\}, \quad (2)$$

where $j(i)$ denotes the two-digit SIC-87 industry corresponding to four-digit industry i, s denotes state, $f \in F$ denotes fuel, which includes coal, distillate oil, natural gas, residual oil, coke, liquefied petroleum gas, and electricity, and (as before) t is year. At the top level, to aggregate prices across the set of fuels, F, we estimate two-digit-industry-by-year fuel shares, $Q_{jt}^{f}/\sum_{f'}^{F} Q_{jt}^{f'}$. The US Energy Information Administration Manufacturing Energy Consumption Survey provides annual fuel consumption by two-digit SIC-87 manufacturing industry and fuel, Q_{jt}^{f}, for 1974–90 and 1991, 1994, 1998, 2002, 2006, and 2010. We construct fuel shares as the ratio of consumption

4. All measures of output, net imports, and prices have been deflated to constant 2009 dollars.

(in MMBTU) for a specific fuel to all energy consumption (in MMBTU) by that two-digit industry in that year. We use linear interpolation to construct fuel shares in nonsurvey years of the MECS post-1991.

To construct a four-digit industry electricity price, P_{it}^{Elec}, we use the Annual Survey of Manufactures SIC-87 classified electricity expenditures and quantity of electricity consumed by four-digit industry for 1974–2001. Wayne Gray provided the same data from the Annual Survey of Manufactures for 1978 and 1997–2009. We construct the electricity price as the ratio of expenditure to quantity. We convert electricity prices to dollars per million BTU to permit comparability with the fuel price data described below. Refer to the data appendix for further details.

For all other fuels, we construct a two-digit-industry-by year fuel price P_{jt}^{f}. We use state-by-year industrial energy prices by fuel, P_{st}^{f}, for 1970–2009 from the US Energy Information Administration State Energy Data System (measured in dollars per million BTU).[5] We map state-by-year fuel prices to two-digit-industry-by-year fuel prices using two-digit industry-by-state-by-year output. We construct a state's share of two-digit industry national output, $GSP_{sjt-1}/\sum_{s'}^{S} GSP_{s'jt-1}$, using US Bureau of Economic Analysis gross state product data. Summing the product of the state-by-year fuel price and the industry-by-year state shares of national output yields two-digit-industry-by-year fuel prices. To address potential endogeneity concerns of using output to construct energy prices, we employ the 1-year lag of state industry share of national output.[6] In sum, we use four-digit industry electricity prices and two-digit industry state-weighted non-electricity fuel prices aggregated by two-digit industry fuel consumption weights to produce our energy price variable.

Energy Price—Energy Intensity Interaction

The flexible function $f(\cdot)$ captures the variation across industries and time in the net import and production elasticities with respect to energy prices in our estimation equation (1′). We expect that energy intensity is the key driver of this variation, as higher energy intensities imply larger cost impacts from rising energy prices. Without knowing exactly how the elasticities would vary, we considered various specifications ranging from a constant value, to linear and quadratic functions of energy intensity. We are unable to reject the hypothesis that the quadratic simplifies to a linear function of logged energy intensity and that remains our preferred specification.

We define energy intensity as the ratio of all energy expenditures to value of shipments. Energy costs are reported in the Annual Survey of Manufactures and Bartlesman et al. (2000). To address endogeneity concerns, we employ the 1-year lag of

5. The Annual Survey of Manufactures collects expenditures but not physical quantities or prices of non-electricity fuel inputs.

6. We thank an anonymous referee for this suggestion.

energy intensity in our various specifications. Figure 1 presents the cumulative distribution function for each industry's average energy intensity in 2009.

Other Determinants of Industry Outcomes

We also control for average industry tariff rates, the physical capital share of value added, and the human capital share of value added, consistent with Ederington et al.'s (2005) analysis of the impacts of domestic environmental regulation on net imports, as well as world oil prices. The average tariff is expressed in percentage points and represents the average industry-level tariff based on the total duties collected scaled by total customs value and multiplied by 100 (constructed from data provided by Schott [2008, 2010]). The physical capital share is represented by one minus the ratio of total payroll to value added (constructed from data provided by Bartlesman et al. [2000]). The human capital share is calculated as total payroll minus payments to unskilled labor, scaled by industry value added. Payments of unskilled labor are estimated from the Current Population Survey Merged Outgoing Rotation Group data files as the number of workers, multiplied by average annual income of workers with less than a high school diploma (constructed from the NBER Current Popula-

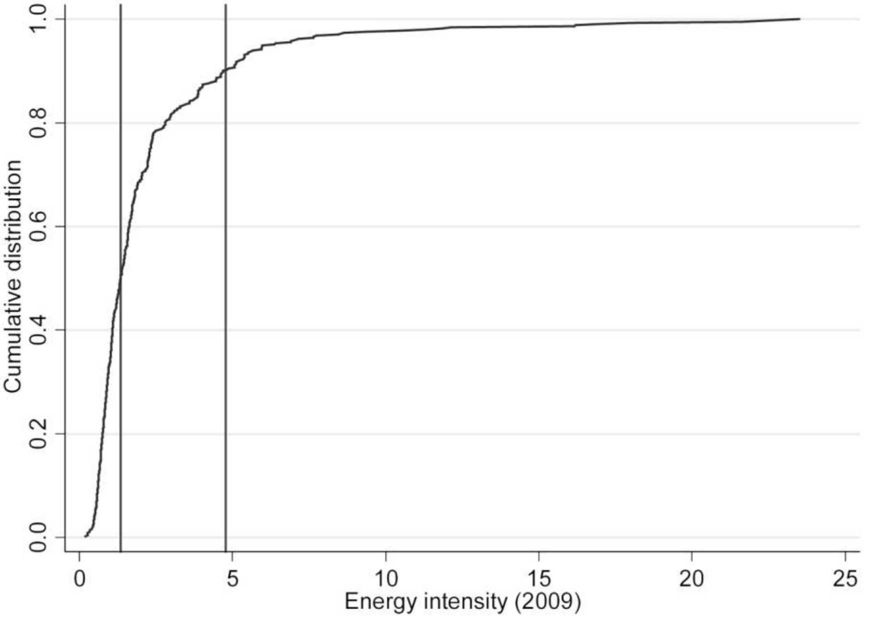

Figure 1. Distribution of 2009 industry classifications by energy intensity (%). The vertical lines present the 50th and 90th percentiles of the manufacturing sector energy intensity distribution. Source: Constructed by the authors from Annual Survey of Manufactures and Bartlesman et al. (2000).

tion Survey and Bartlesman et al. [2000]). The oil price variable is defined as the crude oil acquisition cost from the Energy Information Administration's Annual Energy Review. See the data appendix for more details.

Fixed Effects and Identification

Finally in our specification, industry fixed effects capture time-invariant characteristics of industries that may affect these measures of competitiveness, and year fixed effects account for common shocks, such as those from monetary policy, tax policy, and so on that affect all industries in a given period of time. In addition, we correct the standard error estimates to control for heteroskedasticity across industries as well as autocorrelation within industries.

Given that our sample spans 35 years, we chose a preferred specification with distinct year fixed effects for each of 20 two-digit industry classifications (two-digit-industry-by-year) in order to address the possibility of slow-moving trends in manufacturing and energy prices that might confound our estimation.[7] In section 2, we verify that our results are robust to a simpler model with only a single set of aggregate year effects. This specification of fixed effects reduces the remaining energy price variation to identify the relationship with our outcome variables. Nonetheless, the variation that remains—a standard deviation of 8% (evident in the column reporting standard deviations when accounting for two-digit SIC-by-year fixed effects in table 1)—is still consistent with the magnitude of a price effect we wish to simulate, as discussed in section 3. Qualitatively, we are using variation over time within a four-digit industry relative to the average variation for that industry's two-digit SIC aggregate.

With these flexible trends at the two-digit SIC level, one might question the use of our industry-specific fuel prices that are constructed at approximately the two-digit SIC level (refer to the data appendix for details regarding the exception in the classification of SIC-87 industry 37 by the US Bureau of Economic Analysis). Even without price variation beyond the two-digit level, however, we can still identify the difference in the energy price elasticity between more or less energy-intensive industries. The term $\ln e_{i,t-1} \ln P_{i,t}^{energy}$ in (1′) contains variation in the presence of two-digit-industry-by-year fixed effects $\theta_{g(i)}, t$ even if aggregate energy prices $\ln P_{i,t}^{energy}$ varied only at the two-digit SIC level. Within two-digit SIC classifications, if the high energy intensity industries are more sensitive to price changes, that will show up as a significant $\beta_{\ln P \times \ln e}$ parameter estimate without requiring any within-two-digit SIC energy price variation. Variation in energy prices in the presence of two-digit-industry-by-year fixed effects is necessary to estimate $\beta_{\ln P}$ in (1′). The four-digit industry elec-

7. We thank an anonymous referee for this suggestion.

tricity component of P_{it} thus plays an important role in estimating this coefficient, noting that electricity represents a majority of energy expenditures for 88% of the industries in our sample.

Ultimately, our use of energy prices as a proxy for regulatory stringency circumvents a number of problems noted in the empirical pollution haven literature, which typically uses the ratio of regulatory compliance costs to value added as a proxy for the stringency of environmental regulations. Levinson and Taylor (2008) note that changes in production levels can affect this ratio of pollution abatement cost expenditures (PACE) to output and create an endogeneity problem. Production levels change this regulatory cost burden measure directly, as production or a related variable is the denominator of the PACE share. Production levels can also change the numerator of the PACE share indirectly, as changes in production affect plant turnover, scale economies, and the difficulty in meeting regulatory standards—all of which affect regulatory compliance costs. In contrast, energy prices are less likely to be endogenous to individual industry production decisions. In related work, we find that most of the variation over time in industry-level energy prices (which represent production-weighted state energy prices) comes from variation in state energy prices, not changes in relative production levels across states (Aldy and Pizer 2015).

2. EMPIRICAL ESTIMATES OF THE EFFECTS OF ENERGY PRICES ON PRODUCTION AND NET IMPORTS

Table 2 presents our main results estimating the relationship between energy prices and production (left side of table) and net import share (right side of table). We focus on the results using data from 1979–2005, which permits us to account for available trade and human capital data. We present constant, linear, and quadratic specifications for $f(\cdot)$, describing the elasticity as a function of logged energy intensity. The models (cols. 1 and 4) specifying a constant elasticity are akin to previous papers that regress domestic production and/or net imports on the level of environmental compliance costs or on the ratio of environmental compliance costs to the value of shipments (e.g., Grossman and Krueger 1991; Ederington et al. 2005; and Levinson and Taylor 2008). In each of these three previous papers, the ratio of net imports to value of shipments is regressed on the ratio of pollution abatement costs to value of shipments (or value added), as well as other controls that enter the regression equation linearly. Our estimated net import share elasticity with respect to energy prices is small and not statistically distinguishable from zero (col. 4). Considering a 95% confidence interval, we would rule out an elasticity of more than +0.06. This is true despite a large and statistically significant elasticity of −0.14 on production (col. 1); that is, production clearly declines in response to higher domestic energy prices, but it is not replaced by higher imports. One could interpret these estimates as the average manufacturing sector impacts resulting from changes in energy prices.

Table 2. Production and Net Import Models, Main Parameter Estimates (1979–2005)

	Production			Net Imports		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(P_{i,t}^{energy})$	−.140*	−.049	−.040	−.065	−.103	−.106*
	(.082)	(.080)	(.078)	(.061)	(.064)	(.062)
$\ln(P_{i,t}^{energy}) \times \ln(e_{i,t-1})$		−.129***	−.069		.054**	.065**
		(.039)	(.048)		(.021)	(.032)
$\ln(P_{i,t}^{energy}) \times \ln(e_{i,t-1})^2$			−.032			−.003
			(.028)			(.014)
$\ln(e_{i,t-1})$	−.582***	−.379***	−.479***	−.006	−.091*	−.093
	(.126)	(.116)	(.180)	(.040)	(.052)	(.090)
$\ln(e_{i,t-1})^2$			.088			.018
			(.060)			(.024)
$\ln(P_t^{oil}) \times \ln(e_{i,t-1})$	.087**	.117***	.101***	.013	.000	−.007
	(.034)	(.039)	(.039)	(.013)	(.012)	(.014)
Tariff (average rate)	−.017***	−.016***	−.016***	.003	.003	.003
	(.005)	(.005)	(.005)	(.004)	(.004)	(.004)
Physical capital	1.835***	1.822***	1.825***	−.038	−.033	−.022
	(.387)	(.389)	(.387)	(.286)	(.286)	(.289)
Human capital	2.267***	2.182***	2.201***	.327	.363	.394
	(.765)	(.770)	(.770)	(.575)	(.573)	(.580)
Observations	10,569	10,569	10,569	10,569	10,569	10,569
R^2	.55	.56	.56	.25	.25	.25

Note.—Heteroskedasticity across industries and autocorrelation within industries robust standard errors in parentheses. The regression sample is limited to years 1979 (due to human capital) through 2005 (due to trade data). Columns 2 and 5 indicate preferred models. Energy intensity, *e*, is measured in percent. Regressions also include two-digit-SIC-by-year and industry (four-digit SIC) fixed effects. Regression observations for each industry are weighted by the average value of shipments in that industry over 1974–2009.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

Our more flexible regression specifications (cols. 2–3 and 5–6) allow these elasticities to vary with the previous year's energy intensity through interaction terms between $\ln P_{i,t}^{energy}$ and $\ln e_{i,t-1}$. The energy intensity variable is the log of the percentage value and equals zero when the energy share is 1%. Examining the more flexible specifications, the linear terms, $\ln P_{i,t}^{energy} \times \ln e_{i,t-1}$, are statistically significant and have signs consistent with hypothesized competitiveness impacts. Industries that use more energy per unit of output are more sensitive, in terms of production and net imports, to energy price changes. The negative production-energy price elasticity becomes more negative and the net import-energy price elasticity becomes more positive with higher energy intensity. Neither of the quadratic interaction estimates, $\ln P_{i,t}^{energy} \times (\ln e_{i,t-1})^2$, are statistically significant (cols. 3 and 6). The direct effect of energy intensity is negative and statistically significant in the production models (cols. 1–3) but generally not statistically significant in the net import models (cols. 4–6).

We find that changes in physical capital and human capital shares are positively associated with higher production but have no statistically meaningful impacts on net imports. The interaction of the world oil price and energy intensity is also statistically significant and positive for the production models but small and not statistically different from zero in the net imports models. Our results for tariffs in the net imports models—small, statistical zeroes—are consistent with the results in Ederington et al. (2005), who evaluate the impacts of environmental regulatory costs on net imports while controlling for tariffs in the same way as in our model. We find that tariffs are associated with reduced production, which may reflect the political economy of declining industries fighting against trade liberalization. In our robustness checks (see below), we find that inclusion of tariffs does not materially affect the estimation of our energy price and price interacted with energy intensity coefficients of interest. We chose the linear-interaction models (2 and 5) as our preferred specifications for the illustration of elasticities and policy simulations.

Figure 2 presents the elasticity estimates from models 2 and 5, with associated 95% confidence intervals, over the range of energy intensities for the manufacturing industries in our sample in 2009. The point estimates of the domestic production-energy price elasticity (top panel) are negative for all industries with an energy intensity greater than 0.7% (which corresponds to about 86% of our sample industries in 2009) and statistically significant when greater than 2.5%. Estimates for the most energy-intensive industries are nearly triple the constant elasticity estimate of −0.14 in column 1 of table 2. In particular, we estimate an elasticity slightly larger in magnitude than −0.4 for industries with an energy intensity exceeding 15%, and the lower bound of the 95% confidence interval exceeds the constant elasticity of −0.14. The differences between models 1 and 2 for the production-energy price elasticity are statistically and economically significant.

The point estimates of the net import-energy price elasticity (bottom panel of fig. 2) are all statistically indistinguishable from zero, although those for the most energy-intensive industries rise to almost 0.1. Moreover, the upper end of a 95% confidence interval approaches 0.2 for the most energy-intensive industries, nearly 10 times the upper end for the median industry (measured along the left vertical line). While neither model 4 nor model 5 produces statistically significant elasticity estimates within the observed range for energy intensity, model 5 does reveal statistically that energy intensity makes it more likely that an energy price increase would increase net imports.

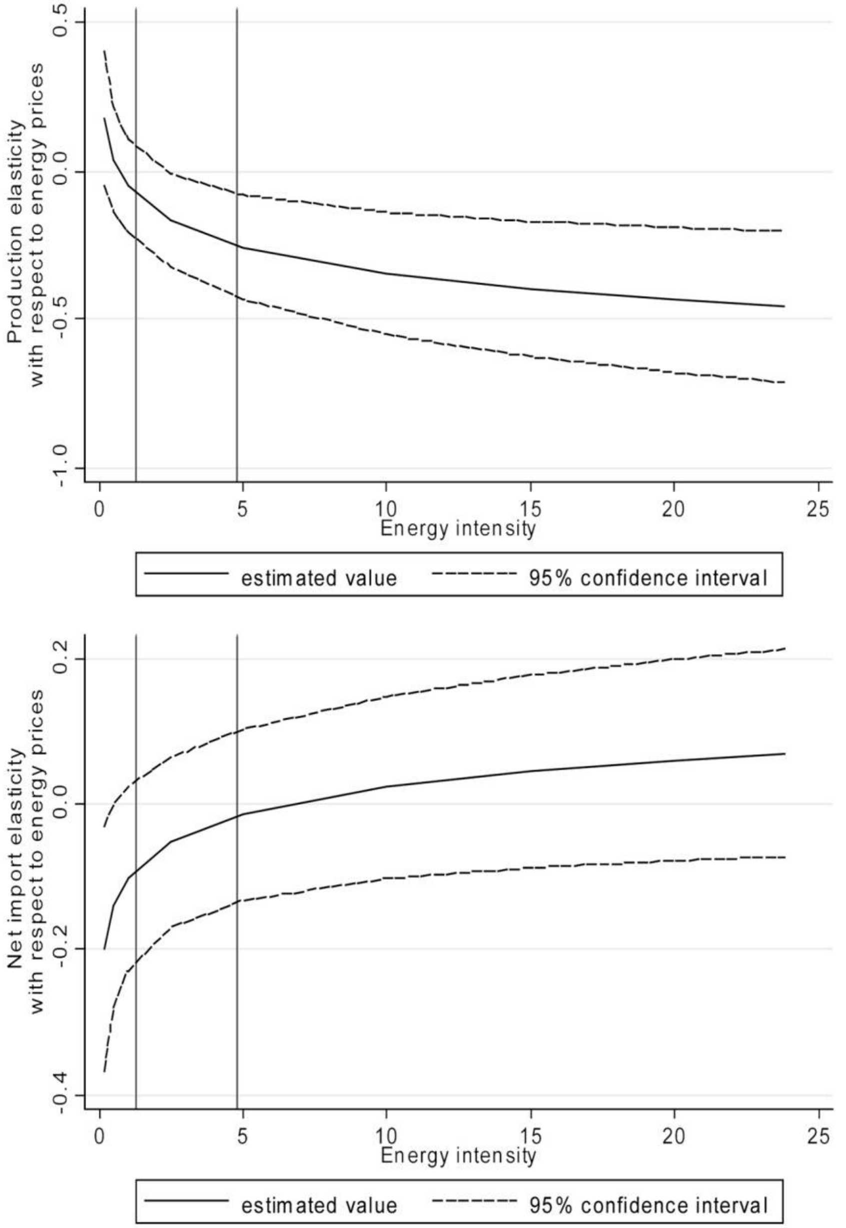

Figure 2. Estimated energy price elasticities as a function of energy intensity (%). Based on columns 2 and 5 in table 2. Note that the linear relationship in the log of energy intensity becomes nonlinear in levels. The vertical lines present the 50th and 90th percentiles of the manufacturing sector energy intensity distribution in 2009. The dashed lines present the 95% confidence interval.

Figure 3 presents what may be the most relevant results for the competitiveness debate, the fraction of domestic production impacts that are associated with increased net imports. The point estimates range from negative values for the median industry to 15% for the most energy intensive. Driven by the net import results, none of the estimates are statistically significant. The upper bound of the 95% confidence interval, however, is consistently about 50% for energy-intensive industries, suggesting a useful upper bound based on our model. In other words, for an industry with 15% energy intensity, we can observe that a 10% increase in energy prices would (*a*) lower production by about 4% and (*b*) raise net imports by about 0.4%. This suggests (*c*) that shifts to foreign production account for around 10% of the domestic decline and (*d*) a reasonable upper limit based on sampling variability is 50%. The share of production decline offset by rising net imports increases to about one-sixth for the most energy-intensive industries. We now turn to various empirical questions and address the robustness of these estimates.

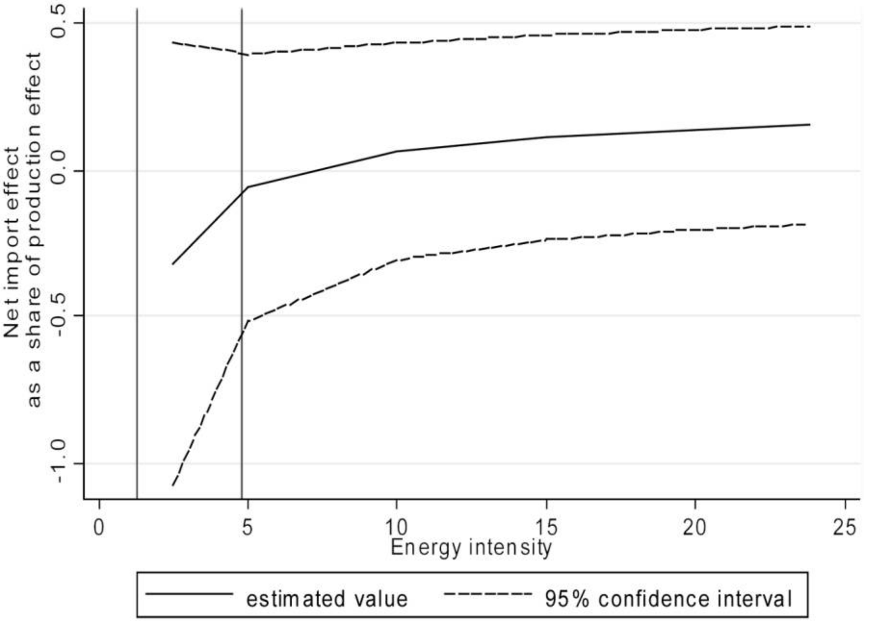

Figure 3. Net import effect as a share of production effect, versus energy intensity (%). Based the ratio of estimates in figure 2. The vertical lines present the 50th and 90th percentiles of the manufacturing sector energy intensity distribution. The dashed lines present the 95% confidence interval. Standard errors account for correlation across equations (by estimating the equations together, clustering the standard errors by SIC code across both equations, and using the delta method to compute the standard error of the ratio). Estimates for low energy intensity are not reported as the production effect tends to zero.

Robustness Checks

We undertook an array of robustness checks regarding data and model construction. Table 3 presents the robustness checks for the production model, and table 4 presents the robustness checks for the net imports model. In each table, column 1 represents our preferred specification for production (table 2, col. 2) and net imports (table 2, col. 5). Our first check, for both production and net imports, considers whether the results are affected by the missing observations associated with tariffs and human capital variables. As table 1 indicates, most of the data are relatively balanced, but we do not have human capital data before 1979 or tariff and trade data after 2005 (and after 1989 for 43 industries). Excluding these two variables permits us to estimate the production model over 1975–2009 (the use of lagged energy intensity precludes inclusion of 1974 data in the estimation) and the net imports model over 1975–2005. Those results, in column 2 of tables 3 and 4, are qualitatively similar to the preferred estimates in column 1. The coefficient estimate on the price-intensity interaction term in the production model is a statistically significant −0.192. This would increase the price elasticity of the most energy-intensive industries in our sample from about −0.4 in our preferred model to about −0.6 in this specification. The coefficient estimates for net imports suggest that net imports increase with energy intensity but still cannot be statistically distinguished from zero.

In our second check, we further streamline the specification by dropping the physical capital share and the oil price-energy intensity interaction. Column 3 presents qualitatively similar results for the energy price and energy price–energy intensity interaction coefficient estimates.

Our third check examines whether there is temporal dynamic pattern to the results we are estimating. In column 4 of tables 3 and 4, we estimate a model that includes two lagged values of energy prices as well as interactions of those lagged energy prices with our lagged energy intensity variable. If there is any change in the effect of energy prices on production or net imports over time, either positive or negative, we would see that in the estimated coefficients on lagged prices (tables 3 and 4 report the sum of the coefficient on those two lagged price variables and the two lagged price interactions). None of the individual coefficients is statistically significant, nor is the sum of each pair reported in the table, nor is a joint test of all four coefficients (p-values of 54% for the production regression and 49% for the net import regression). Similar results were obtained with regressions including anywhere from one to three lags.

Our fourth check employs lagged physical capital and human capital shares. To address concerns about endogeneity, we include 1-year lagged measures of these two variables in the models presented in column 5 of tables 3 and 4. Accounting for lagged capital shares results in no qualitative changes to the magnitudes or statistical significance of the energy price and price-intensity interaction coefficient estimates.

In our fifth check, we substitute year fixed effects for the two-digit industry-by-year fixed effects (col. 6). The two-digit-industry-by-year fixed effects are intended

Table 3. Robustness Checks—Production Model

	Preferred (1)	No HC/Tariff (2)	No Controls (3)	Lag Price (4)	Lag Shares (5)	No SIC2 × Year (6)	Unweighted (7)	Balanced (8)
$\ln(P_{i,t}^{energy})$	−.049	−.052	−.099	−.045	−.069	.199***	−.097	−.146**
	(.080)	(.080)	(.079)	(.060)	(.082)	(.071)	(.065)	(.069)
Sum of two lags				−.038				
				(.084)				
$\ln(P_{i,t}^{energy}) \times \ln(e_{i,t-1})$	−.129***	−.192***	−.099***	−.156***	−.121***	−.082*	−.156***	−.083*
	(.039)	(.044)	(.038)	(.049)	(.039)	(.044)	(.037)	(.044)
Sum of two lags				.050				
				(.036)				
$\ln(e_{i,t-1})$	−.379***	−.292***	−.147*	−.423***	−.382***	−.661***	−.273***	−.470***
	(.116)	(.094)	(.084)	(.132)	(.113)	(.218)	(.081)	(.119)
$\ln(P_t^{oil}) \times \ln(e_{i,t-1})$	.117***	.123***		.115***	.114***	.147***	.119***	.103***
	(.039)	(.034)		(.040)	(.036)	(.041)	(.026)	(.036)
Tariff (average rate)	−.016***			−.016***	−.016***	−.014**	−.012***	−.015***
	(.005)			(.005)	(.005)	(.005)	(.004)	(.005)
Physical capital	1.822***	1.165***		1.703***		1.538***	1.250***	1.434***
	(.389)	(.245)		(.375)		(.377)	(.331)	(.277)
Human capital	2.182***			1.939***		1.443**	1.086	1.513***
	(.770)			(.745)		(.666)	(.798)	(.512)
N	10,569	15,650	15,650	10,301	10,201	10,569	10,569	12,069
R^2	.560	.552	.525	.562	.550	.331	.382	.523

Note.—Heteroskedasticity robust standard errors in parentheses. See note to table 2. The models in columns 2 and 3 employ a 1975–2009 sample. The model in column 6 replaces two-digit-SIC-by-year effects with year effects. The model in column 7 is unweighted. The model in column 8 linearly interpolates all missing data to create a balanced panel of 447 industries × 27 years. HC = human capital.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

Table 4. Robustness Checks—Net Import Model

	Preferred (1)	No HC/Tariff (2)	No Controls (3)	Lag Price (4)	Lag Shares (5)	No SIC2 × Year (6)	Unweighted (7)	Balanced (8)	Alt. Imports (9)	Imports (10)	Exports (11)
$\ln(P_{i,t}^{energy})$	−.103	−.096	−.090	−.070	−.109	−.241***	−.346**	−.052	−.077	−.045	−.037
	(.064)	(.058)	(.056)	(.050)	(.068)	(.077)	(.169)	(.044)	(.052)	(.073)	(.028)
Sum of two lags				−.080							
				(.063)							
$\ln(P_{i,t}^{energy}) \times \ln(e_{i,t-1})$	.054**	.030*	.028*	.040*	.061***	.054**	.158**	.047***	.029	.057**	−.003
	(.021)	(.016)	(.015)	(.024)	(.023)	(.027)	(.069)	(.018)	(.018)	(.024)	(.010)
Sum of two lags				.027							
				(.023)							
$\ln(e_{i,t-1})$	−.091*	−.033	−.029	−.114*	−.111*	−.173***	−.261	−.055	−.055	−.019	−.052*
	(.052)	(.042)	(.035)	(.066)	(.057)	(.052)	(.162)	(.044)	(.055)	(.044)	(.031)
$\ln(P_t^{oil}) \times \ln(e_{i,t-1})$	.000	−.003		−.001	−.003	.019	.057*	−.006	−.010	−.018*	.009
	(.012)	(.013)		(.014)	(.011)	(.012)	(.033)	(.011)	(.015)	(.010)	(.007)
Tariff (average rate)	.003			.003	.003	.013**	.001	.006	.002	.002	.003**
	(.004)			(.004)	(.004)	(.005)	(.010)	(.004)	(.003)	(.005)	(.001)
Physical capital	−.033	−.148		−.051		.011	−.078	−.137	−.132	−.258	−.010
	(.286)	(.173)		(.287)		(.210)	(.750)	(.199)	(.151)	(.273)	(.067)
Human capital	.363			.345		.791**	2.097	−.061	−.230	.130	−.104
	(.573)			(.575)		(.350)	(1.472)	(.336)	(.367)	(.482)	(.164)
N	10,569	12,740	12,743	10,301	10,204	10,569	10,569	12,069	11,020	11,017	11,017
R^2	.249	.247	.247	.251	.248	.048	.260	.230	.192	.271	.249

Note.—Heteroskedasticity robust standard errors in parentheses. See note to table 2. The models in columns 2 and 3 employ a 1975–2009 sample. The model in column 6 replaces two-digit-SIC-by-year effects with year effects. The model in column 7 is unweighted. The model in column 8 linearly interpolates all missing data to create a balanced panel of 447 industries × 27 years. HC = human capital.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

to control for (two-digit) industry time trends that might otherwise confound estimation. By omitting these, we implement a more restrictive model (year effects that do not vary by industry) but increase the remaining price variation used to estimate the elasticities of interest. In doing so, we find that production still declines as energy intensity increases—the price-intensity interaction terms have statistically significant coefficient estimates—but the elasticity function is positive for a large fraction of the range of energy intensity (e.g., those industries where energy intensity < 10%). Likewise, for the net imports specification, we observe the same relationship with respect to energy intensity as with our preferred specification, although the change in magnitudes suggests that a larger fraction of the sample of industries experience negative net import changes. These results are consistent with the idea that there are long-term trends where industrial activity and energy prices are rising together in some areas, hence the more positive association on average (negative for net imports), but this is unrelated to the pattern of energy intensity, which still finds a more negative effect (positive for net imports) for more energy-intensive industries.

In the sixth check, we estimate our preferred specification without regression weights. Regression weights based on the value of shipments are used partly to capture the idea that in our simulations (e.g., table 5), we weight based on value of shipments to construct both an overall industry average and averages for various subgroups of industries. Regression weights also deal with an empirical problem that net import values can be explosive when the denominator, value of shipments, is small. This weighting scheme effectively downweights those observations so they do not dominate the regression (which otherwise requires censoring or robust regression).[8]

For the production model (table 3, col. 7), we again find a statistically significant estimate on the price-intensity interaction term, and the magnitudes of the price and interaction coefficient estimates are larger. As a result, an even larger fraction of the sample of industries—more than 94%—have energy intensities associated with a negative elasticity with respect to energy prices. The elasticity for the industry with the median energy intensity is about −0.14 and the elasticity exceeds −0.55 in magnitude for the most energy-intensive industries. For the net imports model (table 4, col. 7), the price and price-intensity interaction coefficient estimates are each statistically significant and larger than in the preferred specification. The relationship continues to show how net imports increase with energy intensity and the elasticity is about 0.13 for the most energy-intensive industries. The point estimate for those industries with low energy intensity, however, is negative and statistically significant—reflecting sensitivity to a small number of relatively extreme net import values.

In our seventh check, we address concerns about an unbalanced sample by imputing values for missing observations to construct a balanced sample. For all var-

8. We thank an anonymous referee for this suggestion.

iables, we impute values for missing observations via linear interpolation of nearest observations.[9] The results for the balanced with interpolated observations sample in column 8 of tables 3 and 4 are similar to the preferred results for both models.

In addition, table 4 includes three net imports-specific robustness checks. We reran the net imports models using average production as opposed to lagged production as the denominator (table 4, col. 9). Endogeneity concerns motivated our use of lagged rather than current production, and one might worry that persistent errors would make even this lagged approach problematic. Average production over 25 years is unlikely to be as sensitive—but can be increasingly irrelevant for industries that have undergone significant changes. In any case, this does not qualitatively change the magnitudes or statistical significance of the coefficient estimates relative to the preferred specification.

Finally, we estimate the competitiveness model with gross imports (table 4, col. 10) and the negative of gross exports (table 4, col. 11). We find a very similar relationship—in magnitudes and statistical significance—in the gross imports model as in the net imports model. The gross exports model yields small and statistically insignificant coefficient estimates on price and price interacted with lagged energy intensity.

Summary

In summary, our preferred models suggest a statistically significant effect of higher energy prices on domestic production. Our best estimate is an elasticity of −0.08 for the industry with the median energy intensity of 1.5%, rising in excess of −0.4 for the most energy-intensive industries, as reflected in figure 2. We do not find a statistically significant increase in net imports, however, suggesting that the production decline primarily reflects a decline in domestic consumption. Our best estimate is a negative elasticity for the least energy-intensive industry (i.e., a decrease in net imports as domestic energy prices rise) rising to 0.07 for the most energy-intensive industry. This means that for the most energy-intensive firms, we estimate that one-sixth of the reduced production arising from higher domestic energy prices will be offset by increased net imports, with a 95% confidence interval being as high as 50%.

3. SIMULATION OF NEAR-TERM EFFECTS OF A CO_2 MITIGATION POLICY

We can use these statistically estimated relationships to simulate the effects of a unilateral US climate change policy. In particular, we illustrate the potential manufacturing sector competitiveness impacts of an economy-wide $15 per ton CO_2 price. This carbon price is similar to allowance prices expected at the start of cap-and-trade

9. We thank an anonymous referee for this suggestion.

programs proposed in recent legislation, including US EPA's (2009) estimate of a \$13 per ton CO_2 price under the Waxman-Markey Bill (H.R. 2454, 111th Congress), US EPA's (2010) estimate of a \$17 per ton CO_2 price under the American Power Act (draft legislation from Senators Kerry and Lieberman) as well as the first-year carbon tax of \$15 per ton CO_2 in a 2009 Republican-sponsored carbon tax bill (H.R. 2380, 111th Congress).[10] The \$15 per ton CO_2 price is also generally consistent with state-level efforts, ongoing in California cap and trade (with allowance prices averaging \$12/tCO_2 in 2014) and what is expected for the power sector under the proposed Clean Power Plan (US EPA 2014).

Based on the US Energy Information Administration (US EIA 2013) modeling of an economy-wide cap-and-trade program, a \$15 per ton CO_2 price would increase industrial sector energy prices by about 11%, which is slightly larger than a one standard deviation increase in energy prices in our sample.[11] Based on these estimated model parameters, this energy price increase then drives the domestic production and competitiveness impacts in our simulation.

We multiply the elasticity estimates in figure 2 from our preferred model of net import share by 11% to obtain the estimated competitiveness effects shown in the top panel of figure 4. Along with the estimated domestic production effect, shown in the bottom panel, these estimates are exactly a rescaled version of figure 2. We see a net import effect of between negative 2 and (positive) 1% while the production effect is on the order of (negative) 2%–4% for most industries but rises to more than (negative) 4% for the most energy-intensive industries.

Table 5 summarizes the results in figure 4 for all manufacturing and for several of the most energy-intensive industries, with the results weighted by industry-specific value of shipments (cols. 3 and 5).[12] The energy-intensive industries of iron and steel, aluminum, pulp and paper, cement, glass, and industrial chemicals would bear total percentage declines in domestic production, on the order of 3%–5%, in excess of the manufacturing sector average of 1.5%. Most of the lower domestic production appar-

10. The simulation focuses only on carbon dioxide emissions from fossil fuels. Since this represents 98% of all carbon dioxide emissions, and more than 80% of all greenhouse gas emissions in the United States, this should serve as a sufficient simulation of the impact of climate policy on US manufacturing industries' competitiveness. The key exception may be the cement industry, which has substantial process emissions of carbon dioxide.

11. From table 1, the standard deviation of logged energy prices after removing industry fixed effects and two-digit SIC-by-year fixed effects is 0.08 or 8%. We could examine larger effects, but that would involve extrapolating impacts for price changes beyond the scope of this analysis since it would reflect an out-of-sample prediction.

12. In constructing the group aggregates, we estimate each of the component-industry percentage change based on that industry's energy intensity, and then add up these changes based on the component-industry's share of domestic production within the industry group.

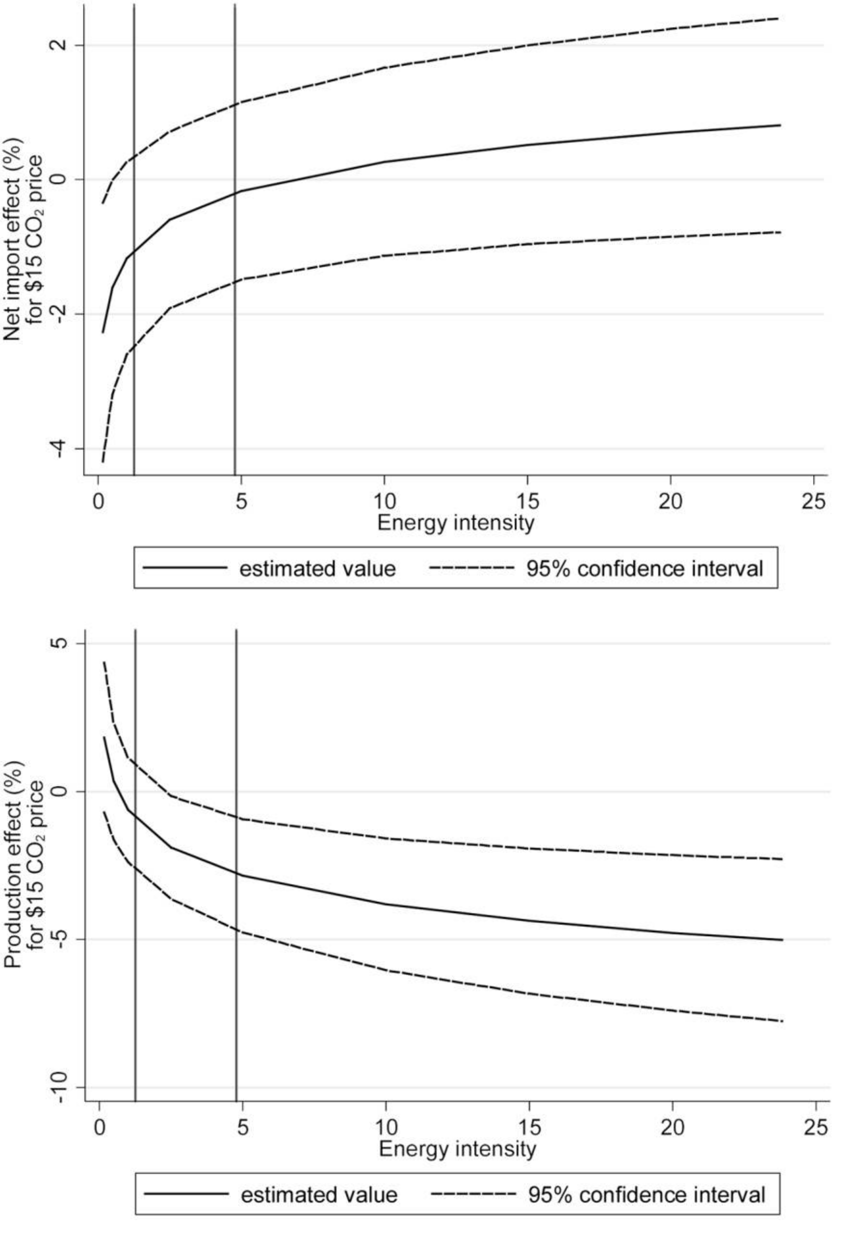

Figure 4. Estimated energy price effects on net imports and production for \$15 CO_2 price as a function of energy intensity. Based on columns 2 and 5 in table 2 and an 11% increase in energy prices. Note that the linear relationship in the log of energy intensity becomes nonlinear in levels. The vertical lines present the 50th and 90th percentiles of the manufacturing sector energy intensity distribution in 2009. The dashed lines present the 95% confidence interval.

Table 5. Predicted Impacts of a $15/ton CO_2 Price on Various Manufacturing Sectors

Industry	Energy Intensity (%) (1)	Production-Energy Elasticity (2)	Production Effect (%) (3)	Net Import Elasticity (4)	Net Import Effect (%) (5)	ΔNI as a % of Δ Production (6)
Iron and steel	5.39	−.27***	−2.99	−.01	−.13	−.04
		(.09)	(1.03)	(.06)	(.68)	(.23)
Chemicals	10.47	−.35***	−3.95	.02	.28	.07
		(.11)	(1.20)	(.06)	(.72)	(.19)
Paper	8.96	−.33***	−3.73	.02	.18	.05
		(.10)	(1.15)	(.06)	(.71)	(.19)
Aluminum	23.51	−.46***	−5.12	.07	.77	.15
		(.13)	(1.46)	(.07)	(.82)	(.17)
Cement	18.00	−.42***	−4.74	.05	.61	.13
		(.12)	(1.37)	(.07)	(.78)	(.18)
Bulk glass	16.99	−.41***	−4.65	.05	.57	.12
		(.12)	(1.35)	(.07)	(.77)	(.18)
Industry average	1.97	−.14*	−1.53	−.07	−.75	−.49
		(.08)	(.88)	(.06)	(.68)	(.53)

Note.—Columns 2 and 4 reflect a linear combination of the estimated logged energy price coefficients from columns 2 and 5 in table 2, based on the energy intensity in column 1 (measured in 2009 for each industry). These follow directly from figure 2. Columns 3 and 5 convert elasticities into changes in production and net imports, expressed as a share of production, based on an estimated carbon dioxide price of $15/ton. The $15/ton effect is translated into an 11% increase in average industrial energy prices predicted under a carbon-pricing policy in US EIA (2013), using a fuel-consumption weighted average. Column 6 shows the net import effect (5) as a share of the overall supply effect (3) and is taken directly from figure 3 (see notes for calculation of standard errors). Chemicals includes industrial inorganic chemicals, SIC codes 2812–2819. Paper includes pulp, paper, and paperboard mills, SIC codes 2611, 2621, and 2631. Iron and steel includes SIC codes 3312, 3321–3325. Aluminum includes primary production, SIC code 3334. Cement includes hydraulic cement, SIC code 3241. Bulk glass includes flat glass, SIC code 3211. For multi-industry aggregates, results are weighted by the average value of shipments among constituent four-digit SIC industries.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

ently reflects lower demand, however, not an influx of net imports; the net import effect ranges from −0.1 to 0.8% for these energy-intensive industries. That is, in these industries no more than about one-sixth of the decline in domestic production results from an increase in net imports (col. 6). If we consider a 95% confidence interval for this ratio, it might be as high as 50%.

Given the empirical model's structure that yields common production and net import elasticities with respect to energy prices for all industries with comparable energy intensity, the simulation produces similar outcomes for industries with similar energy intensity. Therefore, we cannot rule out that some individual industries with a particular energy intensity may face a larger or smaller impact than the average that we calculate.

4. POLICY IMPLICATIONS AND FURTHER RESEARCH

These results suggest that consumers of energy-intensive goods do not respond to higher energy prices by proportionally consuming more imports. To a large part, they economize on their use of these higher-priced manufactured goods, perhaps by using less of the good in the manufacture of their finished products or by substituting with other, less energy-intensive materials. This suggests that the imported versions of domestically produced goods may be imperfect substitutes. Such imports may represent different products, or it may be that other determinants of trade flows—such as transport costs, tariffs, and so forth—may limit the substitution possibilities. Quantitatively, competitiveness effects are less than 1% of production, even among energy-intensive industries, for the carbon dioxide prices that we examined. A 1% change in production due to carbon-pricing induced competitiveness impacts is smaller than the annual fluctuations in production, whose standard deviation during our sample period ranged from 10% to 15% for energy-intensive industries. Compared to the overall effect on production from proposed policies, this competitiveness effect still counts for roughly one-sixth of the production effect among energy-intensive domestic suppliers.

Based on our findings, attempting to "protect" energy-intensive US manufacturing firms from international competitive pressures through various policies may have only a limited impact on these firms. The estimated competitiveness impacts, while fairly modest at $15 per ton CO_2, suggest the need to target policies to those most likely to face adverse impacts, such as some narrowly defined industries that may face competitive pressures from abroad as their energy costs rise with a greenhouse gas mitigation policy. Indeed, given the magnitude of the competitiveness impacts on climate policy in our simulation, the potential economic and diplomatic costs of such policies may outweigh the benefits and justify no action.

Regardless, energy-intensive firms operating under the EU Emission Trading Scheme (ETS), a CO_2 cap-and-trade program, have lobbied extensively to receive free allowances in the post-2012 ETS. Similar firms in the United States have echoed this request as they lobbied Congress during its deliberations of a US cap-and-trade program in 2009 and 2010 (see Interagency Competitiveness Analysis Team 2009). The estimated competitiveness impacts in this analysis could provide a basis for the amount of the gratis allowance allocation necessary to offset output losses associated with a reduced competitive position under climate policy. For example, if primary aluminum production declines 0.8% through competitiveness impacts (see table 5), then the government could grant free allowances equal in value to 0.8% of their output in order to secure broader political support for the cap-and-trade program.[13]

There are limitations to these estimates. First, given the historical experience represented in the data used to estimate our model, we cannot simulate the impacts of significantly higher CO_2 prices.[14] Second, our estimates represent near-term impacts over one (or perhaps a few years). Arguably with more time to adjust, beyond the horizon of our robustness checks using several years of lagged prices, US industry could fare better (if they can reduce energy usage) or worse (if they have more time to move operations). US firms may respond differently to a change in long-run policy (and hence energy prices) than to the temporary variance in energy prices that serves as the basis for our identification. Third, even with our disaggregated data and flexible model, we still cannot flexibly capture all of the features relevant for every industry in every international trading situation. The effects for some firms and sectors could be different than what we have estimated. Fourth, in using historical data, we are necessarily assuming that the past is a useful guide to future behavior. To the extent that there have been or will be substantial institutional or market changes, this assumption is flawed.

Additional research can further inform our understanding of the competitiveness effects of climate policy. First, in 2005 the EU implemented a CO_2 cap-and-trade program covering the most energy-intensive manufacturing firms and the utility sector. A similar analysis could be undertaken of the manufacturing sector in Europe, and the simulated results could be compared with realized outcomes under the EU ETS. Second, as emission-intensive firms shed some capital and labor under climate policy, emission-lean firms may benefit by absorbing some of these factors. While some proponents of climate policy have made anecdotal claims about economic winners under CO_2 regulation, a rigorous econometric analysis of industries in and beyond manufacturing could explore whether the general equilibrium capital and labor effects dominate the modest burdens emission-intensive firms bear under climate policy. It may be especially interesting to also consider how a sectoral (as opposed to

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13. This is analogous to Bovenberg and Goulder's (2001) work showing the magnitude of free allowances necessary to fully compensate firms for the costs of climate policy. Our estimates would represent a fraction of Bovenberg and Goulder's since these would only offset losses associated with increased net imports and not the direct costs of modifying capital to mitigate emissions. And, while such an allocation might address distributional impact, it will not avoid the underlying problem of some emissions reductions in the United States being thwarted by shifts in production overseas.

14. It is important to note that our analysis identifies the effect of energy prices on impact and competitiveness measures after controlling for economy-wide factors. It is the residual variation after accounting for economy-wide energy price shocks that drives our results.

economy-wide) emission mitigation policy affects the allocation of capital and labor in the US economy among regulated and nonregulated sectors. This could complement one of the main findings of this work that the majority of the decline in domestic manufacturing production results from apparent declines in domestic consumption.

DATA APPENDIX

Value of shipments: We use the SIC-87 classification version of the NBER-CES Manufacturing Industry Database. This provides value of shipments data for 459 industries over the 1958–2009 period measured in millions of dollars. www.nber.org/data/nberces5809.html.

Net imports: We use Peter Schott's public database on SIC-87-level trade data. This provides gross imports and gross exports data for 405 industries over the 1972–2005 period and 448 industries over the 1972–89 period measured in millions of dollars. We constructed net imports from the gross imports and gross exports variables and then scaled this value by the lagged value of shipments measure. faculty.som.yale.edu/peterschott/sub_international.htm and faculty.som.yale.edu/peterschott/files/research/data/sic_naics_trade_20100504.pdf.

Energy price: The text describes the construction of the energy price measure. The source data include the four-digit SIC-87 electricity price described below; the US EIA State Energy Data System, which provides state-by-year industrial energy prices by fuel for 1970–2009; the US Energy Information Administration Manufacturing Energy Consumption Survey, which provides annual fuel consumption by two-digit SIC-87 manufacturing industry and fuel for 1974–90 and 1991, 1994, 1998, 2002, 2006, and 2010; the Bureau of Economic Analysis (BEA), which provides gross state product with a data classification scheme very similar to the two-digit SIC-87 over our sample period. For post-1997 data, we merged two BEA categories (motor vehicles and other transport equipment) into one two-digit SIC industry, 37. Over this same time period, we employ nondurables output as a proxy for SIC-87 industry 21 (tobacco products) and industry 31 (leather and leather products), which are not reported separately in the BEA data sets. We convert our four-digit electricity prices to a dollars per million BTU basis (1¢/kWh = $293.297/MMBTU), to permit comparability with the fuel price data from the EIA State Energy Data System. www.eia.gov/state/seds/, www.eia.gov/consumption/manufacturing/index.cfm, and www.bea.gov/regional/downloadzip.cfm.

Electricity price: We use the Annual Survey of Manufactures to extract SIC-87 classified electricity expenditures and quantity of electricity consumed by industry for 1974–2001. Wayne Gray provided the same data from the Annual Survey of Manufactures for 1978 and 1997–2009 (personal communications, August 22, 2007, and June 23, 2012). We construct the average electricity price as the ratio of expenditure to quantity.

Energy intensity: We use the SIC-87 classification version of the NBER-CES Manufacturing Industry Database. This provides the cost of electricity and fuels in millions of dollars. We construct energy intensity as the ratio of this cost to the value of shipments and employ the lagged value of this in the empirical models. www.nber.org/data/nberces5809.html.

Oil price: We use the real ($2005) composite price of crude refiner acquisition costs, from EIA's Annual Energy Review 2011, table 5.21. http://www.eia.gov/totalenergy/data/annual/xls/stb0521.xls.

Tariffs: We use Peter Schott's public database on SIC-87-level trade data. This provides gross imports and duties charged data measured in millions of dollars. We constructed tariffs as 100 × (duties/gross imports). See Ederington et al. (2005) for further details on the construction of this variable. faculty.som.yale.edu/peterschott/sub_international.htm and faculty.som.yale.edu/peterschott/files/research/data/sic_naics_trade_20100504.pdf.

Physical capital share: We use the SIC-87 classification version of the NBER-CES Manufacturing Industry Database. We employ the total payroll variable, measured in millions of dollars, and the total value added variable, also measured in millions of dollars, to construct the physical capital share as: 1 − payroll/value-added. See Ederington et al. (2005) for further details on the construction of this variable. www.nber.org/data/nberces5809.html.

Human capital share: We use the SIC-87 classification version of the NBER-CES Manufacturing Industry Database and the Current Population Survey Multiple Outgoing Rotation Group data provided by the NBER. We employ the total payroll, total value added, and total employment (measured in 1,000s) variables from the NBER-CES database. We estimate from the CPS MORG the industry-specific compensation (based on reported weekly earnings) to unskilled labor (education less than a high school diploma), which are converted into SIC87 based on NBER concordance files from CPS Census-based industry classifications to SIC87. We construct human capital share as: payroll − (unskilled-compensation × employment)/value-added. See Ederington et al. (2005) for further details on the construction of this variable. www.nber.org/data/nberces5809.html and www.nber.org/cps/.

GDP implicit price deflator: We convert the nominal values of value of shipments, net imports, energy prices, electricity prices, and oil prices into 2009 dollars using the GDP implicit price deflator published in the 2014 economic report of the president (CEA 2014).

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