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# ENERGY PRICES, PASS-THROUGH, AND INCIDENCE IN U.S. MANUFACTURING

By

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# Energy Prices, Pass-Through, and Incidence in U.S. Manufacturing*

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**Abstract**

This paper studies how increases in energy input costs for production are split between consumers and producers via changes in product prices (i.e., pass-through). We show that in markets characterized by imperfect competition, marginal cost pass-through, a demand elasticity, and a price-cost markup are sufficient to characterize the relative change in welfare between producers and consumers due to a change in input costs. We find that increases in energy prices lead to higher plant-level marginal costs and output prices but lower markups. This suggests that marginal cost pass-through is incomplete, with estimates centered around 0.7. Our confidence intervals reject both zero pass-through and complete pass-through. We find heterogeneous incidence of changes in input prices across industries, with consumers bearing a smaller share of the burden than standards methods suggest.
JEL: L11, H22, H23, Q40, Q54

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# 1 Introduction

Existing and proposed policies designed to address future climate change implicitly or explicitly place a price on carbon dioxide emissions. Pricing carbon emissions, by design, will make fossil-fuel based energy consumption more expensive. This has led to the dual concern by policymakers that increased energy costs will not only make industries that rely on these energy inputs less competitive but also make consumers of industry products worse off due to higher output prices. Despite these concerns, relatively little is known about how increasing energy costs in U.S. manufacturing affect plant-level operating costs, the output prices that their consumers face, and ultimately the relative welfare of consumers and producers.

This paper uses administrative data from the Census Bureau's Census of Manufactures to study how changes in energy input costs for production of manufactured goods differentially affect producers relative to consumers via changes in manufacturing output prices. We use the relationships between energy prices, marginal costs, and output prices to quantify how energy price-induced changes in marginal cost affect output prices, i.e., to estimate pass-through. We show how this pass-through rate is useful for describing the ways in which cost increases for productive inputs such as energy are differentially split between producers and consumers. Formally, we generalize recent theories of incidence under imperfect competition to derive a sufficient statistic representation for the incidence of producer input taxes that depends on three parameters that we estimate: marginal cost pass-through, a product demand elasticity, and a price-cost markup. The goal of this paper is to use these statistics to characterize the change in consumer relative to producer surplus associated with changes in input prices (i.e., incidence).

To help frame ideas, consider a simple example of a manufacturing plant that faces increases in energy costs either due to a tax levied on carbon emissions or from external factors that increase the price of energy (e.g., oil supply disruptions arising from political events in oil-producing countries). Economists have long recognized that the incidence of a tax, defined in this paper as the impact of a tax on the welfare of producers relative to consumers, is independent of who physically writes the check to pay it (Jenkin, 1872). The same principle applies for shocks to production costs. The reason is that changes in production costs due to taxes or other market forces lead to changes in product prices and quantities. In this example, a carbon tax levied at the level of a manufacturing plant only physically applies to the plant since the government directly collects tax revenue from the plant. If the tax causes plants to increase prices, then the tax burden will shift forward to consumers. Pass-through describes the extent to which shocks to input costs change product prices, and this manufacturing plant example suggests why pass-through rates play an important role in determining tax incidence—because pass-through describes a means by which the party which physically pays a tax can transmit the effects of that tax to others.

The paper proceeds in four steps. We begin by formalizing the incidence of energy price changes for industries characterized by imperfect competition. The existing theory of incidence under imperfect competition focuses primarily on the role of output taxes. The incidence of input price changes can differ from the incidence of output taxes because in response to a change in input

prices, firms can substitute across different inputs. We extend the recent results from Weyl and Fabinger (2013) to derive a sufficient statistic expression for incidence of input taxes.

Second, we use plant-level data on input and output quantities and prices to estimate plant-level markups and marginal costs. We recover markups by combining plant-level production data with assumptions on firm cost minimization. As originally shown by Hall (1986) and further developed by De Loecker and Warzynski (2012), a firm's first-order condition implies that the plant's multiplicative markup (i.e., its price divided by its marginal cost) equals the output elasticity of a variable input like energy or materials divided by the revenue share of that input.[1] An intuition for why this approach identifies markups is that in an imperfectly competitive market, input growth must be associated with disproportionate revenue growth. Thus, the more that revenue increases with respect to input usage, the higher the plant's markup. We recover output elasticities by estimating production functions using methods proposed by Ackerberg, Caves, and Frazer (2015). Revenue shares of variable inputs come directly from the plant-level production data on variable input costs and revenues. We construct output prices by dividing a plant's revenue by its output quantity. With information on plant-level markups and output prices, we recover marginal costs as prices divided by markups.

The third part of the paper relates each of these three outcomes (i.e., output prices, markups, and marginal costs) to two separate measures of energy costs, via linear regression. Our first measure of energy costs relies on the segmented nature of the U.S. electricity market. U.S. electricity prices vary over time and across space depending on the types of fuels used for electricity generation in a region. We use this feature to construct variation in local electricity prices that is designed to be unrelated to changes in local demand for energy. Specifically, we calculate the share of a state's electricity that is generated by coal, petroleum, and natural gas, and we interact these (lagged) generation shares with national changes in the prices of these fuels. For example, when coal prices rise, industrial electricity prices disproportionately rise in areas where coal-fired power plants generate a large share of electricity. These interactions are strong predictors of variation in local electricity prices. The second source of variation in energy input prices stems from the fact that manufacturing industries rely on a range of different energy inputs into the production process. Thus, industries whose production process mainly uses coal will see energy costs increase more when coal prices rise, and industries that rely more on natural gas will see energy costs increase more when the price of natural gas rises. We show how this variation in fuel or electricity input usage across industries interacted with national, industrial fuel and electricity prices differentially affect plant-level markups, marginal costs, and output prices.

The last part of the paper uses the relationships between energy prices and marginal costs to estimate the pass-through of marginal costs to output prices. We estimate pass-through by regressing observed plant-level output prices on estimated plant-level marginal costs. This regression instruments for changes in marginal costs using the two different sources of energy price variation

[1] The output elasticity is defined as the change in a plant's physical output due to a change in a variable input like materials; the revenue share of a variable input like materials is defined as the plant's expenditure on that variable input divided by the plant's total revenue.

discussed above. Using shocks to energy costs as instruments for marginal cost delivers a local average treatment effect for how energy price-induced changes in marginal cost are passed through to product prices. We conclude by combining information on marginal cost pass-through with markups and demand elasticities to characterize incidence separately by industry.

We apply this approach to a set of single-product plants in six homogeneous manufacturing industries for which the Census Bureau collects quantity output data: boxes, bread, cement, concrete, gasoline refining, and plywood. While our methodology can be applied to any industry for which we observe output price data and where we assume that firms minimize costs, we focus on these six industries since these are the industries in which the Census collects price data and since their fairly homogeneous products alleviate concerns about unobserved quality differentiation reflected in prices.[2,3]

The paper has four main findings. First, we estimate that plant-level markups above marginal cost are ten to fifty percent in most industries, though much larger in the cement industry. Cement is also the only industry we study which appears to have substantial increasing returns to scale. Second, we find that increases in energy prices lead to an increase in plant-level marginal costs and output prices but a decrease in markups. For example, a 10 percent increase in the price of natural gas used for in-state electricity generation increases output prices in the industries we study by about 0.6 percent, increases marginal costs by about 0.7 percent, and decreases markups by about 0.1 percent. Third, we estimate that a 1 dollar increase in marginal costs due to higher energy prices translates into a 70 cent increase in output prices for the average firm in our sample. This suggests that manufacturing firms in the industries we study bear at least part of the economic costs of energy price shocks. We observe higher pass-through rates (exceeding one) in industries with inelastic demand and/or relatively high markups, and lower pass-through rates in industries with elastic demand and/or relatively low markups. Pass-through is most substantial in the industry with both the highest markups and the greatest evidence of increasing returns to scale, cement. Finally, we discuss implications for incidence of energy price shocks and carbon taxes for U.S. manufacturing. Most of the studied industries show consumers bearing a majority of the burden, though there remains a substantial amount of cross-industry heterogeneity in the relative burden of consumers versus producers. These cross-industry differences in incidence are explained by cross-industry differences in pass-through, demand elasticities, and markups. Standard methods for studying tax incidence, especially with respect to carbon taxes, assume perfect competition and complete pass-through. In all industries in our sample, we find that consumers bear a smaller share of the burden than these assumptions would suggest.

This paper contributes to a growing literature on the incidence of changes in input costs. The

[2] A few additional industries produce homogenous products and have Census-collected price/quantity data. However, much of the quantity data in these industries has been imputed, and the remaining, non-imputed sample sizes preclude the estimation of production functions.

[3] In theory, we could explore these questions for multi-product plants (e.g., De Loecker, Goldberg, Khandelwal, and Pavcnik (Forthcoming)). In practice, since we measure output prices as the ratio of output revenue to output quantity, we can only study the fairly few U.S. industries that report quantity data. Those industries also happen to produce a single, homogeneous product(Foster, Haltiwanger, and Syverson, 2008).

main contribution of this paper is to develop an approach to analyze the incidence of changes in input costs while accounting simultaneously for four features that the existing literature considers in isolation or not at all – incomplete pass-through, imperfect competition, factor substitution, and multiple industries. Below we briefly discuss each of these features of the literature and the reasons that they might matter for characterizing incidence.

An important literature in public finance studies the incidence of carbon taxes and energy prices, typically by using general equilibrium models based on input-output matrices and detailed expenditure data (Bovenberg and Goulder, 2001; Fullerton and Heutel, 2007; Hassett, Mathur, and Metcalf, 2009; Grainger and Kolstad, 2010; Fullerton and Heutel, 2010; Williams, Gordon, Burtraw, Carbone, and Morgenstern, 2014). These studies generally assume that firms engage in perfect competition and that the industry supply curve is infinitely elastic, which implies complete pass-through of energy input price changes to consumers. Often, these studies pair this complete pass-through assumption with data on consumer expenditures to calculate which consumers would be most affected. This paper departs from this literature by showing that imperfect competition and incomplete pass-through are common in U.S. manufacturing and have important implications for incidence. An example of why these departures matter is the conclusion of this literature that energy taxes are regressive. Estimates of the regressivity of energy taxes may look quite different if firm owners bear part of the burden associated with the increases in energy costs. A related benefit of our analysis is that some benefit-cost analysis depends on a pass-through rate, and our methodology provides data to enhance the accuracy of such analysis. For example, the USEPA (1995)'s analysis of a Clean Water Act standard regulation described two sets of possible costs to industry, one based on zero pass-through and another based on incomplete pass-through; allowing for incomplete pass-through decreased the predicted number of plant closures by half.

A growing body of research does suggest that welfare and incidence of environmental and energy policy may differ dramatically for imperfectly competitive industries (Buchanan, 1969; Barnett, 1980; Ryan, 2012; Fowlie, Reguant, and Ryan, 2016), but the empirical literature on imperfect competition in the context of environmental and energy policy typically studies a single industry (e.g., cement or electricity). Our finding that cement is an outlier from the other industries we study (in returns to scale, markups, and pass-through) underscores that these findings may be hard to generalize to other industries.

A separate but related literature at the intersection of public finance and industrial organization uses microdata to analyze the pass-through of gasoline taxes into retail gasoline or diesel prices (Doyle and Samphantharak, 2008; Marion and Muehlegger, 2011; Kopczuk, Mario, Muehlegger, and Slemrod, 2016) or European Union Emissions Trading System (ETS) allowance prices to electricity wholesale prices (Fabra and Reguant, 2014). These analyses typically account for only one productive input (e.g., coal prices) which makes the methodology difficult to generalize to most manufacturing industries which use multiple factors of production and hence where marginal costs are more difficult to observe. For example, Miller, Osborne, and Sheu (2015) analyze the pass-through of energy costs in a single manufacturing industry – cement – though assume a single

factor of production, which precludes factor substitution. In contrast to this existing literature, we develop an empirical methodology to measure incidence and pass-through for any industry in which we observe price data and where firms engage in cost minimizing behavior. The approach is flexible enough to allow for changes in energy prices that lead to factor substitution in production, and the approach is general enough to calculate incidence across a range of different market structures.

This paper is also related to a set of work analyzing how energy prices differentially affect industries in the United States. The literature on industry impacts of carbon policies is based largely on simulation modeling, although a number of statistical analyses also exist (e.g., Kahn and Mansur (2012) and Aldy and Pizer (2015)). The simulation analyses include both short-term partial equilibrium assessments as well as long-term computable general equilibrium (CGE) models.[4] Relative to existing empirical literature in this area, we examine heretofore unexplored outcomes such as how energy prices affect marginal costs, and markups. Relative to the existing simulation and CGE literature, we provide a framework and methodology for considering incidence that relies on arguably fewer modeling assumptions.[5] As a result, rather than assuming that cost pass-through is complete and that consumers bear 100 percent of the increased in energy costs, we empirically observe that consumers bear relatively less than the full burden of an energy input tax.

Lastly, this project relates to a substantial empirical literature on pass-through of costs other than energy prices. This literature explores the pass-through of input or output tariffs (De Loecker, Goldberg, Khandelwal, and Pavcnik, Forthcoming), exchange rates (Goldberg and Hellerstein, 2008; Gopinath, Gourinchas, Hsieh, and Li, 2011; Campa and Goldberg, 2005), sales taxes (Poterba, 1996; Marion and Muehlegger, 2011), healthcare capitation payments (Cabral, Geruso, and Mahoney, 2015; Duggan, Starc, and Vabson, 2014), and minimum wage laws (Harasztosi and Lindner, 2015). To the best of our knowledge, no literature estimates marginal cost pass-through in U.S. manufacturing, a parameter which is a necessary ingredient for characterizing the incidence of input taxes levied on U.S. manufacturers.

The rest of the paper proceeds as follows. Section 2 describes the role of energy in the output of U.S. manufacturing products. Section 3 describes a general theory of incidence that motivates our empirical analysis. Section 4 describes the data, and Section 5 describes the econometric setting. Section 6 presents results, and Section 7 concludes.

## 2 Energy and U.S. Manufacturing

A brief background on energy use in U.S. manufacturing may clarify this paper's analysis.[6] Manufacturing accounts for a large share of energy demand. Industrial energy consumption (which

[4] Ho, Morgenstern, and Shih (2008) review more than a dozen prior U.S. and European analyses using CGE models.

[5] Existing CGE frameworks must fully specify both the demand side and supply side of the economy as well as calibrate or estimate a set of demand elasticities and cross-price elasticities for each of the industries in the analysis. For example, the IGEM model (Goettle, Ho, Jorgenson, Slesnick, Wilcoxen, and EP-W, 2007), which has been used extensively by the US Environmental Protection Agency and other organizations, features over 2000 equations that jointly fit together to define an equilibrium in each period.

[6] Except where otherwise noted, this section describes data for 2010, the year of the most recent Manufacturing Energy Consumption Survey.

includes manufacturing along with agriculture, mining, and construction) accounts for about 30 percent of U.S. end-use energy consumption and also about 30 percent of end-use greenhouse gas emissions (EIA, 2015; USEPA, 2015). Energy is a limited direct cost for manufacturing on average, at about two percent of revenues for the entire manufacturing sector, though energy costs are much greater in some industries (Becker, Gray, and Marvakov, 2013). In alkali and chlorine manufacturing, cement, gasoline refining, lime manufacturing, and primary aluminum production, for example, energy costs (including energy that is physically formed into the manufactured product, or "feedstock") exceed 20 percent of revenues.

Manufacturing generally uses two categories of energy – electricity and primary fuels. Electricity's price per British thermal unit (BTU) is two to five times the mean price of other energy sources (EIA, 2010), partly because much of the raw fuel used to produce electricity is lost as heat. The main primary fuels used in manufacturing are oil, natural gas, and coal. About 75 percent of BTUs used for fuel in manufacturing come from natural gas, about 20 percent from coal, and the remainder from oil and assorted sources (EIA, 2010). Natural gas is increasingly common, partly because hydraulic fracturing decreased the domestic price of natural gas beginning around 2008 (see e.g., Hausman and Kellogg (2015)), though even in 1990, natural gas provided 75 percent of BTUs used for fuel.

Manufacturing plants use energy for four general tasks: boiler fuels (about 25 percent of BTUs), process production (40 percent), other on-site purposes (10 percent), and feedstock (25 percent). Boiler fuels mainly come from natural gas and coal and are used for combined heat-and power, cogeneration, or related purposes. Process production includes heating or cooling parts of the manufacturing product itself, driving manufacturing machines, or electro-chemical processes. Driving machines almost exclusively use electricity, but other process production tasks use a mix of natural gas, oil, and coal. Other on-site uses of energy include plant lighting, heating, cooling, ventilation, and onsite transportation. Industries differ in their use of fuels based on the prevailing production processes and regional availability of fuel inputs.

Energy is costly to store. Batteries are expensive enough that mass storage of electricity is economically infeasible, and most electricity is consumed at the instant it is generated. Most manufacturing plants obtain natural gas from distribution pipelines and do not store it on-site. Oil and coal can be stored, though their weight and bulk mean they are stored in limited quantities. In addition, industries differ in their use of different fuels based on the prevailing production processes and regional availability of fuel inputs.

Different energy sources also have different spatial market structures. Electricity prices vary both over time and space depending on the fuel mix, efficiency, and scheduling of electricity generating units. In the years we study (pre-1998), which precede deregulation, an electric utility had a monopoly over customers in its service territory, so the electricity prices an industrial customer faced depended heavily on the fuels used by the electric utility serving it. Utilities supply most electricity used in manufacturing, though additional electricity comes from non-utility generators

(e.g., merchant plants) and from on-site generation.[7] Crude oil is traded on a global market. Manufacturing plants generally buy distillate or residual fuel oil, which is processed by refineries. Lack of spatial integration in refinery markets introduces additional spatial variation in prices of these petroleum products that is mostly driven by idiosyncratic changes in local supply and demand.[8] Natural gas is transported by pipeline within the U.S. from producing to consuming regions. In the years we study, much natural gas was extracted in Texas and Louisiana, and natural gas prices increase with distance from those areas due to pipeline transportation costs. The price at the location where an interstate pipeline reaches a population center differs from the price that industrial plants pay for natural gas due to local distribution costs and to distributor markups. Coal is more costly than other fuels to transport, so coal prices vary more over space due to local market conditions.

This discussion should make clear that energy prices vary substantially, and they are an important input into the production process of many manufactured goods. The goal of this paper is to better understand how this temporal and spatial variation in energy prices affect both manufacturing producers and their consumers. The next section formalizes these relationships by describing a general theory of incidence in the context of imperfectly competitive product markets.

# 3 Theory of Incidence

The standard partial equilibrium theory of incidence under imperfect competition analyzes output taxes (Katz and Rosen, 1985; Stern, 1987; Weyl and Fabinger, 2013). We extend this literature to analyze changes in input costs, which for simplicity we describe as input taxes.[9] The difference is that firms must pay an output tax on every dollar of revenue but must only pay an input tax on each unit of the input purchased. Firms can substitute away from the taxed input.

We first describe incidence assuming firms are either perfectly competitive or have a monopoly. These polar cases illustrate the basic intuition for how incidence differs with market power. We then describe a more general setting where firms within an industry are characterized by arbitrary forms of imperfect competition. Finally, we discuss how the results for general forms of oligopoly differ when we assume that firms are symmetric versus where we allow firms to differ within an industry.

The following discussion and subsequent analysis is partial equilibrium. We make the assumption, consistent with most of the literature, that all goods outside the focal industry are supplied perfectly competitively, and thus that the welfare of producers arising from consumer substitution to these goods may be ignored.[10]

[7] Our empirical analysis counts on-site electricity generation as primary fuel consumption since in this case the data record the plant buying fuels rather than the plant buying electricity.

[8] Our analysis refrains from using local price variation in petroleum products to avoid confounding variation in energy prices with variation in local economic conditions.

[9] We abstract from the use of potential tax revenue.

[10] In principle, relaxing this assumption is possible but would require estimates of cross-price elasticities across industries, which are difficult to estimate. Future work could combine the insights from Goulder and Williams III (2003) to derive empirically implementable formulas for incidence in the presence of pre-existing distortions in other markets.

We begin with key definitions. Let $I$ denote the incidence of a marginal increase in the tax rate $\tau$, defined as the ratio of its effects on consumer and producer surplus (CS and PS):

$$I \equiv \frac{dCS/d\tau}{dPS/d\tau}$$

Incidence above one implies that consumers bear a majority of the welfare loss, while incidence below one implies that producers do. Let $\rho$ denote the pass-through rate of a tax, defined as the marginal change in the level of output prices $P$ due to a change in input tax rates:

$$\rho \equiv \frac{dP}{d\tau}$$

Let $\gamma$ denote the cost-shift rate, defined as the marginal effect of the input tax rate $\tau$ on marginal costs: $\gamma \equiv dMC/d\tau$. The cost-shift rate $\gamma$ can be less than or greater than one.

Given these definitions, we now turn to describe the key incidence results.[11] Perfect competition provides a useful baseline since its results are simple and intuitive. In perfectly competitive markets with input taxation, the pass-through rate and the cost shift rate fully characterize tax incidence. The incidence simply equals the pass-through rate divided by the cost shift rate minus the pass-through rate:

$$I^{Competitive} = \frac{\rho}{\gamma - \rho}$$

This result has an intuitive basis that stems directly from an application of the envelope theorem to the consumer and producer side of the market. A marginal increase in a tax decreases consumer surplus by the equilibrium quantity consumed, $Q^*$, times the change in consumer prices, $\rho$. A marginal increase in a tax decreases producer surplus by $Q^*$ times the change in producer prices relative to marginal costs, $\gamma - \rho$. Thus, the incidence of a tax in a competitive market equals the ratio of these two terms, $\rho/(\gamma - \rho)$. Describing the incidence of a tax in a perfectly competitive market only requires knowing the pass-through rate and the cost-shift rate, making pass-through and cost-shifting parameters "sufficient statistics" for incidence of changes in input costs.

Figure 1 illustrates incidence under perfect competition. Panel A shows a shift in marginal costs, $\gamma$, due to an input tax, and Panel B shows the levels of consumer and producer surpluses in the new equilibrium. As visualized, a small change in marginal costs causes consumer surplus to decrease by the change in prices, $\rho$, times the output quantity $Q^*$. Producers now receive an additional $\rho$ per unit sold, however this is offset by the change in additional production costs, $\gamma$. An output tax simplifies this analysis, as $\gamma = 1$, reflecting how an output tax cannot be avoided through input factor substitution.

Similar results are available for an input tax faced by a monopolist – the incidence of a tax

[11] We describe the incidence of infinitesimal changes in tax rates. Characterizing the incidence of discrete changes in tax rates requires integrating over changes in consumer and producer surplus from the initial tax rate to the new tax rate. The incidence of a discrete change in tax rates then depends on the average pass-through rate between the baseline and new tax rate, where the average is weighted by the quantities consumed at each tax rate (Weyl and Fabinger, 2013).

on an input for a monopolist is simply $I^{Monopoly} = \rho/\gamma$.[12] For any standard pass-through rate (greater than zero), consumers bear a greater share of the burden under perfect competition than under monopoly. Figure 2 illustrates incidence under monopoly with increasing marginal costs. The change in consumer surplus is identical to the perfect competition case, and equals the change in price $\rho$ times quantity $Q^*$. However, the change in producer surplus is entirely determined by the change in marginal costs $\gamma$, as the change in prices is offset by the additional change in quantity.

We now turn to the market structure more relevant to our empirical analysis – arbitrary forms of imperfect competition. We start by assuming all firms in the market are identical. Let $\epsilon_D \equiv -[dQ/dP][P/Q]$ denote the elasticity of demand. This elasticity describes price shocks and quantity decisions for an individual firm. Let $L \equiv (P-MC)/P$ denote the Lerner (1934) index, a measure of markups, which equals the gap between price and marginal cost, divided by price. In the presence of imperfect competition, the incidence of an input tax depends on four statistics: the pass-through rate $\rho$, the cost-shift rate $\gamma$, the Lerner index $L$, and the demand elasticity $\epsilon_D$. We also report bounds where monopoly and perfect competition represent polar extremes of possible incidence, and which do not depend on estimates of $L$ or $\epsilon_D$.

$$I = \frac{\rho}{\gamma - (1 - L\epsilon_D)\rho} \tag{1}$$

This incidence equation also has an intuitive explanation. The loss to consumers equals the change in product price, $\rho$. The loss to producers equals the change in marginal costs, $\gamma$, minus the change in product price, $\rho$. The firm's change in product prices depends on the term $1 - L\epsilon_D$.

Differentiating $I$ in equation (1) with respect to each of its arguments gives several interesting comparative statics. The share of the tax burden that consumers bear is decreasing in the cost-shift rate $\gamma$. Conceptually, a higher value of $\gamma$ means that a firm's marginal costs change relatively more with the tax rate, so that firms bear relatively more of the tax burden. Since $\gamma$ can be less than or greater than one, input taxes do not necessarily have greater or lower incidence than output taxes. Equation (1) also implies that increasing the Lerner index $L$ or demand elasticity $\epsilon_D$ while holding other parameters fixed decreases the consumer share of the tax burden. Finally, increasing the pass-through rate $\rho$ increases the consumer share of the tax burden, since pass-through is a means by which producers convey the tax burden to consumers.

When taking equation (1) to the data, we use a slightly simpler though analytically equivalent version. Recall that $\rho$ is the pass-through of the tax rate to product prices. Let $\rho_{MC}$ denote the pass-through of marginal costs to product prices, so $\rho_{MC} \equiv dP/dMC$. Dividing (1) through by $\gamma$ and using $\rho = \gamma\rho_{MC}$ gives

$$I = \frac{\rho_{MC}}{1 - (1 - L\epsilon_D)\rho_{MC}} \tag{2}$$

[12] The consumer side of the market is calculated in the same way as with perfect competition. The producer side of the market is derived by differentiating producer surplus with respect to the tax rate, then aggregating across firms (Weyl and Fabinger, 2013).

This second version requires estimating only three parameters: marginal cost pass-through $\rho_{MC}$, the Lerner index $L$, and the demand elasticity $\epsilon_D$.[13] In taking equation (2) to the data, we also report a measure of incidence which is slightly easier to interpret: the change in consumer surplus as a share of the total change in consumer and producer surplus, or $I/(1+I)$.

These expressions show that pass-through is a key ingredient in the calculation of incidence, but it is also useful to clarify what determines pass-through. In perfectly competitive markets, pass-through is a simple function of demand and supply elasticities $\epsilon_D$ and $\epsilon_S$:

$$\rho^{Competitive} = \frac{1}{1 + (\epsilon_D/\epsilon_S)}$$

This leads to the standard rule-of-thumb that the side of the market (producer or consumer) which is relatively more inelastic bears more of the tax burden. Under imperfect competition, pass-through depends not only on demand and supply elasticities but also the curvature of demand and market power.[14]

These results can be extended to the case of generalized imperfect competition, where firms are not symmetric. Consider the following statistics specific to firm $i$: pass-through $\rho_i \equiv dP_i/d\tau$, marginal cost pass-through $\rho_{MC,i} \equiv dP_i/dMC_i$, the demand elasticity $\epsilon_{D,i} \equiv -[dQ_i/dP_i][P_i/Q_i]$, the Lerner index $L_i \equiv (P_i - MC_i)/P_i$, the cost-shift rate $\gamma_i \equiv dMC_i/d\tau$, and the output quantity $Q_i$. Incidence is similar to equation (1), but uses these firm-specific parameters and is weighted by firm-specific output quantities $Q_i$:

$$I^A = \frac{\sum_i Q_i \rho_i}{\sum_i Q_i \left[\gamma_i - (1 - L_i \epsilon_{D,i})\, \rho_i\right]} \tag{3}$$

As above, an equivalent but slightly more parsimonious version is useful for empirical results:

$$I^A = \frac{\sum_i Q_i \rho_{MC,i} \gamma_i}{\sum_i Q_i \left[\gamma_i - (1 - L_i \epsilon_{D,i})\, \rho_{MC,i} \gamma_i\right]} \tag{4}$$

Therefore, the incidence of a change in input taxes under generalized imperfect competition requires estimates of the pass-through rate, the cost shift rate, the markup, and the demand elasticity *separately for every firm*. This is a more challenging empirical setting, but we can make progress with a few additional assumptions discussed in subsequent sections. We now turn to describe the data and then the methods we use to estimate these parameters.

[13] We estimate marginal cost pass-through for two reasons. First, it avoids the need to estimate the cost-shift parameter $\gamma$. Second, we lack good data on plant-level energy input prices. The census reports plant-level energy expenditures but not prices; some plants in the census data do report electricity input prices though these suffer from widespread imputation.

[14] Weyl and Fabinger (2013) show that pass-through under symmetric imperfect competition may be written as

$$\left[1 + \frac{L\epsilon_D}{\epsilon_\theta} + \frac{\epsilon_D - L\epsilon_D}{\epsilon_S} + \frac{L\epsilon_D}{\epsilon_{ms}}\right]^{-1}$$

Pass-through depends on demand and supply elasticities $\epsilon_D$ and $\epsilon_S$, the elasticity of inverse marginal surplus $\epsilon_{ms} \equiv MS/MS'Q$, where $MS$ is the marginal consumer surplus $MS \equiv -P'Q$, and $\epsilon_\theta \equiv \theta/[q(d\theta/dq)]$, and where $\theta \equiv L\epsilon_D$.

# 4 Data

The primary data for our analysis comes from administrative survey records collected by the U.S. Census Bureau. We supplement this data with information from the Energy Information Agency (EIA) on energy prices, consumption, and generation.

### Census of Manufacturers (CM)

We use administrative data on annual plant-level inputs and outputs from the Census Bureau's Census of Manufacturers (CM). We use this data to measure plant level inputs, such as capital, labor, and materials.[15] The CM is conducted quinquennially in years ending with a 2 or 7, and we draw upon CM years from 1972 through 1997. These sample years are chosen based upon the availability and quality of physical output data in the CM.[16] We measure labor inputs in hours, capital as plants' reported book values of equipment and structures, and materials and energy inputs as the reported expenditures on each. We deflate capital, material, and energy expenditures using the corresponding industry-specific input price indices from the NBER Productivity Database.

CM output prices, which we calculate as product-level revenue divided by quantity, involve several challenges. Since output prices can reflect unobserved product quality, we follow Foster, Haltiwanger, and Syverson (2008, hereafter FHS) in limiting analysis to single-product plants in six industries that produce homogenous products: Boxes, Bread, Cement, Concrete, Gasoline, and Plywood.[17,18] A minority of firms within these industries have multiple products. For the plants that satisfy these criteria but still produce other products, we follow FHS and scale the focal product output by the inverse of the revenue share. This input-adjustment method assumes inputs are used proportionately to each product's revenue share. Another challenge is widespread imputation. We exclude any observation identified as an "administrative record," and we also exclude records where any input or output is imputed.[19]

Since a few observations still appear to be errors, we make additional sample restrictions similar to those of Roberts and Supina (1996, 2000) and FHS. We exclude a small number of plants

[15] Labor inputs are measured as plants' reported production-worker hours adjusted using the method of Baily, Hulten, and Campbell (1992) (i.e., multiplying production-worker hours by the ratio of total payroll to payroll for production workers).

[16] In more recent years, the amount of quantity data collected in the CM has declined considerably, making analyses of more recent time periods infeasible for most, if not all, industries.

[17] Following FHS, we define a plant as single product if it receives over half its revenue from the homogeneous product of interest. This definition uses revenue and not quantity shares since different products are measured in different units. When selecting single-product plants, we ignore revenues from product codes for contract work, miscellaneous receipts, product resales, and balancing codes. The Census Bureau creates balancing codes when the summed value of shipments for reported individual products does not equal the plant's reported total value of shipments.

[18] This adds cement to the FHS industries but excludes several of FHS' industries (sugar, carbon black, coffee, flooring, block and processed ice), for two reasons. Unlike FHS, we exclude observations with imputed quantity, which substantially reduces sample sizes. Also unlike FHS, we estimate industry-specific coefficients in translog production functions. To have sufficient sample size, we exclude industries which, after imposing our sample restrictions, have less than 100 plant-year observations.

[19] We thank Kirk White for providing the product-level imputation data for the first half of our sample.

reporting physical quantities that imply prices greater than ten times or less than one-tenth the median price in a given industry-year. We also exclude observations missing any one of the main production function variables (i.e., labor, capital, materials, or output quantity). Additionally, we exclude observations where the plant's labor or materials cost share is less than one-tenth of the corresponding industry's average cost share for that year or when the cost share is more than one. Finally, we trim the one-percent tails of a productivity index measure.[20] All output prices are adjusted to a common 1987 basis using the revenue-weighted geometric mean of the product price in a given year across all of the plants producing the product in our sample.

It is worth commenting a bit further on the six industries that remain the focus of this paper. Some of these industries are particularly important consumers of energy in U.S. manufacturing. A fourth of U.S. greenhouse gas emissions come from transportation, and most fuels for the transportation sector pass through oil refineries. Cement is one of the largest sources of greenhouse gas emissions in the world. We have chosen these industries because they have price/quantity data and are relatively homogenous, though the relative homogeneity of their products limits product differentiation as a source of market power.

### Manufacturing Energy Consumption Survey (MECS) and Annual Survey of Manufacturers Fuels Trailer

We supplement the CM with plant-level data on fuels from the Manufacturing Energy Consumption Survey (MECS), which was collected about every 3 years beginning in 1981, and from the Annual Survey of Manufacturers (ASM) Fuels Trailer, which accompanied the ASM annually between 1973 and 1979, excluding 1977. These surveys report physical fuel consumption separately for each fuel. Energy expenditures in these data exclude feedstocks used for production. Since gasoline refining spends a significant fraction of material costs on energy feedstocks, we augment the energy cost shares for gasoline refining to include the costs of energy feedstocks, which we get from the ASM and CM materials input trailers.

### Energy Information Association - State Energy Data System (SEDS)

We use data from the EIA's State Energy Data System (SEDS) to measure the annual national and state fuel prices for coal, oil, and natural gas. We also use these data to measure the share of electricity generation in a state generated with each of these fuels. The EIA compiles SEDS primarily from surveys of energy suppliers. We convert all fuel prices to real 1987 dollars using the average of the industry-specific energy price deflators for the industries in our sample from the NBER Productivity Database.

[20] The productivity index is constructed using a gross-output, Cobb-Douglas production function with labor, capital, and materials as inputs. The output elasticities are computed using industry-level cost shares under the assumption of constant returns to scale, and output is measured using physical quantities.

# 5 Econometrics of Markups and Pass-Through

We now turn to describe our methodology, in six steps. First, we describe how we recover markups and marginal costs from production data. Second, we describe how we use production functions to recover output elasticities, which are needed to calculate markups and marginal costs. Third, we describe the two research designs for energy prices. Fourth, we describe the analysis of how energy prices affect marginal costs, markups, and output prices. Fifth, we describe how we estimate pass-through. Finally, we describe how we estimate demand elasticities.

## 5.1 Recovering Markups and Marginal Costs

Our approach to recovering markups and marginal costs follows Hall (1986) and De Loecker and Warzynski (2012). Let $Q_{it}$ denote the physical output $Q$ of plant $i$ in year $t$. Output is a function of variable inputs $V_{it}$ (i.e., those not subject to adjustment costs) like materials and energy; dynamic inputs $K_{it}$ like capital or sticky labor, which are subject to adjustment costs; and plant-specific productivity $\Omega_{it}$: $Q_{it} = Q_{it}(V_{it}, K_{it}, \Omega_{it})$. We assume a firm minimizes the cost of the variable input(s), conditioning on the dynamic inputs. The firm solves the following Lagrangian:

$$\mathcal{L}(V_{it}, K_{it}, \lambda_{it}) = P_{it}^{V} V_{it} + R_{it} K_{it} + \lambda_{it}[Q_{it} - Q_{it}(V_{it}, K_{it}, \Omega_{it})]$$

Here $P_{it}^{V}$ is the price of variable inputs, $R_{it}$ is the price of dynamic inputs, and $\lambda_{it}$ is the Lagrange multiplier.

The firm's first-order condition for a variable input like materials is

$$\frac{\partial \mathcal{L}}{\partial V_{it}} = P_{it}^{V} - \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial V_{it}}$$

Rearranging terms for an optimum where $\partial \mathcal{L} / \partial V_{it} = 0$ and multiplying the right-hand side by $V_{it} Q_{it} / V_{it} Q_{it}$ and both sides by $P_{it}$ shows how we recover markups:

$$\frac{P_{it}}{\lambda_{it}} = \left[ \frac{\partial Q_{it}(\cdot)}{\partial V_{it}} \frac{V_{it}}{Q_{it}} \right] \left[ \frac{P_{it}^{V} V_{it}}{P_{it} Q_{it}} \right]^{-1} \tag{5}$$

The left-hand side of this equation is the multiplicative markup $\mu_{it}$, which equals prices divided the Lagrange multiplier. The Lagrange multiplier represents marginal costs, since it reflects the costs of relaxing the output constraint. The right-hand side is the product of two bracketed terms; we construct empirical analogues to both. The first is the elasticity of output with respect to a variable input, or the "output elasticity." We estimate the output elasticity from production functions, described in the next subsection. The second bracketed term is the cost of the variable input divided by the firm's revenue, or the "revenue share." Our data report the revenue share of each input.

We can then compute a markup by using the estimated output elasticity of a variable input and the revenue share of that input. Since we observe plant-level output prices, we then recover marginal

costs from the accounting identity that price equals markups times marginal costs: $MC_{it} = P_{it}/\mu_{it}$ where $MC_{it}$ is the marginal cost of plant $i$ in year $t$.

### 5.2 Output Elasticities and Production Functions

The previous subsection showed that estimating markups requires the output elasticity of a variable plant-level input like materials. We estimate this output elasticity by using proxy methods to estimate production functions (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2015). We focus on production functions with a scalar, Hicks-neutral productivity term and estimate elasticities separately by industry, assuming common technology across firms and over time within an industry.[21] We show a Cobb-Douglas specification here to simplify exposition, though our results use a more flexible translog, gross-output production function:[22]

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it} \tag{6}$$

Throughout the paper, lowercase represents variables in logs. Here $y_{it}$ represents a plant's output quantity. We use quantity rather than revenues here to avoid well-known bias in revenue-based productivity estimates.[23] Firms use three inputs: capital, labor, and materials ($k_{it}$, $l_{it}$, and $m_{it}$). Materials includes energy inputs in addition to other intermediate inputs used for production. The parameter vector which we estimate, $\beta \equiv (\beta_k, \beta_l, \beta_m)$, contains the output elasticities of these three inputs. The term $\omega_{it}$ represents productivity, which is known to the firm when making static input decisions but unobserved to the econometrician. The residual $\epsilon_{it}$ includes measurement error and unanticipated shocks to output.

Ordinary least squares estimates of equation (6) may suffer from omitted variables bias due to the unobserved productivity term $\omega_{it}$ (Marschak and Andrews, 1944). A firm observes its productivity, so input choices $k_{it}$, $l_{it}$, and $m_{it}$ may depend on it, but productivity directly affects output, and data do not report it.

To address the possible omitted variable bias associated with OLS estimates of equation (6), we use control-function or proxy methods to control for the unobserved and omitted productivity term. Consider a general demand function for materials:[24] $m_{it} = m_t(k_{it}, l_{it}, \omega_{it})$. Assuming that

[21] Output elasticities could in principle differ by industry and time period. Such flexible output elasticities are difficult to estimate with our data, however, since we have few years of data, require one lag to construct instruments, and have few observations for most industries.

[22] Translog coefficients are the same across firms within an industry. Markups and output elasticities, however, differ across firms within an industry, because input demands differ across firms. This is an advantage of translog over Cobb-Douglas production functions, which would have the same output elasticity across firms within an industry. Under Cobb-Douglas, all variation in markups across firms within an industry would come from revenue shares.

[23] Unobserved variation in input prices may bias production function coefficients (De Loecker, Goldberg, Khandelwal, and Pavcnik, Forthcoming). The homogeneity of our products potentially gives less scope for input price variation and associated bias (De Loecker and Goldberg, 2014). We have explored specifications that attempt to control for any remaining input price variation using a polynomial in the output price, and results are largely similar.

[24] We focus on materials as a variable input into the production function, where materials include both purchased intermediates as well as energy input expenditures. In theory, we could estimate a separate output elasticity for energy in the production function. In practice, adding a fourth input into a translog production function substantially increases the number of parameters to be estimated. With relatively small sample sizes and relatively few degrees of

$m_t(\cdot)$ is strictly monotonic in inputs, we invert this input demand equation to solve for productivity as a function of the observable inputs:

$$\omega_{it} = m_t^{-1}(m_{it}, k_{it}, l_{it})$$

This inversion provides a control function for productivity.[25]

We apply this approach in two steps, following Ackerberg, Caves, and Frazer (2015). The first step regresses plant output $y_{it}$ on a function $\phi_t(\cdot)$ of observed inputs. This first step is designed to purge output data of measurement error and unanticipated shocks to output $\epsilon_{it}$:

$$y_{it} = \phi_t(k_{it}, l_{it}, m_{it}) + \epsilon_{it}$$

We approximate $\phi_t(\cdot)$ using a polynomial expansion. We use estimates from this first step to calculate $\epsilon_{it}$ from

$$\hat{\epsilon}_{it} = y_{it} - \hat{\phi}_t(k_{it}, l_{it}, m_{it}) \tag{7}$$

where $\hat{\phi}$ contains the fitted values from this first step, and $\hat{\epsilon}_{it}$ are the residuals from this regression. Since $\epsilon_{it}$ contains measurement error and unanticipated shocks to production, we can use it to obtain a measure of output which is purged of both. After this first step, the only missing information needed to know the output elasticity vector $\beta$ is the productivity vector $\omega_{it}$. Given any candidate elasticity vector $\tilde{\beta}$, we can estimate productivity by manipulating equations (6) and (7) to get

$$\omega_{it}(\tilde{\beta}) = \widehat{\phi}_{it} - \tilde{\beta}_k k_{it} - \tilde{\beta}_l l_{it} - \tilde{\beta}_m m_{it} \tag{8}$$

The second step selects the coefficient vector that best fits the data by relying on the law of motion for productivity. We follow Ackerberg, Caves, and Frazer (2015) and assume that productivity follows a first-order Markov process.[26] We define productivity shocks $\xi_{it}$ as the difference between

freedom, output elasticities become more sensitive and less robust. Moreover, many indirect energy input costs are embodied in material expenditures through feedstock purchases for example.

[25] Inverting materials demand to recover productivity requires a one-to-one mapping between plant-level productivity and materials. This assumption fails if unobserved plant-level variables besides productivity drive changes in materials or if there is measurement error in materials. Alternative production function estimators, such as the dynamic panel methods developed by Blundell and Bond (2000) are not appropriate in our setting since we have few time periods to construct differences and lags. Some evidence suggests these may not be first-order concerns. Syverson (2004) finds robustness among producer TFP measures (and hence output elasticities) for one of our industries, ready-mixed concrete, with a specification incorporating idiosyncratic demand shocks. Van Biesebroeck (2007) also finds high TFP correlations across various measurement alternatives. Given the strong assumptions needed to estimate output elasticities, however, subsequent sections explore alternative methods to characterize incidence in the absence of information on output elasticities and/or markups and marginal costs.

[26] We use the AR(1) process to derive a plausibly exogenous productivity shock $\xi_{it}$ along the lines of Ackerberg, Caves, and Frazer (2015). We have also allowed for the potential of additional lagged decision variables to affect current productivity outcomes (in expectation) in order to accommodate the concerns raised by De Loecker (2011) pertaining to the exogeneity of productivity process. For example, we have allowed productivity to depend on export status and the nonrandom exit of firms (De Loecker, 2011; Olley and Pakes, 1996). In practice, our output elasticity estimates are not particularly sensitive to these modifications.

productivity and the expectation of last period's productivity given last period's information set $\mathbb{I}_{it-1}$:

$$\xi_{it} = \omega_{it} - \mathbb{E}[\omega_{it}|\mathbb{I}_{it-1}]$$

where $\mathbb{E}$ is the expectation operator. Equivalently, $\xi_{it}$ represents the component of current productivity which was unexpected at time $t-1$.

The second step estimates the production function coefficients using the assumption that this productivity innovation must be orthogonal to a set of current and lagged input demands $d_{it}$. We summarize these conditions as

$$\mathbb{E}[\xi_{it}(\beta)d_{it}] = 0 \tag{9}$$

With the translog production function we use for the empirical implementation, the vector $d_{it}$ is

$$d_{it} = \{l_{it}, m_{it-1}, k_{it}, l_{it}^2, m_{it-1}^2, k_{it}^2, l_{it}m_{it-1}, l_{it}k_{it}, m_{it-1}k_{it}\}$$

These moments above are similar to those suggested by Ackerberg, Caves, and Frazer (2015). They exploit the fact that capital and labor have adjustment costs and therefore lagged capital and labor should not be correlated with the current productivity innovation. We use lagged rather than current materials to identify the materials coefficients since current material expenditures may react to contemporaneous productivity innovations. For lagged materials to be a valid instrument for current materials, input prices must to be correlated over time.

Finally, we use generalized method of moments to choose the production function coefficients $\beta$ which minimize the moment conditions in equation (9). With translog production functions, the coefficients $\beta$ combined with input data give the output elasticities $\hat{\theta}$:[27]

$$\hat{\theta}_{it} = \theta(\hat{\beta}, l_{it}, m_{it}, k_{it})$$

### 5.3 Two Research Designs for Energy Prices

The previous two subsections show how we estimate output elasticities and marginal costs. These two objects are theoretically sufficient to identify pass-through from a regression of output prices on marginal costs. We enrich this analysis with measures of energy prices for two reasons. First, understanding how energy prices affect output prices, marginal costs, and markups is new to the literature for many of these industries. A second reason to focus on the role of energy prices in production is that OLS regressions of output prices on marginal costs may suffer from measurement error in marginal costs. Variation in energy prices can serve as an instrumental variable for marginal costs, providing an unbiased estimate of pass-through in the presence of classical measurement error. Existing research uses other types of instrumental variables for marginal costs, such as exchange rate shocks for imported intermediate inputs (e.g., De Loecker, Goldberg, Khandelwal, and Pavcnik (Forthcoming)), though not in the context of U.S. manufacturing.

[27] The estimated output elasticity for materials, for example, is $\hat{\theta}_{it} = \hat{\beta}_m + 2\hat{\beta}_{mm}m_{it} + \hat{\beta}_{lm}l_{it} + \hat{\beta}_{km}k_{it} + \hat{\beta}_{lmk}l_{it}k_{it}$.

Our two measures of variation in local energy prices leverage the fact that national changes in the price of a fuel disproportionately affect regions and industries heavily dependent on that fuel. For example, when the national price of natural gas rises more than the national price of oil or coal, energy prices in regions and industries heavily dependent on natural gas will disproportionately increase.

We first focus on variation in industrial *electricity* prices that are driven by regional differences in electricity generation by fuel type. Figure 3 depicts the share of total state-level electricity generation that comes from coal, natural gas, and petroleum/oil, respectively. The maps make clear that the primary fuels used for electricity generation vary considerably over space. Coal accounts for more than three-fourths of fuel for electricity generation in the Upper Midwest but practically no electricity generation in the Western coastal states. Natural gas accounts for 15 percent of generation in the South but over 40 percent of generation in California. We interact this cross-sectional variation in energy input shares (i.e., the shares of fuel costs devoted to electricity generation in a state) with national trends in fuel prices to generate predicted changes in regional electricity prices. Figure 4 shows time-series patterns in the real price of the three primary fuel inputs for electricity — coal, oil, and natural gas. All three fuels had low prices around 1970, a spike during the OPEC crisis in 1975, a decline in the mid-1980s as the crisis subsided, and lastly an increase in the 2000s due in part to rapid economic growth in Asia. While the secular trends are similar among all three fuels, each fuel has independent variation. Coal, for example, was the most costly fuel in the 1970s but the cheapest in the 2000s. While the 1980s crisis produced abrupt changes in oil and natural gas prices, it led to only gradual and smooth changes in coal prices. As fuel prices vary nationally, differences in fuel input shares cause that national fuel price variation to differentially affect regional electricity prices and/or industries dependent on those fuels.

We formalize the relationship between regional electricity prices and regional heterogeneity in fuel inputs used for electricity as follows. We interact (lagged) cross-sectional differences in the share of fuels used to generate electricity in a state-year with national time-series variation in the prices of these fuels:

$$z_{st}^{A} = \sum_{f \in \{\text{coal, gas, oil}\}} \left[ e_{-s,t,f}^{A} \cdot \sigma_{s,t-k,f}^{A} \right] \tag{10}$$

The variable $e_{-s,t,f}^{A}$ represents the unweighted national mean over state-level log mean fuel prices $f$ in year $t$, excluding the state $s$ mean. This research design considers three fuels: coal, oil, and natural gas. The variable $\sigma_{s,t-k,f}^{A}$ represents the cost of fuel $f$ in year $t-k$, expressed as a share of total fuel expenditure of these three fuels for electricity generation in state $s$. We present results using lags $k$ of zero, two, and five years. We use the leave-out mean and lagged shares to ensure that energy price variation is independent of local demand for fuels and electricity.

The second source of variation in energy input costs stems from the fact that different industries use different fuel inputs to produce outputs. Table 1 shows the allocation of energy expenditure across fuels as a fraction of total input expenditures, by industry. Total input expenditures are defined as annual expenditures on salary and wages, capital rental rates, materials, electricity, and

fuels. For example, 0.7% of total input costs for box manufacturing come from natural gas, but 13 percent of total input costs in cement come from coal. We formalize the predicted variation in industrial energy prices by interacting national, leave-out mean energy input prices for industrial consumers with the (lagged) share of energy input costs in an industry-year devoted to a particular fuel.

$$z_{it}^{B} = \sum_{f \in \{\text{coal, gas, oil, electricity}\}} \left[ e_{-s,t,f}^{B} \cdot \sigma_{i,t-k,f}^{B} \right] \tag{11}$$

The variable $\sigma_{i,t-k,f}^{B}$ represents the share of total expenditures in industry $i$ and year $t-k$ devoted to fuel $f$. The variable $e_{-s,t,f}^{B}$ denotes the national, leave-out mean input price of fuel $f$ for industrial consumers.[28] This research design considers four energy inputs: coal, oil, natural gas, and electricity.

There are three main differences between the equations used in the two research designs (10) and (11). First, the electricity price research design uses national energy input prices for electricity $e_{-s,t,f}^{A}$, whereas the energy price research design uses national energy input prices for industrial consumers $e_{-s,t,f}^{B}$. Second, the energy price research design includes electricity along with the three primary fuels as energy inputs, while the electricity price research design only uses the three primary fuels since it is modeling electricity price variation faced by industrial consumers. Lastly, energy input shares $\sigma$ are calculated differently in both equations; equation (10) calculates shares as the fraction of electricity generation in a state that comes from fuel $f$, and equation (11) calculates energy expenditures as a fraction of total expenditures for a given industry, fuel, and year.

### 5.4 Effects of Energy Prices on Output Prices, Marginal Costs, and Markups

The goal of these "shift-share" research designs is to use the predicted sources of variation in energy prices to analyze the pass-through of marginal costs to product prices. However, it is also informative to understand how changes in energy prices directly affect output prices, marginal costs, and markups. We investigate this question with the following fixed effects regression model:

$$y_{ist} = z_{ist}'\beta + X_{st}'\gamma + \eta_i + \pi_t + \nu_{ist} \tag{12}$$

Equation (12) describes a regression of outcome $y$ in logs (output prices, marginal costs, or markups) for plant $i$ in state $s$ and year $t$. The vector $z_{ist}$ represents either the interaction between national fuel prices and state-level electricity generation shares from $z_{st}^{A}$ (i.e., equation (10)) or the interaction between national energy prices and industry-level energy input shares from $z_{it}^{B}$ (i.e., equation (11)). The vector $X_{st}$ includes the leave-out mean energy/fuel prices $e_{-s,t,f}$ separately for each fuel. It also includes the either the generation share $\sigma_{s,t-k,f}^{A}$, measured $k$ years ago in state $s$, or the industry energy input share $\sigma_{i,t-k,f}^{B}$, measured $k$ years ago in industry $i$. Some specifications also control

[28] We calculate energy input expenditure shares at the industry level using the data from MECS and the ASM fuel trailers. In principle, we could compute energy input expenditure shares by plant or industry×region. Small sample sizes in both the MECS and the ASM preclude the use of more granular industry energy input expenditure share definitions. Industry×region energy input expenditure share definitions deliver similar but less precise results.

separately for differential trends by state, region by year fixed effects, and industry by year fixed effects. The regression also includes plant fixed effects $\eta_i$ and year fixed effects $\pi_t$.

The interpretation of the coefficient vector of interest $\beta$ differs across the two research designs. When estimating equation (12) using the electricity price shift-share $z_{st}^A$, the vector $\beta$ describes the elasticity of outcome $Y_{ist}$ with respect to the national (leave-out mean) fuel price for fuel $f$ for a state that produces 100 percent of its electricity using fuel $f$. In practice, no state generates all of its electricity from a single fuel source, so these coefficients should be evaluated at the mean value of a fuel's generation share. During our sample, this is about 20 percent for natural gas. When estimating equation (12) using the energy price shift-share $z_{it}^B$, the vector $\beta$ describes the elasticity of outcome $Y_{ist}$ with respect to the national (leave-out mean) fuel price for fuel $f$ in an industry for which 100 percent of the industry's total annual expenditures are devoted to energy input $f$, where $f$ is electricity, fuel oil, natural gas, or coal. Again, no industry uses a single fuel input for production, and so these coefficients should be evaluated at the mean value of respective energy expenditure share (see Table 1).

### 5.5 Pass-Through

We use our observed data on output prices, recovered estimates of marginal costs, and constructed energy price variation to estimate marginal cost pass-through. We estimate the marginal cost pass-through elasticity from the following plant-level regression of (log) output price on (log) marginal costs:

$$p_{ist} = \rho_{MC,\epsilon} mc_{it} + X_{st}'\gamma + \eta_i + \pi_t + \epsilon_{ist} \tag{13}$$

The main coefficient of interest, $\rho_{MC,\epsilon}$, measures the elasticity of output prices with respect to marginal costs. Note that $\rho_{MC,\epsilon}$ differs from the marginal cost pass-through rate $\rho_{MC}$ outlined earlier in that $\rho_{MC,\epsilon}$ represents an elasticity whereas $\rho_{MC}$ is pass-through in levels. The marginal cost pass-through rate can be calculated by multiplying the pass-through elasticity by the markup: $\rho_{MC} = \rho_{MC,\epsilon} \times P/MC$.

Equation (13) includes the same vector of controls $X_{st}$ as above, along with plant fixed effects $\eta_i$, year fixed effects $\pi_t$, and an idiosyncratic error $\epsilon_{ist}$. As above, we report additional regression estimates that control separately for differential trends by state, region by year fixed effects, and industry by year fixed effects. We instrument for $mc_{it}$ using either $z_{st}^A$ or $z_{it}^B$. Hence, equation (12) describes both the first stage and reduced form from an instrumental variables regression of price on marginal cost in equation (13).

### 5.6 Demand Estimation

Finally, estimating incidence under imperfect competition requires industry-specific demand elasticities. We estimate demand for each industry using methods proposed by FHS. They estimate log-linear demand by regressing log quantity on log price, instrumenting price with a measure of physical total factor productivity, and controlling for year fixed effects and the log of county in-

come. As FHS discuss, physical productivity measures producers' idiosyncratic technologies (physical production costs), and it strongly predicts prices. Further, it is unlikely it will be correlated with short-run, plant-specific demand shocks embodied in the error term of an OLS regression of log quantity on log price. We use the same physical productivity index used in FHS. We create this index by subtracting log inputs from log outputs, using industry-level cost shares as proxies for output elasticities. We use capital, materials, labor, and energy inputs, where capital, materials, and energy are deflated by industry-year input price deflators, and labor is measured in production hours. The industry specific input price deflators come from the NBER-CES Productivity database. County income measures come from the BEA Local Area Employment Statistics.

This methodology estimates exactly the demand elasticity described in the incidence theory section. The formulas in that section depend on the demand elasticity for an individual firm, i.e., the effect of a change in a specific firm's price on that firm's quantity. Because this methodology uses the physical productivity level for an individual plant and year, it corresponds well with the theory. Importantly, this is a different elasticity from the change in demand if the entire market faced a cost shock.

# 6 Results

Now that we have described the theory, data, and methodology, we turn to describe four sets of results: mean levels of prices, markups, and marginal costs; the effects of energy input cost shocks on these variables; marginal cost pass-through; and incidence.

## 6.1 Average Levels of Marginal Costs, Output Prices, and Markups

Table 2 presents some key summary statistics by industry. Column (1) shows that total annual expenditures on electricity and fuels comprise a limited fraction of input costs.[29] The mean energy cost share for most industries in our sample is 2 percent of total annual input expenditures, though cement and gasoline refining are obvious outliers with 32 and 84 percent of total expenditures devoted to electricity and fuels.[30]

Columns (2) through (4) show median estimates of output elasticities separately for labor, materials, and capital. As described in the previous section, we estimate production functions, and hence output elasticities, separately for each industry using a translog, gross-output production function, so output elasticities vary by plant. A few properties of the estimated output elasticities are worth noting. First, median output elasticities for all industries and factors of production are positive. Second, elasticities vary considerably across industries. The estimated output elasticity for labor, for example, is 0.04 for boxes but 0.91 for cement. For each of the three factors of

[29] Energy cost shares are defined as annual energy and electricity expenditures at a plant divided by salary and wage payments, rental payments on capital stocks, and expenditures on materials, electricity, and fuels.

[30] As mentioned earlier, the energy cost share for gasoline is high in large part because much of the crude oil used at refineries is physically transformed into gasoline (i.e., it is "feedstock") rather than being combusted at the refinery for heat or fuel.

production, cement has the largest estimated output elasticity among all industries. Third, the output elasticities differ considerably across factors of production. For all industries, materials has the largest output elasticity, at between 0.6 and 1.1. Capital and labor output elasticities are much smaller.

Column (5) of Table 2 presents the median of the sum of the three output elasticities, which is a measure of returns to scale in the industry. The results suggest that, except for cement, all the industries in our study cement have approximately constant returns to scale, with estimated returns to scale of 0.92 to 1.13. Cement is an obvious outlier, with strongly increasing returns to scale at 2.46. Foster, Haltiwanger, and Syverson (2008) find constant returns to scale for all of these industries except cement, which they do not analyze. Since cement uses some of the largest industrial equipment in the world, it may not be surprising that we estimate cement to have increasing returns to scale. Column (6) shows average markups of ten to fifty percent across industries except for cement, which is an outlier with markups of 130 percent. The product with the lowest estimated markup is gasoline, with markups of only 11 percent. These levels of industry markups are largely consistent with the existing literature that estimates markups using production function methods (Hall, 1986; De Loecker, Goldberg, Khandelwal, and Pavcnik, Forthcoming; Collard-Wexler and De Loecker, 2015).[31]

Columns (7) and (8) present mean output prices and marginal costs by industry. Output prices are constructed by dividing revenue by output quantities, and marginal costs are constructed by subtracting the log markup from the log output price. Lastly, column (9) presents the share of materials expenditures as a fraction of total revenue, which is used to construct markups in Column (6).

### 6.2 Effects of Energy Prices on Marginal Costs, Output Prices, and Markups

Table 3 presents our baseline set of results describing how variation in fuel input costs for electricity generation differentially affects markups, marginal costs, and output prices for U.S. manufacturing plants. Table 4 presents similar estimates using industry heterogeneity in energy input cost shares. These two tables reflect the two research designs in equations (10) and (11), and they stem from various versions of equation (12) which are estimated using OLS. Standard errors in this table and all subsequent regression output are clustered by state, unless otherwise mentioned.

Panel A of Table 3 analyzes how variation in fuel prices affects plant-level marginal costs. We report coefficients on the interactions between fuel prices and (lagged) state-level electricity generation shares. The regression models also control separately for the levels of fuel prices and for generation shares. Since both the dependent variable and the fuel variables are measured in logs,

[31] De Loecker, Goldberg, Khandelwal, and Pavcnik (Forthcoming) find industry median markups in Indian manufacturing ranging from 1.15 to 2.27. Collard-Wexler and De Loecker (2015) explore markups in the U.S. steel industry ranging from 1.2 to 1.5 depending on the time period studied. Hall (1986) explores markups using more aggregated industry definitions (2-digit SIC) but finds results that are largely consistent with our own. For example, Hall (1986) finds an estimated markup for SIC 34, which consists of both Cement and Ready Mix Concrete, of 1.81. Similarly, Plywood manufacturing, SIC 24, has an estimated markup above marginal cost of 1.0.

the reported interaction terms represent an elasticity for states in which 100 percent of generation comes from a given fuel. Each column in the table shows a slightly different specification. Columns (1) and (4) use the contemporaneous state-level generation mix for each fuel; columns (2) and (5) use two year lags, and columns (3) and (6) use five-year lags of the generation shares. Columns (1) through (3) control for plant fixed effects, year fixed effects, and state trends, whereas columns (4) through (6) control for product-year fixed effects, region-year fixed effects, and state trends. The identifying variation across all columns comes from within-plant variation in fuel shares and prices, while adjusting for various forms of time-varying observed and unobserved determinants of marginal costs that may be correlated with changes in predicted regional fuel prices.

These regressions give expected signs and plausible magnitudes. The coefficients in Panel A of Table 3 are mostly positive, which is expected since shocks to fuel input prices are likely to increase electricity prices that firms face and hence increase their marginal costs of production. The magnitudes of these coefficients are also reasonable. Recall that energy is on average 2 percent of production costs for most of these industries, and electricity expenditures represent an even smaller share. Column (6), which includes a 5-year lag in generation shares, implies that if natural gas provides 100 percent of in-state electricity generation, then a 1 percent increase in the price of natural gas used for electricity results in a 0.29 percent increase in the marginal costs of manufacturing production. In practice, natural gas constitutes about 20 percent of electricity generation over this time period.[32] Thus, these estimates imply that a 1 percent increase in natural gas prices would cause an 0.06 percent increase in marginal costs.[33] The magnitude of this coefficient varies across fuels. The response of power plants and regulators to energy price shocks through fuel substitution, efficiency improvements, or strategic production decisions, however, may also vary across fuels.

Panel B of Table 3 presents a version of equation (12) which uses log output prices as the dependent variable. The signs and precision are similar to the marginal cost estimates of Panel A. The positive and precise estimates in Panel B provide a first piece of evidence that energy price shocks are passed through to plant-level output prices. The fact that the effects of energy price shocks on output prices (in Panel B) are smaller than the estimated effects on marginal costs (in Panel A), however, suggests that these cost shocks are less than fully passed through to prices.

Finally, Panel C of Table 3 presents a version of equation (12) which uses log markups as the dependent variable. Since markups are defined as the ratio of prices to marginal costs, the effects of changes in energy prices on markups approximately equal the difference between their effects on marginal costs and output prices. Thus, the numbers in Panel C can largely be inferred from the numbers in Panels A and B. The point estimates suggest that increasing the price of fuels used for electricity causes modest decreases in markups. The more stringent specifications of columns (4)-(6) imply that increasing the natural gas price by 1 percent for in-state electricity generation

[32] 20 percent natural gas generation corresponds to the fraction of production that is generated by coal, natural gas, and oil (i.e., excluding other methods of generation such as nuclear or hydroelectric).

[33] Note that the results in Table 3 do not control for and/or model industry specific variation in fuel input usage. Thus, to the extent that national fuel prices affect the marginal cost of production through channels other than electricity prices (e.g., through increased fuel costs used directly for production), these estimates implicitly incorporate this variation.

decreases markups by around 0.01 percent.[34]

Table 4 presents a similar set of results, exploring how markups, marginal costs, and output prices differentially respond to changes in energy input costs used for production. As before, we report the coefficients from the interaction between energy input shares, which is defined as the share of total input costs devoted to a specific energy input, with national energy prices, which are defined as the leave out mean national industrial energy price, omitting the focal state's average industrial energy price. We focus on the four primary energy inputs into manufacturing production: coal, natural gas, oil, and electricity. Since we use information from MECS and the ASM fuel trailers to construct energy input shares, and the ASM trailers only begin in 1975, we are not able to lag these shares more than 2 years without losing an extra year in our analysis sample.

Panel A of Table 4 suggests that increases in the costs of energy used for manufacturing increase marginal costs. The interaction term represents the elasticity of marginal costs with respect to energy input prices in a plant for which 100 percent of total expenditures comes from one of the four energy sources. Thus, if we were able to perfectly measure fuel prices faced by a plant, we might expect that the coefficient should be close to 100. In practice, there are many reasons that the coefficients may deviate from 100, not the least of which is that fuel expenditure shares in the neighborhood of 100 percent are far out of sample. Moreover, we observe average industrial fuel prices which might be quite different than marginal fuel prices faced by the firms in our sample. As before, Panels B and C suggest that increases in energy input prices are correlated with increases in output prices and reductions in markups. The broad takeaway is that relative fuel input usage interacted with national fuel prices strongly predicts changes in marginal costs, output prices, and markups. Subsequent sections use these relationships to quantify by how much fuel and electricity price induced increases in marginal costs are passed through to consumers in the form of higher output prices.

### 6.3 Marginal Cost Pass-Through

We now take the estimated relationships between prices, marginal costs, markups, and energy prices and embed them into a pass-through regression of output prices regressed on marginal costs. Table 5 presents OLS regression estimates corresponding to various versions of equation (13). Column (1) presents estimates with plant fixed effects, year fixed effects, and state trends. Columns (2) and (3) add product-year and region-year fixed effects, respectively. Column (4) includes the full set of product-year and region-year controls to the model from Column (1). Since both the dependent and independent variables are in logs, the coefficient estimates measure an elasticity. The estimates across the four columns are broadly similar, suggesting that a 1 percent increase in marginal costs is associated with a 0.6 percent increase in the output price. In order to convert this pass-through elasticity into a pass-through rate, we multiply the coefficient by the average markup in the sample of 1.15, which gives a marginal cost pass-through rate of 0.7.

[34]This comes from calculating the means across columns (4) through (6), weighting by the inverse standard error, and then multiplying by the average generation share of natural gas in our sample of 0.2.

To address possible measurement error and/or other forms of endogeneity in marginal costs, Table 6 presents instrumental variable estimates of equation (13), where marginal costs are instrumented in two separate ways. Panel A presents pass-through estimates where marginal costs are instrumented using the interactions between the lagged electricity generation mix in a state and the log of the leave out mean electricity fuel input prices. Panel B instruments marginal costs with the interaction between an industry's share of annual expenditures devoted to one of four energy inputs multiplied by the national, leave-out mean of that energy input price. As before, columns (1) through (3) include plant fixed effects, year fixed effects, and state-specific trends. These columns vary the lag in the fuel share component of the marginal cost instrument between zero, two, and five years. Columns (4) through (6) of Panel A add region-year fixed effects and product-year fixed effects, whereas Columns (4) through (6) of Panel B add only region-year fixed effects.[35] We present estimates showing zero, two, and five lags of the fuel share. All columns include the uninteracted log of the fuel prices and the uninteracted, lagged generation mix (not reported).

Panel A suggests that pass-through elasticities range between 0.62 and 0.72, which translates into pass-through rates of 0.71 to 0.83. The strength of the identifying variation in the instrument varies slightly across the specifications, with first stage partial F statistics ranging from 4 to 14. These first stage F-statistics suggest there may be bias stemming from a weak first stage, where the bias is towards the OLS counterpart. The results in Panel B are broadly consistent with those in Panel A, though they were estimated using a different instrument for marginal costs. The energy price instrument in Panel B is also a stronger predictor of marginal costs than the electricity price instrument in Panel A, as reflected by the first stage F-statistics of between 66 and 137. The average pass-through elasticity in Panel B is around 0.51, which translates into a pass-through rate of 0.59.

This overall pass-through elasticity may hide important cross-industry heterogeneity. Table 7 reports estimates of pass-through rates separately for each of the six industries in our sample. Panel A presents specifications that instrument marginal costs with our electricity price instrument, controlling for year fixed effects and state specific linear time trends. Panel B presents estimates that also include region-year fixed effects. All regressions control for plant fixed effects. Note that year fixed effects in an industry-level regression correspond to industry-year fixed effects from a pooled cross-industry regression. These tables reveal substantial cross-industry heterogeneity in the pass-through of marginal costs into output prices. Pass-through elasticities vary from a high of 0.96 for boxes to a low of 0.33 for gasoline refining. Table 7 also reports the corresponding pass-through rates, which are calculated by multiplying the elasticity estimate by the industry-specific markup. These estimates suggest that boxes, cement, and plywood "overshift" changes in marginal costs into changes in output prices. The pass-through rates for these industries vary between 1.02 and 1.78. Conversely, bread, concrete, and gasoline refining have comparatively low pass-through rates ranging from 0.36 to 0.82.

How reasonable are these numbers? Some industries exhibit pass-through rates that exceed

[35] Industry expenditure shares for fuel inputs are collinear with product-year fixed effects in Panel B.

one, suggesting that producer surplus may actually increase due to a change in tax. Various researchers have shown the conditions under which overshifting can occur under oligopoly (see e.g., Bulow and Pfleiderer (1983); Seade (1985); Delipalla and Keen (1992)). The general intuition from this literature suggests that in the presence of oligopoly, a single firm can raise industry prices by reducing its own output, but it fails to do so because it is costly for the single firm in terms of foregone profits. A tax-induced cost increase will necessarily induce output-reductions for all firms, imposing upon the producers some of the collusion they themselves had been unable to achieve.[36] Empirically, studies have found pass-through rates ranging from below unity (Goldberg and Hellerstein, 2008; Gopinath, Gourinchas, Hsieh, and Li, 2011; Campa and Goldberg, 2005), to above unity (Besley and Rosen, 1999), to equal to unity (Poterba, 1996; Fabra and Reguant, 2014), depending on the methodology, market, time-period, or data used. We observe higher pass-through rates in industries where we see relatively inelastic demand and higher markups. Conversely, we observe lower pass-through rates in industries with elastic demand and lower markups. As emphasized by Seade (1985) and more recently by Weyl and Fabinger (2013), pass-through in imperfectly competitive product markets is closely related to the curvature of demand—very convex demand will typically have pass-through rates exceeding one, whereas concave demand will have pass-through rates below one.

Whether firms actually benefit from the increase in input costs is an empirical question that turns on whether the pass-through of the tax increases revenues enough to overcome both the lower demand due to higher prices as well as the direct cost increase due to the tax. We now turn to this question by computing incidence for each of the six industries in our study.

## 6.4 Incidence

### 6.4.1 Symmetric Oligopoly

Table 8 describes the incidence of an energy input tax separately for each of the six industries. Panel A presents the necessary components for calculating incidence using equation (2). We require estimates of pass-through rates, demand elasticities, and the Lerner index, by industry. We use the average industry pass-through rate from Table 7.[37] This panel also presents our estimates of demand elasticities and combines results from previous tables to construct the Lerner index. Cement has fairly inelastic demand with an elasticity of 1.82, which fits with its high estimated markup. Gasoline refining has relatively elastic demand of 8.70 percent, which fits with its low

[36] Seade (1985) describes this as a "public-goods problem" – restraint by any one firm in the industry in question raises the prices they all face for their outputs, constituting a common benefit. But the cost of this restraint, in the form of profitable revenue foregone, is borne by that one firm alone. Hence, too little of that good is produced (i.e., there is too little restraint). A cost increase will necessarily reduce output, thus raising the supply of the public good "restraint." In other words, in the absence of explicit collusion, the tax acts as a coordinating device allowing oligopolists to restrict output and thereby increase profit.

[37] We average the two pass-through estimates for each industry weighting by the inverse of the standard error of each estimate.

markups.[38] Appendix Table A1 presents a table of our demand elasticity estimates that contains both OLS and instrumental variable estimates.

Panel B presents incidence estimates under the assumption of symmetric firms. To simplify exposition, we report the change in consumer surplus as a share of the total change in surplus between producers and consumers, or $I/(I+1) = \frac{(dCS/d\tau)}{dCS/d\tau+dPS/d\tau}$. The results suggest, that even in industries with pass-through rates below 1, consumers bear a majority of the burden of a change in input costs. Gasoline refining is a notable exception, with producers bearing 76 percent of the burden of an energy price induced increase in marginal costs. In general, for industries with lower pass-through rates, consumers bear a smaller share of the burden of the increase in input costs – 53 percent in the bread industry, 49 percent in concrete, and about a 25 percent of the burden in gasoline refining. In all industries, consumers bear substantially less than 100 percent of the burden.

### 6.4.2 Asymmetric Oligopoly

Panel C of Table 8 presents incidence results when we relax the symmetric firm assumption in Panel B. Incidence under asymmetric firms is described by equation (4), which requires firm-specific estimates of pass-through, markups, and demand elasticities. This is more empirically challenging, and we are forced to make several simplifying assumptions to reduce the dimensionality of the problem. We assume that marginal cost pass-through is identical across all firms $\rho_{MC,i} = \rho_{MC}$; that firms face identical demand $\epsilon_{D,i} = \epsilon_D$; and that the production function exhibits constant returns to scale $Q_i(aV_i, aK_i) = aQ_i(V_i, K_i)$.[39] The first and second assumptions are shaped by data availability and empirical tractability. Our econometric specification recovers a mean $\rho_{MC}$ across all firms, and we only have industry level demand elasticity estimates. The constant returns to scale assumption allows us to compute a firm-specific cost-shift directly from the production function estimates without accounting for differential economies of scale across various firms.

The results in Panel C are quite similar to those in Panel B. All industries except gasoline refining have consumers bearing a majority of the burden, though substantially less than 100 percent of the burden. Incidence estimates under asymmetric oligopoly are all similar to incidence estimates under symmetric oligopoly, though all imply a relative increase in the burden faced by consumers.

[38] Many studies use time-series data estimate the "demand elasticity for gasoline" as the change in national consumer gasoline consumption due to a national change in retail gasoline sales. As discussed earlier, our paper analyzes a different demand elasticity, which represents the change in wholesale gasoline sales from a single refinery due to a price increase at that single refinery. Because gasoline is homogenous and easily substitutable between refineries, it is perhaps not surprising that we estimate a somewhat large demand elasticity.

[39] Constant returns to scale requires that the output elasticities of the factors of production sum to one. Under the Cobb-Douglas specification used for exposition, this requires $\beta_k + \beta_l + \beta_m = 1$. While the constant returns to scale assumption may be particularly strong for some of the industries we study (in particular concrete), it allows us to directly compute $dMC_i/d\tau$ without considering $dMC_i/dQ$. In particular, a tax $\tau$ will induce a change in quantity $Q_i$, and it is not clear how tax $\tau$ will differentially affect firm quantity without further details on market structure.

### 6.4.3 Incidence Bounding

Panels D and E of Table 8 present our estimates of incidence under the assumption that firms engage in perfect competition or monopoly, respectively. Incidence under monopoly assumes the Lerner index is the inverse of the demand elasticity, and incidence under perfect competition assumes that the Lerner index equals zero, since perfectly competitive firms do not charge markups. Therefore, computing incidence for the polar cases of perfect competition or monopoly only require estimates of marginal cost pass-through and does not require either demand elasticities or firm markups. Moreover, if products in an industry are substitutes and there is no collusion, these polar cases will bound the "true" incidence in the presence of market power.

The results in panel D under monopoly are somewhat similar to those under both symmetric and asymmetric oligopolies. In general, under the assumption of monopoly, incidence shifts more towards producers relative to consumers. The greatest difference occurs in the plywood industry, where consumers go from facing 67-87% of the burden to only 52% of the burden.

Panel E presents incidence of input costs under the assumption of perfect competition. The incidence of the increase in input costs under perfect competition are identical to the pass-through rates. When pass-through rates are greater than .50, consumers face more than 50% of the burden. In the box, cement, and plywood industries, consumers face more than 100% of the burden as producers pass through over 100% of marginal cost increases onto the consumer.

## 7 Conclusion

In this paper we develop a methodology for estimating the incidence of input cost shocks in imperfectly competitive product markets under relatively weak assumptions on preferences or market structure. The approach leverages the fact that equilibrium prices, and the extent to which they respond to cost shocks, are sufficient statistics for more primitive demand and supply parameters describing a market. With further information on markups and demand elasticities, we are able to extend this intuition to general forms of imperfect competition.

We consider the specific application of energy cost shocks for U.S. manufacturing, and we assess the extent to which the welfare consequences of these shocks are borne by manufacturing producers versus consumers. Standard analyses of the incidence of various types of energy cost shocks, such as climate change mitigation regulations, typically assume perfect competition and complete pass-through. Our results suggest that the incidence of a change in input costs, defined as the ratio of the change in consumer to producer surplus, differs dramatically from these assumptions. In one industry consumers bear almost 90 percent of the total change in input costs. This result stems from the ability of producers to more than fully pass through the change in input prices into output prices. In other industries, especially those with elastic demand, producers bear a greater incidence of the change in input costs.

This paper also arrives at a few additional conclusions that may be of broader interest. First, the standard assumptions of complete pass-through and perfect competition in research on the incidence

of commodity price shocks may be overly strong; these assumptions appear to be incorrect for all the industries we study. This existing research has led to politically sensitive conclusions on the extent to which greenhouse gas mitigation policies are regressive, and it would be productive to revisit those conclusions while accounting for market power and incomplete pass-through. For example, firm owners may shoulder more of the burden than existing research would suggest. On the other hand, some industries may actually benefit from increasing energy prices through a carbon tax. For example, in industries that "overshift" input taxes, the firm-level gains from reducing output in an economy with market power may exceed the direct detrimental effect of the tax for the firm. While we do not observe energy price-induced increases in producer surplus in this setting, more work is needed to understand how these results generalize into other industries and time periods. The second more general takeaway is the considerable heterogeneity across industries; the one industry which has been the subject of scrutiny in research on market power and the environment – cement – seems to be an outlier in much of our analysis.

One productive avenue for future work is to overcome the existing limitations associated with the paucity of producer price data linked to information on firm input and output decisions in the United States. Another is to incorporate our conclusions about incomplete pass-through and market power into an economy-wide, general equilibrium framework that can both account for pre-existing distortions in other markets while analyzing incidence by different consumer demographics. Lastly, the technology developed here is well-suited to think about incidence of other changes in input costs across industries, for example, stemming from changes in minimum wage laws or increased capital costs. We leave these avenues for future work.

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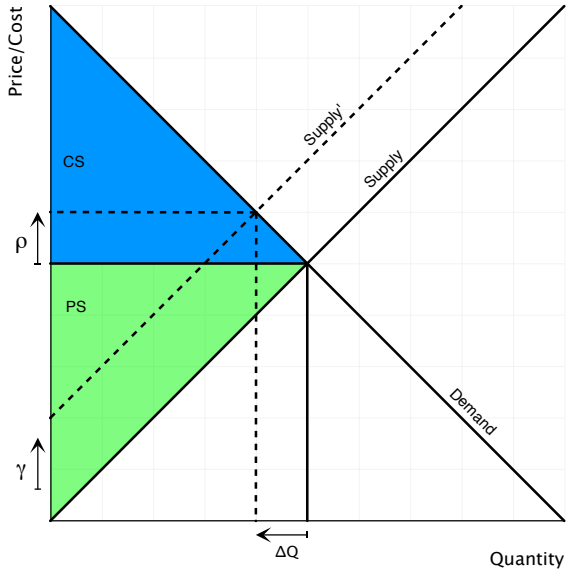
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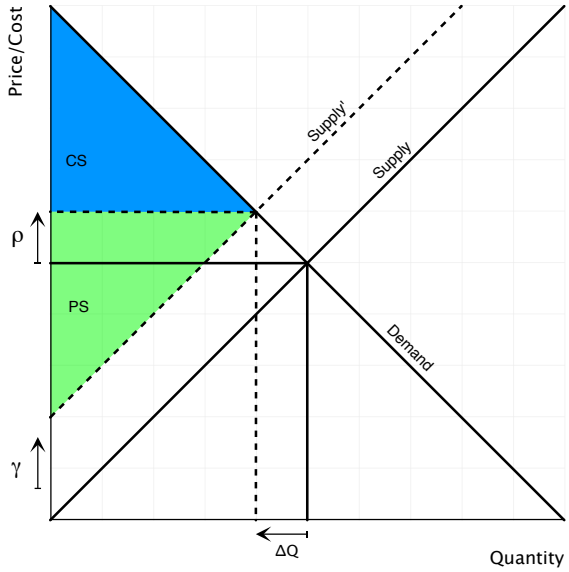
# Figures

Figure 1: Pass-Through and Incidence under Perfect Competition

(a) Shift in Marginal Cost



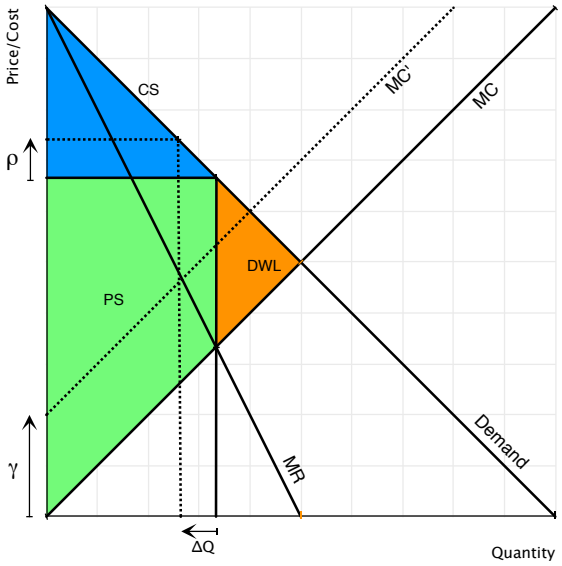

(b) New Market Equilibrium



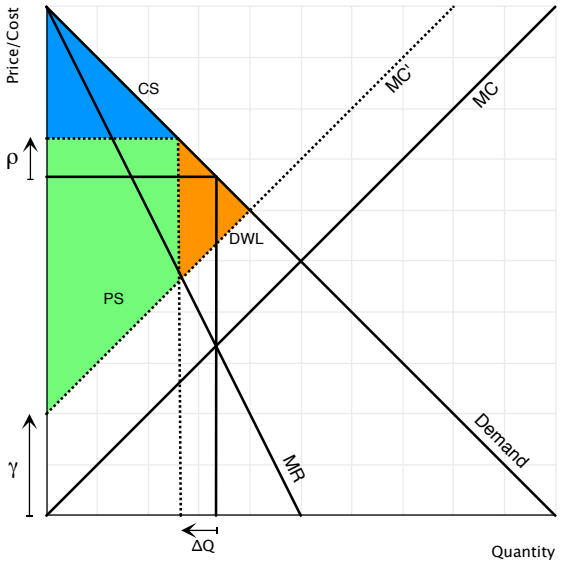

NOTES: See text for full description. The top panel shows consumer and producer surplus (denoted CS and PS, respectively) under general supply and demand curves in a market exhibiting perfect competition. The bottom panel shows consumer and producer surplus following a tax rate $\tau$ that changes marginal costs by $\gamma$, prices by $\rho$, and quantity sold by $\Delta Q$.

Figure 2: Pass-Through and Incidence under Monopoly

(a) Shift in Marginal Cost



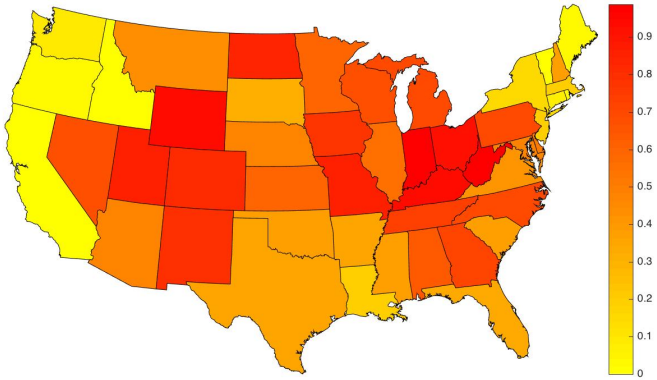

(b) New Market Equilibrium



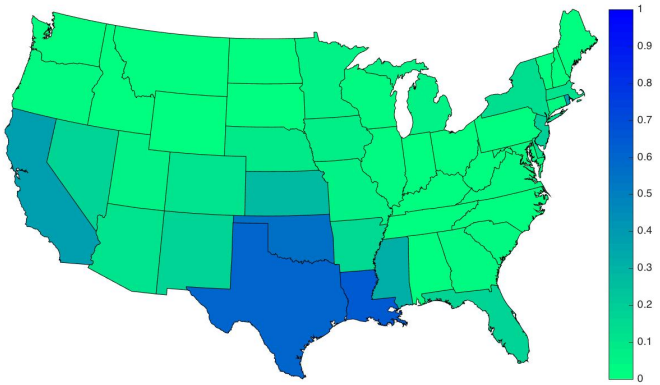

NOTES: See text for full description. The top panel shows consumer surplus, producer surplus, and the deadweight loss (denoted CS, PS, and DWL respectively) in a market with a single constant marginal cost monopolist. The MR line denotes marginal revenue and the MC line reflects an increasing marginal cost production function. The bottom panel shows consumer and producer surplus, as well as deadweight loss following a tax $t$ that changes marginal costs by $\gamma$, prices by $\rho$ and quantity sold by $\Delta Q$.

Figure 3: Electricity Fuel Mix by Region

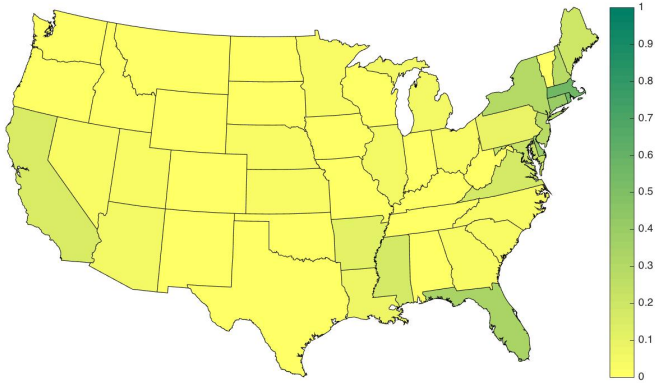
(a) Coal




(b) Natural Gas

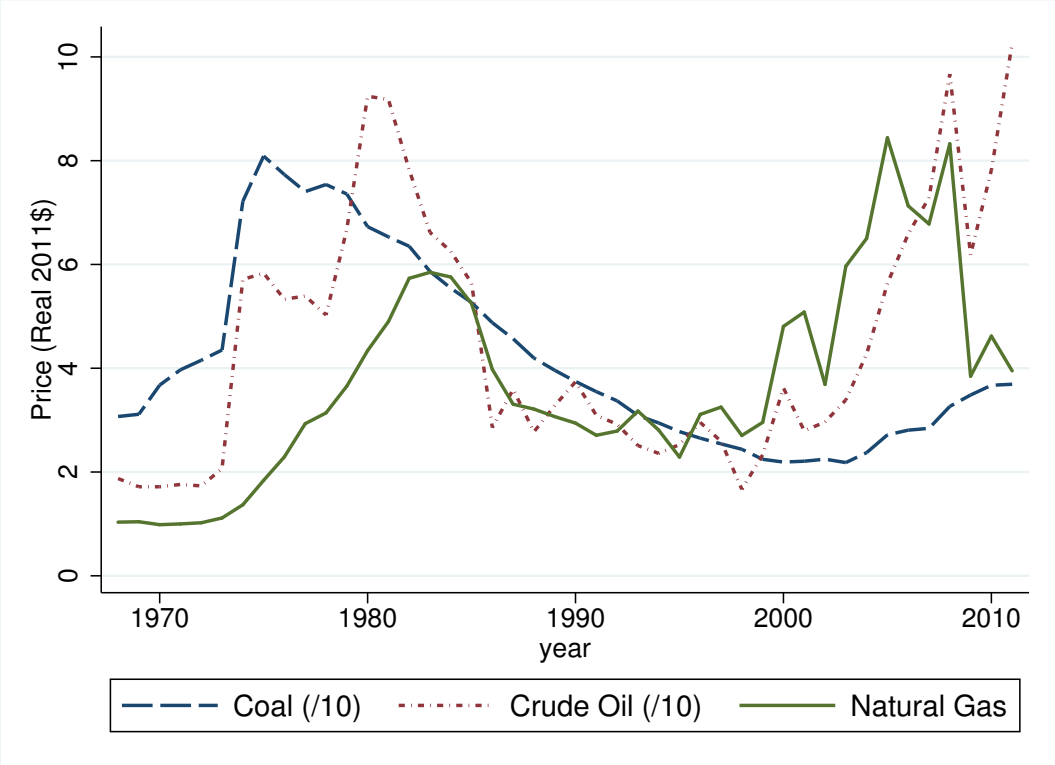



(c) Petroleum




NOTES: These maps show the spatial distribution of electricity generation by fuel type by state averaged over our sample period, 1972-1997. Panel A shows the fraction of electricity generation in a state that comes from coal-fired generation; Panel B shows the fraction of electricity generation in a state that comes from natural gas; Panel C shows the fraction of electricity generation in a state that comes from petroleum.
Source: Energy Information Association, State Energy Data System.

Figure 4: National Fuel Prices, 1967-2012




NOTES: This figure plots a time series of national fuel prices from 1967 to 2012. Prices have been converted to real 2011 dollars using the consumer price index. Crude oil prices reflect the price of U.S. crude oil net imports in dollars per barrel. Natural gas prices reflect wellhead prices in dollars per thousand cubic feet. Coal prices reflect dollars per short ton. Prices for coal and crude oil have been divided by 10 to facilitate a common axis across the 3 fuels. Source: Energy Information Association, Annual Energy Review.

# Tables

Table 1: Allocation of Energy Input Expenditures Across Fuels, by Industry

| | Coal | Natural Gas | Fuel Oil | Electricity |
|---|---|---|---|---|
| Boxes | 0.000 | 0.007 | 0.002 | 0.009 |
| Bread | 0.000 | 0.007 | 0.002 | 0.011 |
| Cement | 0.130 | 0.049 | 0.010 | 0.134 |
| Concrete | 0.000 | 0.002 | 0.011 | 0.007 |
| Gasoline | 0.000 | 0.014 | 0.817 | 0.007 |
| Plywood | 0.000 | 0.005 | 0.002 | 0.012 |

*Notes*: This table shows the average energy input percentage by industry for each of the four primary energy inputs into manufacturing production. These statistics are calculated by dividing the expenditure on each of the four energy inputs by the total annual expenditures (salary and wages; capital rental rates; materials; electricity; fuels) in the industry. Expenditures on energy inputs for gasoline refining include energy feedstocks. Source: Manufacturing Energy Consumption Survey, Census and Annual Survey of Manufacturers.

Table 2: Summary Statistics

| | Energy Cost Share | Output Elasticities | | | Returns to Scale | Markup | Output Price | Marginal Costs | Materials Share of Revenue | Observations |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Labor | Materials | Capital | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Boxes | 0.02 | 0.04 | 0.95 | 0.04 | 1.00 | 1.47 | 0.63 | 0.43 | 0.65 | 1414 |
| Bread | 0.02 | 0.28 | 0.63 | 0.09 | 1.13 | 1.20 | 0.47 | 0.39 | 0.53 | 248 |
| Cement | 0.32 | 0.91 | 1.08 | 0.19 | 2.46 | 2.30 | 0.05 | 0.02 | 0.46 | 229 |
| Concrete | 0.02 | 0.11 | 0.68 | 0.16 | 1.09 | 1.12 | 43.82 | 39.82 | 0.61 | 3369 |
| Gasoline | 0.84 | 0.01 | 0.99 | 0.03 | 1.02 | 1.11 | 23.08 | 20.84 | 0.89 | 284 |
| Plywood | 0.02 | 0.02 | 0.95 | 0.11 | 0.92 | 1.48 | 0.68 | 0.57 | 0.62 | 139 |
| Sample Mean | 0.02 | 0.10 | 0.70 | 0.14 | 1.09 | 1.15 | — | — | 0.62 | 5683 |

*Notes*: This table shows mean values of energy cost shares, output elasticities, and markups. An observation is a plant-year. Energy cost shares are the sum of fuel and electricity expenditures divided by total annual expenditures (salary and wages; capital rental rates; materials; electricity; fuels). Plant-level markups come from estimating production functions by industry using GMM-Proxy methods (Ackerberg, Caves, and Frazer, 2015). Output elasticity estimates come from a three factor, gross-output, translog production function, where the inputs consist of labor, capital, and materials. Price and costs are measured in 1000s of 1987 dollars. Boxes are measured in short tons; bread is measured in thousands of pounds; cement is measured in cubic yards; concrete is measured in thousands of cubic yards; gasoline is measured in thousands of barrels; plywood is measured in thousands of square feet surface measure. See text for details. Source: Census of Manufacturers.

Table 3: Relationship Between Marginal Costs, Output Prices, Markups and Electricity Input Prices

| | (1) Lag (t-0) | (2) Lag (t-2) | (3) Lag (t-5) | (4) Lag (t-0) | (5) Lag (t-2) | (6) Lag (t-5) |
|---|---|---|---|---|---|---|
| | Panel A: Marginal Costs | | | | | |
| Coal Price × Coal Share | 0.092 | 0.156 | -0.110 | 0.357 | 0.374 | 0.123 |
| | (0.387) | (0.363) | (0.311) | (0.244) | (0.293) | (0.255) |
| Gas Price × Gas Share | 0.779*** | 0.788*** | 0.866*** | 0.235*** | 0.225*** | 0.291*** |
| | (0.175) | (0.140) | (0.191) | (0.086) | (0.084) | (0.061) |
| Oil Price × Oil Share | 0.136 | 0.229 | 0.013 | -0.070 | 0.047 | -0.029 |
| | (0.341) | (0.290) | (0.201) | (0.121) | (0.118) | (0.139) |
| | Panel B: Output Prices | | | | | |
| Coal Price × Coal Share | 0.081 | 0.063 | -0.061 | 0.259 | 0.159 | 0.065 |
| | (0.259) | (0.254) | (0.197) | (0.263) | (0.257) | (0.223) |
| Gas Price × Gas Share | 0.491*** | 0.502*** | 0.532*** | 0.186** | 0.204*** | 0.222*** |
| | (0.109) | (0.088) | (0.101) | (0.074) | (0.061) | (0.054) |
| Oil Price × Oil Share | 0.101 | 0.172 | 0.078 | -0.008 | 0.057 | 0.079 |
| | (0.181) | (0.168) | (0.131) | (0.102) | (0.094) | (0.108) |
| | Panel C: Markups | | | | | |
| Coal Price × Coal Share | -0.012 | -0.092 | 0.049 | -0.098 | -0.215 | -0.058 |
| | (0.220) | (0.183) | (0.171) | (0.156) | (0.172) | (0.172) |
| Gas Price × Gas Share | -0.288*** | -0.286*** | -0.334*** | -0.049 | -0.021 | -0.069* |
| | (0.080) | (0.066) | (0.096) | (0.045) | (0.053) | (0.038) |
| Oil Price × Oil Share | -0.035 | -0.056 | 0.065 | 0.062 | 0.010 | 0.107 |
| | (0.181) | (0.134) | (0.097) | (0.090) | (0.069) | (0.077) |
| N | 5892 | 5892 | 5892 | 5892 | 5892 | 5892 |
| Plant FE | X | X | X | X | X | X |
| Year FE | X | X | X | | | |
| State Trends | X | X | X | X | X | X |
| Product-Year FE | | | | X | X | X |
| Region-Year FE | | | | X | X | X |

*Notes*: This table presents regression coefficients from 18 separate regressions, 6 per panel and 1 per column. An observation is a plant-year. Panel A presents a set of regressions, regressing plant-level marginal costs on national fuel prices interacted with lagged shares of state-level electricity generation mix. Panels B and C present a similar set of regressions, using plant-level output prices and plant-level markups as the dependent variable, respectively. The regression includes the uninteracted fuel prices and generation shares as controls (not reported). Columns (1) and (4) report results using contemporaneous electricity generation shares, columns (2) and (5) present results lagging generation shares by 2 years, and columns (3) and (6) present results lagging generation shares by 5 years. Standard errors are in parentheses and are clustered by state. Regressions are weighted by Census sampling weights. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. See text for details. Source: Census of Manufacturers, EIA-SEDS.

Table 4: Relationship Between Marginal Costs, Output Prices, Markups and Energy Prices

| | (1) Lag (t-0) | (2) Lag (t-2) | (3) Lag (t-0) | (4) Lag (t-2) |
|---|---|---|---|---|
| | Panel A: Marginal Costs | | | |
| Coal Price × Coal Share | 38.54*** | 67.60*** | 38.69*** | 66.79*** |
| | (7.91) | (8.90) | (7.95) | (8.97) |
| Gas Price × Gas Share | 139.60*** | 100.65** | 136.44*** | 97.41** |
| | (29.29) | (41.61) | (29.32) | (40.44) |
| Oil Price × Oil Share | 358.58*** | 427.31*** | 354.57*** | 419.99*** |
| | (23.31) | (84.93) | (22.63) | (83.01) |
| Electricity Price × Electricity Share | -69.48** | 118.43 | -70.59** | 112.69 |
| | (32.15) | (113.81) | (32.25) | (116.56) |
| | Panel B: Unit Prices | | | |
| Coal Price × Coal Share | 13.95*** | 31.68*** | 13.84*** | 31.06*** |
| | (4.70) | (5.75) | (4.67) | (5.76) |
| Gas Price × Gas Share | 76.65*** | 54.92** | 75.80*** | 53.09** |
| | (22.60) | (24.18) | (22.71) | (23.65) |
| Oil Price × Oil Share | 183.76*** | 251.67*** | 181.91*** | 247.12*** |
| | (20.47) | (53.38) | (20.05) | (52.57) |
| Electricity Price × Electricity Share | -12.66 | 81.70 | -12.18 | 78.83 |
| | (18.75) | (69.18) | (19.10) | (68.15) |
| | Panel C: Markups | | | |
| Coal Price × Coal Share | -24.59*** | -35.92*** | -24.85*** | -35.73*** |
| | (4.79) | (5.34) | (4.83) | (5.33) |
| Gas Price × Gas Share | -62.95** | -45.73** | -60.64** | -44.31** |
| | (25.89) | (20.41) | (25.59) | (19.87) |
| Oil Price × Oil Share | -174.82*** | -175.64*** | -172.66*** | -172.87*** |
| | (17.73) | (33.45) | (17.15) | (32.35) |
| Electricity Price × Electricity Share | 56.88** | -36.72 | 58.41** | -33.85 |
| | (23.70) | (47.93) | (23.64) | (46.82) |
| N | 5683 | 5683 | 5683 | 5683 |
| Plant FE | X | X | X | X |
| Year FE | X | X | | |
| State Trends | X | X | X | X |
| Region-Year FE | | | X | X |

*Notes*: This table presents regression coefficients from 12 separate regressions, 4 per panel and 1 per column. An observation is a plant-year. Panel A presents a set of regressions, regressing plant-level marginal costs on national energy input prices interacted with lagged industry energy expenditure shares. Panels B and C present a similar set of regressions, using plant-level output prices and plant-level markups as the dependent variable, respectively. The regression includes the uninteracted fuel prices and expenditure shares as controls (not reported). Columns (1) and (3) report results using contemporaneous electricity generation shares, and columns (2) and (4) present results lagging expenditure shares by 2 years. Standard errors are in parentheses and are clustered by state. Regressions are weighted by Census sampling weights. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. See text for details. Source: Census and Annual Survey of Manufacturers, MECS, and EIA-SEDS.

Table 5: Pass-Through Rate of Marginal Costs into Output Prices: OLS

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Marginal Costs | 0.598*** | 0.680*** | 0.598*** | 0.681*** |
| | (0.018) | (0.033) | (0.018) | (0.032) |
| N | 5892 | 5892 | 5892 | 5892 |
| Plant FE | X | X | X | X |
| State Trends | X | X | X | X |
| Year FE | X | | | |
| Product-Year FE | | X | | X |
| Region-Year FE | | | X | X |

*Notes*: This table presents regression coefficients from 4 separate regressions, one per column. An observation is a plant-year. The dependent variable is the plant-level unit-price, and the independent variable is plant-level marginal cost. Standard errors are in parentheses and are clustered by state. Regressions are weighted by Census sampling weights. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. See text for details. Source: Census of Manufacturers, EIA-SEDS.

Table 6: Pass-Through Rate of Marginal Costs into Output Prices: Instrumental Variables

| | (1) Lag (t-0) | (2) Lag (t-2) | (3) Lag (t-5) | (4) Lag (t-0) | (5) Lag (t-2) | (6) Lag (t-5) |
|---|---|---|---|---|---|---|
| | Panel A: Electricity Shift-Share Instrument | | | | | |
| Marginal Costs | 0.628*** | 0.623*** | 0.625*** | 0.660*** | 0.654*** | 0.715*** |
| | (0.031) | (0.031) | (0.029) | (0.099) | (0.088) | (0.086) |
| N | 5892 | 5892 | 5892 | 5892 | 5892 | 5892 |
| First Stage F-Statistic | 9.53 | 14.33 | 6.99 | 8.89 | 3.95 | 12.09 |
| Plant FE | X | X | X | X | X | X |
| Year FE | X | X | X | | | |
| State Trends | X | X | X | X | X | X |
| Product-Year FE | | | | X | X | X |
| Region-Year FE | | | | X | X | X |
| | Panel B: Fuel Shift-Share Instrument | | | | | |
| Marginal Costs | 0.511*** | 0.514*** | — | 0.505*** | 0.508*** | — |
| | (0.013) | (0.014) | — | (0.012) | (0.014) | — |
| N | 5683 | 5683 | — | 5683 | 5683 | — |
| First Stage F-Statistic | 137.48 | 78.68 | — | 120.74 | 66.18 | — |
| Plant FE | X | X | X | X | X | X |
| Year FE | X | X | X | | | |
| State Trends | X | X | X | X | X | X |
| Region-Year FE | | | | X | X | X |

*Notes*: This table presents regression coefficients from 10 separate regressions, 6 regressions in Panel A and 4 regressions in Panel B. An observation is a plant-year. The dependent variable is the plant-level unit-price, and the independent variable is plant-level marginal cost. In Panel A, marginal cost is instrumented by the interactions between national fuel prices for electricity generation and lagged electricity generation shares. In Panel B, marginal cost is instrumented by the interactions between national fuel prices for industrial production and lagged industry energy expenditure shares. Columns (1) and (4) report results using contemporaneous electricity generation shares, columns (2) and (5) present results lagging generation shares by 2 years, and columns (3) and (6) present results lagging generation shares by 5 years. Standard errors are in parentheses and are clustered by state. Regressions are weighted by Census sampling weights. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. See text for details. Source: Census and Annual Survey of Manufacturers, MECS, EIA-SEDS.

Table 7: Pass-Through Rate of Marginal Costs into Output Prices, by Product: Instrumental Variables

| | (1) Boxes | (2) Bread | (3) Cement | (4) Concrete | (5) Gasoline | (6) Plywood |
|---|---|---|---|---|---|---|
| | Panel A: Baseline - Electricity Price Instrument | | | | | |
| Marginal Costs | 0.963*** | 0.681*** | 0.775*** | 0.711*** | 0.327** | 0.692*** |
| | (0.038) | (0.150) | (0.087) | (0.082) | (0.143) | (0.082) |
| N | 1414 | 308 | 293 | 3369 | 345 | 163 |
| Pass-Through Rate | 1.42 | 0.82 | 1.78 | 0.80 | 0.36 | 1.02 |
| First Stage F-Statistic | 23.41 | 1.67 | 49.29 | 23.36 | 2.43 | 38.55 |
| Plant FE | X | X | X | X | X | X |
| Year FE | X | X | X | X | X | X |
| State-Trends FE | X | X | X | X | X | X |
| | Panel B: Region-Year FE - Electricity Price Instrument | | | | | |
| Marginal Costs | 0.992*** | 0.458*** | 0.801*** | 0.624*** | 0.242** | 0.758*** |
| | (0.057) | (0.172) | (0.100) | (0.066) | (0.111) | (0.068) |
| N | 1414 | 308 | 293 | 3369 | 345 | 163 |
| Pass-Through Rate | 1.46 | 0.55 | 1.84 | 0.70 | 0.27 | 1.12 |
| First Stage F-Statistic | 2.04 | 3.39 | 22.90 | 13.5 | 4.22 | 30.10 |
| Plant FE | X | X | X | X | X | X |
| Region×Year FE | X | X | X | X | X | X |
| State-Trends FE | X | X | X | X | X | X |

*Notes*: This table presents regression coefficients from 14 separate regressions; one per column in each of the two panels. Each column represents a separate sample, where the sample is indicated in the column headings. An observation is a plant-year. The dependent variable is the plant-level unit-price, and the independent variable is plant-level marginal cost. Marginal cost is instrumented by the interactions between national fuel prices for electricity generation and 5-year lagged electricity generation shares. Standard errors are in parentheses and are clustered by state. Regressions are weighted by Census sampling weights. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. See text for details. Source: Census and Annual Survey of Manufacturers, MECS, EIA-SEDS.

Table 8: Incidence: Change in Consumer Surplus as Share of Change in Total Surplus

| | (1) Boxes | (2) Bread | (3) Cement | (4) Concrete | (5) Gasoline | (6) Plywood |
|---|---|---|---|---|---|---|
| | Panel A: Incidence Components | | | | | |
| MC Pass-Through ($\rho_{MC}$) | 1.43 | 0.69 | 1.81 | 0.74 | 0.31 | 1.08 |
| Demand Elasticity ($\epsilon_D$) | 3.24 | 2.42 | 1.82 | 5.53 | 8.70 | 1.39 |
| Mean Lerner Index (L) | 0.33 | 0.18 | 0.57 | 0.13 | 0.12 | 0.41 |
| | Panel B: Consumer Share of Burden (by Market Structure) | | | | | |
| Symmetric Oligopoly | 0.57 | 0.53 | 0.63 | 0.49 | 0.24 | 0.67 |
| Asymmetric Oligopoly | 0.60 | 0.66 | 0.69 | 0.63 | 0.25 | 0.87 |
| Monopoly | 0.59 | 0.41 | 0.64 | 0.43 | 0.24 | 0.52 |
| Perfect Competition | 1.43 | 0.69 | 1.81 | 0.74 | 0.31 | 1.08 |

*Notes*: This table presents results for welfare incidence by industry, where incidence is defined as the change in consumer surplus as a share of the change in consumer and producer surplus. Columns (1) - (6) reflect separate calculations for industries defined in the column heading. Panel A displays the necessary components for measuring incidence using equation (2). Marginal cost pass-through ($\rho_{MC}$) is calculated as the average of the industry specific pass-through rates in Table 7. Panel B displays incidence under different market structures. The first two lines display incidence under arbitrary forms of oligopoly that next both perfect competition and monopoly, where asymmetric oligopoly uses the simplifying assumptions described in Section 6.4.2. The third and fourth rows of Panel B display incidence under monopoly and perfect competition using equation (2) where $L = 1/\epsilon_D$ and $L = 0$ respectively. Source: Census and Annual Survey of Manufacturers, MECS, EIA-SEDS.

# A Appendix Figures and Tables

Table A1: Demand Elasticity Estimates

| | (1) Boxes | (2) Bread | (3) Cement | (4) Concrete | (5) Gas | (6) Plywood |
|---|---|---|---|---|---|---|
| | Panel A: OLS | | | | | |
| Demand Elasticity ($\epsilon_D$) | -2.24*** | -0.11*** | -0.78*** | -0.60*** | -0.59 | -1.27*** |
| | (0.59) | (0.12) | (0.12) | (0.08) | (0.76) | (0.14) |
| | Panel B: Productivity IV Estimates | | | | | |
| Demand Elasticity ($\epsilon_D$) | -3.24*** | -2.42*** | -1.82*** | -5.53*** | -8.70* | -1.39*** |
| | (0.18) | (0.41) | (0.47) | (0.55) | (4.94) | (0.15) |
| N | 1414 | 308 | 293 | 3369 | 345 | 163 |
| First Stage F-Statistic | 816.9 | 33.9 | 15.6 | 174.0 | 8.4 | 1180.0 |
| Year FE | X | X | X | X | X | X |
| ln(County Per Capita Income) | X | X | X | X | X | X |

*Notes*: This table presents 12 separate regressions, 6 per panel. An observation is a plant-year, where the dependent variable in all regressions is log(quantity). The independent variable is log(output price). Panel A presents OLS estimates, separately by industry. Panel B presents estimates where price is instrumented with plant total factor productivity. Total factor productivity is constructed using a quantity-based productivity index. The index is constructed by subtracting log inputs from log outputs using industry-level cost shares as proxies for output elasticities. We use capital, materials, labor, and energy inputs, where capital, materials, and energy are deflated by industry-year input price deflators, and labor is measured in production hours. Source: Census of Manufacturers, BEA Local Area Employment Indicators.