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How Relative Prices Affect Fuel Use Patterns in Manufacturing

Plant-Level Evidence from Chile

Charles C. Guo
James R. Tybout

Fuel taxes will induce fuel substitution and reductions in pollution. But evidence from manufacturing firms in Chile suggests that the response will be very uneven — and that the costs of adjustment may be borne more by some sectors and types of producers than others.

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Summary findings

Some economists have urged reliance on fuel taxes and other fiscal incentives to reduce air pollution in semi-industrialized countries. They argue that policies that act on relative prices are easier to enforce than those based on emission monitoring, create less misallocation of resources, and are relatively free of the rent-seeking and corruption that accompany regulations administered at the plant level.

To be effective, however, fuel-specific taxes and subsidies must inspire manufacturers to significantly adjust their input use as relative prices change. Moreover, these policies must not create politically unacceptable income redistribution.

Guo and Tybout shed light on both issues by analyzing detailed panel data on Chilean manufacturing plants.

Overall, their estimates suggest that there is substantial scope for fuel taxes to encourage fuel substitution, but that the response will be very uneven — not only across sectors but across producers of different sizes. Although Eskeland and Jimenez (1990) may be correct in arguing that fiscal incentives are easier to implement than are direct emission controls, the costs of adjustment are likely to be concentrated fairly narrowly for some fuels.

The authors found bakeries, for example, to be very responsive to changes in the relative prices of alternative fuels. By contrast, energy demand in metal products plants appears to be very insensitive to relative prices, no matter what estimates are used. Meatpackers fall somewhere between the two — with little price responsiveness in electricity demand, but more in the demand for energy from other sources, especially if coherency-constrained figures are used.

It seems that the effects of fuel taxes would depend in significant measure on the sectoral composition of manufacturing, since input composition varies and some sectors have little flexibility.

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How Relative Prices Affect Fuel Use Patterns in Manufacturing: Plant-Level Evidence from Chile

Charles C. Guo
and
James R. Tybout
Georgetown University

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I. Overview

In the major cities of many semi-industrialized countries, air pollution has become a serious problem. The most cursory tour of Mexico City, Santiago, or Jakarta is sufficient to convince one that the externalities are massive. Now, after decades of neglect, many policy-makers are turning their attention to the issue and debating the relative merits of alternative corrective measures.

Some economists have urged reliance on carbon taxes and other fiscal incentives (Eskeland and Jimenez, 1990). Policies that act on relative prices are easier to enforce than direct controls, create less misallocation of resources, and are relatively free of the rent-seeking and corruption that accompany regulations administered at the plant level. To be effective, however, fuel-specific taxes and subsidies must inspire manufacturers to significantly adjust their production techniques as relative prices change. Moreover, these policies must not create politically unacceptable income redistribution. The purpose of this paper is to generate new evidence on both issues by analyzing detailed panel data on Chilean manufacturing plants.

There is already a large body of evidence on fuel elasticities of demand. However, the relevance of this literature is limited by several factors. First, most studies are based on sectoral time series from OECD economies, so the product mix and technologies they describe differ to an unknown extent from those in the semi-industrialized countries. Second, to have a reasonable number of sectoral observations, many years of data are necessary.[1] But technology is unlikely to remain fixed over the twenty to thirty year time spans that are typically studied. Third, the econometric literature almost always begins from the assumption that production technologies are homothetic in factor inputs. This is especially unlikely to be true in developing countries, where the population of manufacturers ranges from cottage industry to large multinationals. Finally, this literature also presumes complete flexibility to adjust all factor stocks every year. But adjustments in fuel use patterns often require lumpy investments in retrofitting

[1] Not all analyses at the sectoral level are pure time series. Some use relatively short time periods but pool across regions or countries, e.g., Fuss (1977).

or new capital equipment, so observed fuel use patterns reflect adjustment costs and and expectations about the future.

We can do better on all counts by using plant-level panel data from Chile. First, we can explicity account for non-homotheticities by allowing technologies to vary across plants of different sizes. Second, because transportation costs and infrastructure induce substantial spatial variation in prices, we need not use the time dimension of our data to identify parameters. This means we can describe the technology at a recent point in time, rather than some ill-defined temporal average for the past thirty years. Finally, by taking plant-specific temporal averages of all variables before fitting our model, we come closer to a representation of long run behavior than estimators based on a simple cross section or annual time series.[2]

We estimate substitution elasticities using plant-level panel data that describe expenditure and physical consumption levels for each of 12 alternative energy sources, *inter alia*. The data describe virtually all Chilean manufacturing plants with at least ten workers for the period 1979-1986.[3] We find, first, that the degree of substitutability between fuels is substantial in some sectors, but very limited in others. Second, the variation in elasticities across the plant size spectrum is at least as large as it is across industries. For both reasons, the incidence of carbon taxes is likely to be concentrated in certain types of plants.

Several troublesome econometric issues complicate the analysis. First, although an industry consumes many fuels in the aggregate, each individual plant is unlikely to consume no more than several.

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[2] In principle, of course, we could do better by specifying an explicitly dynamic model (e.g., Rust, 1987). However, the returns to this strategy are limited by the fact that we don't observe details of the capital stock. Moreover, dynamic panel data models suffer from the "initial conditions" and "incidental parameters" problems, which would necessitate going to considerably more complicated estimation techniques (Heckman, 1981).

[3] These data were originally obtained from the Chilean government by the World Bank for the research project "Industrial Competition, Productive Efficiency, and their Relation to Trade Regimes," RPO 674-46.

This suggests that at the typical plant, some fuels cost more than their marginal revenue products at zero consumption, and accordingly, the first-order conditions that are used to estimate fuel demads with sectoral data cannot be justified. We adopt the technique developed by Lee and Pitt (1987) to deal with this problem.

Another problem is that to estimate fuel demands we must observe a plant-specific price for every fuel, whether it is actually used or not. Given that we observe physical quantities and expenditures for each fuel that *is* used, we surmount this problem by estimating fuel price equations that relate unit values of the fuels to exogenous plant characteristics such as geographic region, industry and size. These equations are fitted fuel by fuel, using the subset of plants for which unit fuel prices could be calculated. Then fitted values from these equations are constructed for *all* plants and treated as the market prices that producers face. We view this technique as not only solving the problem of unobservable prices, but removing noise from plant-specific unit values.

II. The Empirical Model

The Likelihood Function: Our representation of producer behavior is a slight generalization of Lee and Pitt's (1987). Suppose that output is a function of capital (K), labor (L), materials (M), and a vector of energy inputs (X), some of which may not be used. Then the profit maximizing choice of energy inputs can characterized be using the Lagrangian:

$$L = P_K K + P_L L + P_m M + P_x \cdot X + \lambda(Y - F[K,L,M,X]) - \phi \cdot X$$

where ϕ is a vector of Kuhn-Tucker multipliers that impose non-negativity constraints on the elements of X. The relevant first-order conditions are:

$$\lambda \frac{\partial F}{\partial X_j} = P_{X_j} - \phi_j \equiv \xi_j;$$

$$\phi_j \geq 0 \tag{1}$$

So if producers were confronted with virtual prices, ξ, instead of actual prices, they would behave as if they were at an interior solution. Accordingly, standard first-order conditions can be used to identify the production technology once this substitution has been made.

Proceeding to do so, suppose that the production function is weakly separable in energy inputs:

$$Y = F[K,L,M,e(X)]$$

This ensures that for a given input of the energy aggregate, E, and a given vector of factor input prices, the choice of energy inputs satisfies the cost minimization problem:

$$\min_{X} \ \xi \cdot X \quad \textit{subject to} \quad E = e(X)$$

The mix of energy inputs that solves this problem yields some level of costs, C_e, which we approximate with a standard translog function:

$$ln C_e = \alpha_0 + \sum_i \alpha_i ln \xi_i + +\gamma lnE + \frac{1}{2}\sum_i \sum_j \beta_{ij} \ ln\xi_i ln\xi_j + \frac{1}{2}\sum_i \beta_{Ei} \ lnE ln\xi_i + \sum_i \epsilon_i ln\xi_i \tag{2}$$

Here the disturbance vector $\epsilon = (\epsilon_1,\epsilon_2,\epsilon_3)$ picks up plant-specific variation in technology. Then the associated share equations implied by Sheppard's lemma are:

$$S_i^* = \alpha_i + \beta_{Ei} \ E + \sum_j \ \beta_{ij} \ ln \ \xi_j + \epsilon_i, \qquad i = 1, 2, 3 \tag{3}$$

Combined with the bounds on virtual prices implied by (1),

$$\xi_i = P_{X_i} \quad \textit{if } s_i^* > 0$$

$$\xi_i < P_{X_i} \quad \textit{if } s_i^* = 0$$

and with the assumption that ϵ is distributed $N(0,\Sigma)$, these share equations form the basis for Lee and Pitt's (1987) likelihood function. Details are provided in the appendix.

Parameter constraints: The cost function (2) must be homogeneous of degree 1 in prices, which implies the following standard parameter constraints:

$$
\begin{aligned}
&\Sigma_i \alpha_i + \Sigma_i \epsilon_i = 1, \\
&\Sigma_j \beta_{ij} = \Sigma_i \beta_{ji} = 0 \text{ for all i and j}, \\
&\Sigma_i \beta_{Ei} = 0, \\
&\beta_{ij} = \beta_{ji},\ i \neq j.
\end{aligned}
\tag{4}
$$

To normalize disturbances, we restate the first restriction as: $\Sigma_i \alpha_i = 1$ and $\Sigma_i \epsilon_i = 0$.

Depending upon which combination of inputs is consumed, there are seven possible demand regimes for any plant. Each of these may be classified as one of three basic types: all three inputs are used, only two inputs are used, and only one kind of input is used. The likelihood function will be well defined only if the seven regime probabilities sum to one for each possible realization on exogenous variables. Lee and Pitt term this condition "coherency," and show that it amounts to concavity of the log cost function (2) in log prices. Coherency will hold automatically if the underlying production technology is strictly concave in factor inputs. Unfortunately, concavity does not hold globally for translog functions. Thus, to ensure a well-defined likelihood function we impose and test the coherency constraints that $\beta_{11} < 0$, $\beta_{22} < 0$, $\beta_{33} < 0$, $\beta_{11}\beta_{22} - \beta_{12}^2 > 0$, $\beta_{11}\beta_{33} - \beta_{13}^2 > 0$, and $\beta_{22}\beta_{33} - \beta_{23}^2 > 0$. We caution that even this is insufficient to gaurantee that our estimated cost function is concave in prices at all data points in the sample.[4]

[4] In estimating the parameters of their energy cost function, Lee and Pitt (1987) only impose the restrictions that all the own-price parameters β_{ii} are non-positive.

Homotheticicty: Notice that we have departed from Lee and Pitt (1987), and most others, by letting e(**X**) be non-homothetic. (That is, $\beta_{Ei} \neq 0$ may occur for particular i values.) As mentioned in the introduction, we do so because we believe technologies in semi-industrialized countries are very size-specific. Others have presumably imposed homotheticity to simplify estimation, given that E is both unobserved and endogenous. In principle, the simultaneity problem can be dealt with by instrumenting E with its exogenous determinants: $\boldsymbol{Q}$, $\boldsymbol{P_X}$, and non-energy factor prices. But since E is not actually observed, we simply include the instrumental variables directly in our cost function, sans non-energy factor prices (which were not available). Since $\boldsymbol{P_X}$ already appears directly as a cost determinant, this amounts to replacing E with Q in equation (3).

One disavantage of our approach is that it does not permit one to isolate the role of energy prices in changing E from the direct effect of factor prices on shares. But this problem may well be negliglible since the vast majority of the variation in E is due to Q, and in any case, a more severe bias is present when homotheticity *is* wrongly imposed. At a minimum, our model constitutes a generalization of the standard specification, and affords a framework for testing the homotheticity restriction.[5]

III. Estimation

A. Price Data

As mentioned in the introduction, we use predicted values of fuel prices for all plants. There are two reasons for doing so. First, most plants report zero consumption for some fuels. For these plants and fuels, the unit price is not available. Second, even though unit fuel prices are available for plants with non-zero consumption, these are likely to partly reflect cross-plant differnces in fuel quality. Hence

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[5] An alternative way to motivate our specification is to simply begin from a cost function that takes the form: $C = C(P_K, P_L, P_M, C_e(P_X, Q), Q)$ where r is the rental rate on capital, w is the wage rate, m is the price of materials, and P_e is the price of the energy aggregate.

if we were to use unit values instead of *predicted* unit values, we would probably be introducing measurement error bias in our estimator, biasing elasticities toward zero. (Given that we treat the predicted prices as the "true" ones, we make no correction to the standard errors in our estimated share equations.)

The regression model used to impute price for energy j is given by

$$\ln P_{ijt} = \theta_j + \gamma_j' Z_{jt} + \eta_{ijt},$$

where i indexes plant, t indexes year, and Z is the vector of exogenous variables. It includes dummies for year, 3-digit or 4-digit industry, region, and business type, and the logrithm of number of workers. For each energy source j, θ_j and γ_j are estimated for plants with positive consumption. The estimated regression equation for each energy source is then used to impute its predicted price for all plants. Further analysis of the sources of price variation in our data can be found in Moss and Tybout (1992).

B. Choice of Sector and Fuel Grouping

The panel data at our disposal describe virtually all Chilean manufacturing establishments with at least ten workers over the period 1979-86. For each plant and year, they includes expenditure and volume data on 12 energy sources: electricity, coal, carbon, coke, fuel oil, diesel, benzine, parafin, liquid gas, canned gas, fuel wood, and other fuels. There are 29 3-digit industries in total, but we limit our attention to two 4-digit and three 3-digit industries which are large and/or energy intensive: meat processing (SIC 3111), bakeries (SIC 3117), textile (SIC 321), chemical products (SIC 351), and metal products (SIC 381). Descriptive statistics for these sectors are presented in Table 1.

Because all sectors use a substantial amount of electricity, this is always defined as the first energy source. We define the second and third energy sources as aggregations over subgroups of the eleven fuel types, using different aggregations for different sectors. In forming these groups we considered two factors: shares in total energy expenditure, and similarity of the fuels. The second subgroup is firewood for meatpackers and bakeries; it is coal, carbon and coke for textiles; it is fuel oil and diesel for chemical products and metal products. The third subgroup is, of course, everything else.

Table 1: Basic Characteristics

	Meatpacking		Bakeries		Textiles		Chemicals		Metal Products	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Electricity Share	0.497	0.236	0.419	0.215	0.790	0.251	0.562	0.346	0.667	0.284
2nd Input Share	0.107	0.177	0.326	0.244	0.010	0.069	0.220	0.290	0.077	0.175
3rd Input Share	0.396	0.253	0.256	0.270	0.200	0.245	0.218	0.281	0.256	0.248
Electricity Price (ln)	1.460	0.138	1.622	0.105	1.485	0.130	1.404	0.151	1.537	0.130
2nd Input Price (ln)	0.748	0.190	0.690	0.136	1.576	0.104	2.564	0.107	2.665	0.099
3rd Input Price (ln)	2.487	0.073	2.469	0.064	2.445	0.087	2.228	0.081	2.159	0.084
Output Value (ln)	10.422	1.647	9.284	0.790	9.746	1.271	11.215	1.496	9.658	1.299
Sample Size	173		1176		631		100		671	
Cases of Positve Consumption:										
Electricity	171		1176		631		98		671	
2nd Input	88		936		31		58		197	
3rd Input	152		992		392		71		491	

The second and third inputs are aggregated from several actual fuels (11 types in total) used by firms. The groupings of the second input are firewood for meatpacking and bakeries; coal, carbon, and coke for textiles; fuel oil and diesel for chemicals and metal products.

Once the two non-electric energy sources had been constructed we constructed price indicies for each as weighted averages of the prices of the individual components:

$$P^a = \Sigma_{j \in G} w_j \hat{P}_j,$$

Here G is the set of fuels being aggregated, w_j is the weight of expenditure of fuel j in that group, and $\hat{P}_j$ is its imputed price in logarithms. The groupings of fuels for each sector are shown in Table 1.

IV. Results

A. Tests of the Coherency Constraint

Before discussing parameter estimates it is necessary to test whether the coherency constraints required by the Lee and Pitt framework are consistent with our data. In sectors where they are not, it is difficult to proceed. On the one hand, if the constraints are not imposed the likelihood function is ill-defined. On the other hand, if they *are* imposed, we have found that it usually means that β_{11} or β_{22} are pushed to zero, implying in turn that β_{12} is zero, so it becomes impossible to solve for virtual prices using equations A2 or A5 (see the Appendix). Under these circumstances the only sensible conclusion is that the Lee and Pitt framework does not provide a reasonable representation of the process that generated the data. This may be due to unmodelled dynamics, to heterogenous technologies, or to inappropriate aggregation across the individual fuels when we form our three categories.

Table 2 reports values of the likelihood function, with and without the coherency constraint imposed, for the non-homothetic version of our model. Notice that the constraint is accepted in the cases of bakeries, metal products, and (at α values less than .05) meatpacking. On the other hand, it is strongly rejected for chemicals, and we were unable to obtain constrained results for the textile industry.

Accoringly, in what follows we will focus on the former three sectors.

Table 2: Tests of The Coherency Restrictions*

Industry	No. of Observations	Unconstrained Log Likelihood Function	Constrained Likelihood Function	Likelihood Ratio Statistic
Meatpacking	173	-88.86	-93.85	9.98
Bakeries	1176	-463.06	-463.06	0.00
Textiles	631	-370.18	no convergence	n.a.
Chemicals	100	-61.75	-98.72	73.94
Metal Products	671	-567.52	-568.94	2.84

* Critical values for the $\chi^2(4)$ distribution are 7.78 at $\alpha=.01$, 9.49 at $\alpha=.05$, 11.14 at $\alpha=.025$ and 13.28 at $\alpha=.01$.

B. Homotheticity

We next turn to parameter estimates sector by sector. These are presented in table 3. Given that coherency is a necessary condition for the likelihood function to be well-defined, there is no clear interpretation for tests based on sectors where coherency fails. However, following Lee and Pitt, we report them nonetheless for completeness.

The first issue we wish to address is whether energy demands are homothetic of degree one with respect to output. This hypothesis amount to the claim that $\beta_{Q1} = \beta_{Q2} = \beta_{Q3} = 0$. Clearly for the sectors where inference is possible, it can be rejected.[6] In fact, almost *every* β_{Qi} value for which standard errors are obtained is highly significant. (Caution must be exercized when interpreting standard errors for chemicals, since this sector fails the coherency test.)

[6] For bakeries, the likelihood ratio statistic that tests $\beta_{Q1} = \beta_{Q2} = \beta_{Q3} = 0$ is 98.57. The critical $\chi^2(2)$ value is 9.21 when testing at the $\alpha=.01$ level.

Table 3A: Unconstrained Parameter Estimates by Sector[a]

Parameter	Meatpacking	Bakeries	Textiles[b]	Chemicals	Metal Products[b]
α_1	.651 (.165)	.267 (.090)	3.40	1.05 (.346)	.515
α_2	.039 (.148)	.291 (.122)	-1.27	-.739 (.232)	-1.26
α_3	.310 (.240)	.442 (.165)	-1.13	.692 (.208)	1.74
β_{Q1}	.001 (.015)	-.056 (.010)	-.177	-.071 (.035)	.015
β_{Q2}	-.029 (.013)	-.058 (.013)	.062	.101 (.023)	.106
β_{Q3}	.027 (.022)	.114 (.017)	.115	-.030 (.019)	-.121
β_{11}	.428 (.163)	-.329 (.069)	.666	-.288 (.403)	.182
β_{12}	-.108 (.045)	-.214 (.035)	-.570	.158 (.221)	-.003
β_{13}	-.320 (.124)	.542 (.073)	-.096	[illegible] (.182)	-.179
β_{22}	-.088 (.049)	-.207 (.044)	.464	-.046 (.065)	-.005
β_{23}	.196 (.088)	.421 (.074)	.105	-.112 (.157)	.008
β_{33}	.123 (.062)	-.963 (.121)	-.009	-.018 (.026)	.171
σ_1	.227 (.017)	.201 (.005)	.407	.343 (.038)	.258
σ_2	.239 (.023)	.311 (.008)	.491	.267 (.025)	.405
σ_{12}	.012 (.011)	-.003 (.003)	-.169	-.072 (.017)	-.046
Log Likelihood	-88.864	-463.064	-370.176	-61.751	-567.518
No. Observations	173	1176	631	100	671

[a]Figures in parentheses are standard deviations.

[b]Standard deviations were not obtained for textiles and metal products due to irregularity of the estimated Hessian.

Table 3B: Constrained Parameter Estimates by Sector[a]

Parameter	Meatpacking	Bakeries	Textiles[b]	Chemicals[c]	Metal Products[c]
α_1	.653	.267 (.090)	n.a.	1.28	.556
α_2	-.184	.291 (.122)	n.a.	-1.00	-1.25
α_3	.531	.442 (.165)	n.a.	.727	1.70
β_{Q1}	-.014	-.056 (.010)	n.a.	-.070	-7.5e-4
β_{Q2}	-.052	-.058 (.013)	n.a.	.121	.106
β_{Q3}	.066	.114 (.017)	n.a.	-.051	-.105
β_{11}	-5.0e-6	-.329 (.069)	n.a.	-.062	.000
β_{12}	-3.9e-5	-.214 (.035)	n.a.	.062	.000
β_{13}	4.4e-5	.542 (.073)	n.a.	-1.9e-5	.000
β_{22}	-.422	-.207 (.044)	n.a.	-.062	.000
β_{23}	.422	.421 (.074)	n.a.	2.3e-5	.000
β_{33}	-.422	-.963 (121)	n.a.	-5.0e-6	.000
σ_1	.255	.201 (.005)	n.a.	.348	.260
σ_2	.269	.311 (.008)	n.a.	.407	.406
σ_{12}	-.013	-.003 (.003)	n.a.	-.083	-.047
Log Likelihood	-93.849	-463.064	n.a.	-98.721	-568.935
No. Observations	173	1176	631	100	671

[a] Figures in parentheses are standard deviations.

[b] Our solution algorithm failed to converge for this sector.

[c] Standard deviation were not obtained for meatpacking, chemicals, and metal products because the coherency constraint was binding, making the Hessian singular.

Larger plants appear more likely to use fuel oil, carbon, and coke; but less likely to use firewood. For example, in metal products, a doubling of plant size leads to about a ten percentage point increase in the share of these fuels. This finding has clear implications concerning the incidence of dirty fuel taxes; it also implies that virtually all of the existing econometric literature on energy substitution is mis-specified. As we will discuss shortly, the implications concerning substitution elasticities are also non-trivial.

C. Implied Elasticities

At the Plant Level Because we allow for non-homothetic technologies, each plant has its own matrix of price elasticities. To dramatize this heterogeneity, we construct plant-specific elasticities using *predicted* shares in equation (6), which are evaluated at the cross-plant mean price vector, but at plant-specific output levels. Given energy shares, partial own and cross-price elasticities of at a particular plant can be constructed as:[7]

$$\eta_{ii} = \begin{cases} 0 & \text{if } S_i = 0 \\ [\beta_{ii} + S_i(S_i - 1)]/S_i & \text{otherwise} \end{cases} \tag{6-1}$$

and

$$\eta_{ij} = \begin{cases} 0 & \text{if } S_i = 0 \\ (\beta_{ij} + S_iS_j)/S_i & \text{otherwise.} \end{cases} \tag{6-2}$$

These elasticities are partial because they account only for substitution between fuels, and do not reflect any adjustments in overall energy usage by the plant. Allen (1938) showed that the partial price elasticities are related to the partial elasticities of substitution (σ_{ij}) as $\eta_{ij} = \sigma_{ij}S_j$. Hence, even though the

[7] See, for example, Griffin and Gregory (1976) and Pindyck (1979).

Allen partial cross elasticities of substitution are symmetric, plant-level partial cross-price elasticities (and sector elasticities) will generally *not* be.

Figures 1 through 9 are based on the parameter estimates in Table 3A. They show how own- and cross-price elasticities depend upon plant size in the bakery industry, which we choose because it seems to fit the model best. Each circle corresponds to an actual plant, so most plants lie in the ranges of solid black along the curve. Notice that the (partial) elasticity of demand for electricity ranges from around -1 for small plants to -2 for moderately sized plants, implying that bigness leads to more flexibility in electricity use (figure 1). On the other hand, with the exception of a handful of outliers, ther is very little variation in own-price elasticity of demand for firewood (figure 2). Moreover, small plants are *much* more responsive to changes in the price of other fuels than their larger counterparts (figure 3).

Given these patterns it is unsurprising that cross-price partial elasticities are also very size-dependent. This is particularly true for elasticities that involve energy sources other than electricity and firewood. Interestingly, not only are cross-price elasticities non-symmetric, but the tend to change in opposite directions as plant size grows. This is a consequence of the structure of equation (6-2), which has a negative partial derivative with respect to S_i and a positive partial derivative with respect to S_j.

At the Sector Level: The principal issue of policy interest is the sensitivity fuel demands to changes in relative fuel prices. We construct these as consumption-weighted averages of the plant-specific elasticity expressions above:

$$E_{ii} = \Sigma_m \eta^m_{ii}(x^m_i/X_i) \text{ and } E_{ij} = \Sigma_m \eta^m_{ij}(x^m_i/X_i).$$

Here m indexes the plant, x^m_i is its consumption of energy source i, and X_i is industry-wide consumpition of energy source i. Also, to obtain standard errors for these expressions, we begin by approximating the standard errors of the plant-specific elasticities with:

$$\mathrm{Var}[\hat{\eta}_{i\,i}] = \mathrm{Var}[\hat{\beta}_{i\,i}]/\hat{S}_i^2 \text{ , and}$$

$$\mathrm{Var}[\hat{\eta}_{i\,j}] = \mathrm{Var}[\hat{\beta}_{i\,j}]/\hat{S}_i^2.$$

For this expression we have treated predicted cost shares S_i as non-stochastic. We then aggregate up to standard errors for the sectoral elasticities, treating consumption levels x_i^m as non-stochastic:

$$\mathrm{Var}[\hat{E}_{i\,i}] = (\Sigma_m \hat{\lambda}_i^m/\hat{S}_i^m)^2 \mathrm{Var}[\hat{\beta}_{i\,i}], \text{ and}$$

$$\mathrm{Var}[\hat{E}_{i\,j}] = (\Sigma_m \hat{\lambda}_i^m/\hat{S}_i^m)^2 \mathrm{Var}[\hat{\beta}_{i\,j}],$$

where $\hat{\lambda}_i^m = \hat{x}_i^m/\hat{X}_i$. Obviously our assumptions about exogeneity are not strictly justified, but they should have only a minor effect on the estimated variances.

Table 4a: Partial Sectoral Price Elasticities, Meatpacking[a]

	Elasticity of Demand for:		
With Respect to:	Electricity	Fuel wood	Other Fuels
$P_{electricity}$	.513 (.384) -.498 (n.a.) .161 (.302) -.498 (n.a.)	-.335 (.324) .444 (n.a.) -.044 (.242) .444 (n.a.)	-.257 (.243) .371 (n.a.) -.044 (.193) .371 (n.a.)
$P_{fuel\ wood}$	-.103 (.106) .131 (n.a.) -.016 (.079) .131 (n.a.)	-1.35 (.351) -3.75 (n.a.) -1.09 (.226) -3.03 (n.a.)	.577 (.173) 1.12 (n.a.) .393 (.125) .880 (n.a.)
P_{other}	-.318 (.292) .445 (n.a.) -.059 (.231) .445 (n.a.)	1.99 (.633) 3.90 (n.a.) 1.35 (.456) 3.05 (n.a.)	-.170 (.122) -1.24 (n.a.) -.233 (.101) -1.05 (n.a.)

The top figure in each cell is based on our nonhomothetic model without coherency restrictions; the second figure is based on the same model *with* coherency restrictions; the third figure is based on our homothetic model without coherency restrictions; and the last figure is based on the same model *with* coherency restrictions. Standard deviations are in parentheses when available.

Table 4b: Partial Sectoral Price Elasticities, Bakeries[a]

	Elasticity of Demand for:		
With Respect to:	Electricity	Fuel wood	Other Fuels
$P_{electricity}$	-1.36 (.181) -1.36 (.181) -.715 (.131) -.715 (.131)	-.401 (.125) -.401 (.125) .890 (.157) .890 (.157)	1.45 (.157) 1.45 (.157) .153 (.050) .153 (.050)
$P_{fuel\ wood}$	-.301 (.093) -.301 (.093) .661 (.117) .661 (.117)	-1.26 (.155) -1.26 (.155) -1.80 (.316) -1.80 (.316)	1.29 (.157) 1.29 (.157) .723 (.166) .723 (.166)
P_{other}	1.82 (.193) 1.82 (.193) .180 (.061) .180 (.061)	1.88 (.261) 1.88 (.261) 1.04 (.275) 1.04 (.275)	-2.44 (.259) -2.44 (.259) -.685 (.126) -.685 (.126)

See footnote to table 4a.

Table 4c: Partial Sectoral Price Elasticities, Textiles[a]

	Elasticity of Demand for:		
With Respect to:	Electricity	Coal, Carbon, Coke	Other Fuels
$P_{electricity}$	0.967 (n.a.) n.a. (n.a.) 5.20 (1.04) n.a. (n.a.)	-3.10 (n.a.) n.a. (n.a.) -11.9 (2.77) n.a. (n.a.)	.206 (n.a.) n.a. (n.a.) -.941 (.490) n.a. (n.a.)
$P_{coal\ etc.}$	-1.13 (n.a.) n.a. (n.a.) -4.33 (.956) n.a. (n.a.)	2.30 (n.a.) n.a. (n.a.) 13.6 (3.33) n.a. (n.a.)	.321 (n.a.) n.a. (n.a.) -.640 (.574) n.a. (n.a.)
P_{other}	.217 (n.a.) n.a. (n.a.) -1.02 (.511) n.a. (n.a.)	1.06 (n.a.) n.a. (n.a.) -2.21 (1.73) n.a. (n.a.)	-.445 (n.a.) n.a. (n.a.) 1.53 (.263) n.a. (n.a.)

See footnote to table 4a.

Table 4d: Partial Sectoral Price Elasticities, Chemicals[a]

	Elasticity of Demand for:		
With Respect to:	Electricity	Fuel Oil, Diesel	Other Fuels
$P_{electricity}$	-.884 (.823) -.423 (n.a.) 1.02 (.693) n.a. (n.a.)	.618 (.364) .407 (n.a.) -.779 (.412) n.a. (n.a.)	1.33 (1.38) .337 (n.a.) -.969 (.763) n.a. (n.a.)
$P_{fuel\ oil\ etc.}$	.593 (.452) .384 (n.a.) -.787 (.511) n.a.(n.a.)	-.273 (.107) -.300 (n.a.) .249 (.261) n.a. (n.a.)	-.445 (1.19) .459 (n.a.) 2.11 (.922) n.a. (n.a.)
P_{other}	.371 (.371) .092 (n.a.) -.276 (.205) n.a. (n.a.)	-.145 (.258) .100 (n.a.) .546 (.200) n.a. (n.a.)	-.883 (.197) -.748 (n.a.) -.999 (.195) n.a. (n.a.)

See footnote to table 4a.

Table 4e: Partial Sectoral Price Elasticities, Metal Products[a]

	Elasticity of Demand for:		
With Respect to:	Electricity	Fuel Oil, Diesel	Other Fuels
$P_{electricity}$	-.004 (n.a.) -.401 (n.a.) n.a. (n.a.) n.a. (n.a.)	.302 (n.a.) .310 (n.a.) n.a. (n.a.) n.a. (n.a.)	-.172 (n.a.) .373 (n.a.) n.a. (n.a.) n.a. (n.a.)
$P_{fuel\ oil\ etc.}$	.254 (n.a.) .262 (n.a.) n.a. (n.a.) n.a. (n.a.)	-.465 (n.a.) -.451 (n.a.) n.a. (n.a.) n.a. (n.a.)	.213 (n.a.) .184 (n.a.) n.a. (n.a.) n.a. (n.a.)
P_{other}	-.134 (n.a.) .288 (n.a.) n.a. (n.a.) n.a. (n.a.)	.169 (n.a.) .146 (n.a.) n.a. (n.a.) n.a. (n.a.)	.043 (n.a.) -.479 (n.a.) n.a. (n.a.) n.a. (n.a.)

[a] See footnote to table 4a.

Table 4 presents our estimates of partial price elasticity of demand at the sector level along with their standard errors. The top figure in each cell is based on our nonhomothetic model without coherency restrictions (Table 3A); the second figure is based on the same model *with* coherency restrictions (Table 3B); the third figure is based on our homothetic model without coherency restrictions (unreported parameter estimates); and the last figure is based on the same model *with* coherency restrictions (unreported parameter estimates). As already discussed, the framework we are using does not seem to fit the data for textiles and chemicals well, so we confine our attention to the remaining three sectors.

The most noteworthy feature of these results is that elasticities differ substantially across sectors. It appears that bakeries are very responsive to changes in the relative prices of alternative fuels, especially carbon-based energy sources. In contrast, energy demand appears to be very insensitive to relative prices among metal products plants, regardless of what set of estimates are used. Finally, meatpackers fall somewhere in between, with little price responsiveness in electricity demand, but more for other energy sources, especially if coherency-constrained figures are used. Therefore, it appears that the incidence of carbon taxes would depend in significant measure on the industrial sector, with metal products plants least able to adjust. Of course, more information on market structure and demand in these sectors would be needed before a full analysis of incidence could be accomplished.

In their closely related work, Lee and Pitt found elasticities that tended to be larger than the ones we report here. There are a number of possible explanations. One is that by imposing homotheticity, they forced cross-plant variation in technologies to show up as price-induced substitution since fuel prices vary across the plant size spectrum (Moss and Tybout, 1992). Support for this explanation is provided by contrasts between our elasticity estimates with and without homotheticity imposed. Another possibility is that physical quantities or expenditures are measured with error, so that when physical prices are imputed, they are contaminated by spurious negative correlation with quantities (e.g., Deaton, 1987). Our approach should not be subject to this bias because we have instrumented noise out of prices.

It is difficult to compare our results with those in most other studies because we are working with data from a semi-industrialized country, and estimating industry-specific parameters. However, several observations are worth making. First, sectoral-level studies tend to find partial own-price elasticities of demand that are similar in magnitude to ours, and lower than Lee and Pitt's. Second, like us, studies based on aggregated data tend to find that the own-price elasticity of demand for electricity is lower than elasticities for other energy sources (e.g., Fuss (1977) and Pindyck (1979)).

V. Concluding Remarks

Overall, our estimates suggest that there is substantial scope for carbon taxes to induce fuel substitution, but that the response will be very uneven, not only across sectors, but across producers of different sizes. Therefore, although Eskeland and Jimenez (1990) may be correct in arguing that fiscal incentives are less susceptible to manipulation by special interest groups than direct emission controls, the costs of adjustment *are* likely to be concentrated fairly narrowly for some fuels.

Unfortunately, the evidence on elasticities we report is not sufficient to assess the distribution of adjustment burdens. It is limited to several sectors, and it must be combined with information on the shares of energy spending in total costs, and on product market demand elasticities. However, combined with descriptive statistics on energy use patterns in all manufacturing sectors (see Moss and Tybout, 1992), our figures should provide the basis for an assessment of all but the latter.

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Appendix

In this appendix we summarize the likelihood function that Lee and Pitt (1987) developed. For our purposes it is sufficient to consider three types of regimes: all three fuels are used, two of the three fuels are used, and only one of the three fuels are used. As in the text, let asterisks denote observed (as opposed to notional) shares, so that the first type of regime occurs whe.. all elements of $S^* = (S_1^*, S_2^*, S_3^*)$are strictly positive. Under these conditions notional and observed shares coincide, thus in terms of exogenous variables and disturbances, equation (3) implies that the first regime is observed when:

$$\delta_1 + \beta_1'\ln P + \epsilon_1 > 0, \tag{A1-1}$$

$$\delta_2 + \beta_2'\ln P + \epsilon_2 > 0, \tag{A1-2}$$

$$\delta_1 + \delta_2 + (\beta_1 + \beta_2)'\ln P + \epsilon_1 + \epsilon_2 < 1 . \tag{A1-3}$$

Here $\beta_i' = (\beta_{i1},\beta_{i2},\beta_{i3})$, $\ln P = (\ln P_1,\ln P_2,\ln P_3)'$, and $\delta_i = \alpha_i + \beta_{Qi}\ln Q$. Given that one of the three disturbances is redundant by equation (4), the conditional likelihood function for observations from this regime is:

$$f(S_1^* - \delta_1 - \beta_1'\ln P,\ S_2^* - \delta_2 - \beta_2'\ln P),$$

where $f(\cdot)$ is the bivariate normal density function for (ϵ_1,ϵ_2).

An example of the second type of regime occurs when $S^* = (0, S_2^*, S_3^*)$, where $S_2^* > 0$ and $S_3^* > 0$. Here the logarithmic vi.tual price for input 1 at S^* is obtained by setting $S_1 = \delta_1 + \beta_1'\ln P + \epsilon_1 = 0$:

$$\ln\xi_1 = -(\delta_1 + \beta_{12}\ln P_2 + \beta_{13}\ln P_3 + \epsilon_3)/\beta_{11}. \tag{A2}$$

Substituting $\ln\xi_1$ for $\ln P_1$ in equation 5, the observed cost share for the second energy subgroup satisfies.

$$
\begin{aligned}
S_2^* &= \delta_2 + \beta_2'\ln P + \epsilon_2 + \beta_{21}(\ln\xi_1 - \ln P_1) \\
&= \delta_2 + \beta_2'\ln P + \epsilon_2 - (\beta_{21}/\beta_{11})(\delta_1 + \beta_1'\ln P + \epsilon_1). \qquad \text{(A3)}
\end{aligned}
$$

Hence the regime conditions $\xi_1 \leq P_1$ and $0 < S_2^* < 1$ can be expressed in terms of exogenous variables and disturbances as:

$$(1/\beta_{11})(\delta_1 + \beta_1'\ln P + \epsilon_1) \geq 0, \qquad \text{(A4-1)}$$

$$1 > \delta_2 + \beta_2'\ln P + \epsilon_2 - (\beta_{21}/\beta_{22})(\delta_1 + \beta_1'\ln P + \epsilon_1) > 0. \qquad \text{(A4-2)}$$

If $\beta_{11} < 0$, the set of (ϵ_1,ϵ_2) values that satisfy these conditions will not overlap with the (ϵ_1,ϵ_2) values in conditions (A1). This "coherency" requirement ensures, from (A4-1), that

$$\epsilon_1 < -(\delta_1 + \beta_1'\ln P),$$

and the conditional likelihood function, given $S^* = (0,S_2^*,S_3^*)$, becomes

$$\int_{-\infty}^{-(\delta_1 + \beta_1'\ln P)} f(\epsilon_1,\bar{\epsilon}_2(S_2^*,\epsilon_1))\, d\epsilon_1,$$

where $\bar{\epsilon}_2(S_2^*,\epsilon_1) = S_2^* - \delta_2 - \beta_2'\ln P + (\beta_{21}/\beta_{11})(\delta_1 + \beta_1'\ln P + \epsilon_1)$, a rearrangement of (A3).

An example of the third type of regime occurs when $S^* = (0,0,1)$, that is, inputs 1 and 2 are not consumed. By setting $S_1 = 0$ and $S_2 = 0$, the virtual prices for input 1 and 2 can be expressed as

$$\begin{bmatrix} \ln\xi_1 \\ \ln\xi_2 \end{bmatrix} = \begin{bmatrix} \ln P_1 \\ \ln P_2 \end{bmatrix} - \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}^{-1} \begin{bmatrix} \delta_1 + \beta_1' \ln P + \epsilon_1 \\ \delta_2 + \beta_2' \ln P + \epsilon_2 \end{bmatrix} \tag{A5}$$

The regime conditions are $\xi_1 \leq P_1$ and $\xi_2 \leq P_2$, or using (A5):

$$(1/(\beta_{11}\beta_{22} - \beta_{12}^2))[\beta_{22}(\delta_1 + \beta_1'\ln P + \epsilon_1) - \beta_{12}(\delta_2 + \beta_2'\ln P + \epsilon_2)] \geq 0, \tag{A6-1}$$

$$(1/(\beta_{11}\beta_{22} - \beta_{12}^2))[-\beta_{21}(\delta_1 + \beta_1'\ln P + \epsilon_1) \quad \beta_{11}(\delta_2 + \beta_2'\ln P + \epsilon_2)] \geq 0. \tag{A6-2}$$

The (ϵ_1, ϵ_2) values that satisfy conditions (A6) will not overlap with those in (A1) or (A3) only if $\beta_{11}\beta_{22} - \beta_{12}^2 > 0$. Using this coherency requirement, (A6) becomes

$$\epsilon_1 - (\beta_{12}/\beta_{22})\epsilon_2 \leq (\beta_{12}/\beta_{22})(\delta_2 + \beta_2'\ln P) - (\delta_1 + \beta_1'\ln P),$$

$$-(\beta_{12}/\beta_{11})\epsilon_1 + \epsilon_2 \leq (\beta_{21}/\beta_{11})(\delta_1 + \beta_1'\ln P) - (\delta_2 + \beta_2'\ln P),$$

and the conditional likelihood function, given $S^* = (0,0,1)$, can be written as

$$\int_{-\infty}^{(\beta_{12}/\beta_{22})(\delta_2+\beta_2'\ln P) - (\delta_1+\beta_1'\ln P)} \int_{-\infty}^{(\beta_{21}/\beta_{11})(\delta_1+\beta_1'\ln P) - (\delta_2+\beta_2'\ln P)} g(\epsilon_1^*, \epsilon_2^*) d\epsilon_1^* d\epsilon_2^*,$$

where g is the bivariate normal density function of ϵ_1^* and ϵ_2^*, with

$$\epsilon_1^* = \epsilon_1 - (\beta_{12}/\beta_{22})\epsilon_2 \text{ and } \epsilon_2^* = -(\beta_{12}/\beta_{11})\epsilon_1 + \epsilon_2.$$

The likelihood functions for the other regimes can similarly be derived. The coherency requirements β_{22}

< 0, $\beta_{33} < 0$, $\beta_{11}\beta_{33} - \beta_{13}^2 > 0$, and $\beta_{22}\beta_{33} - \beta_{23}^2 > 0$ are also needed to ensure that the seven regimes not overlap one another, that is, that the regime probabilities sum to one.

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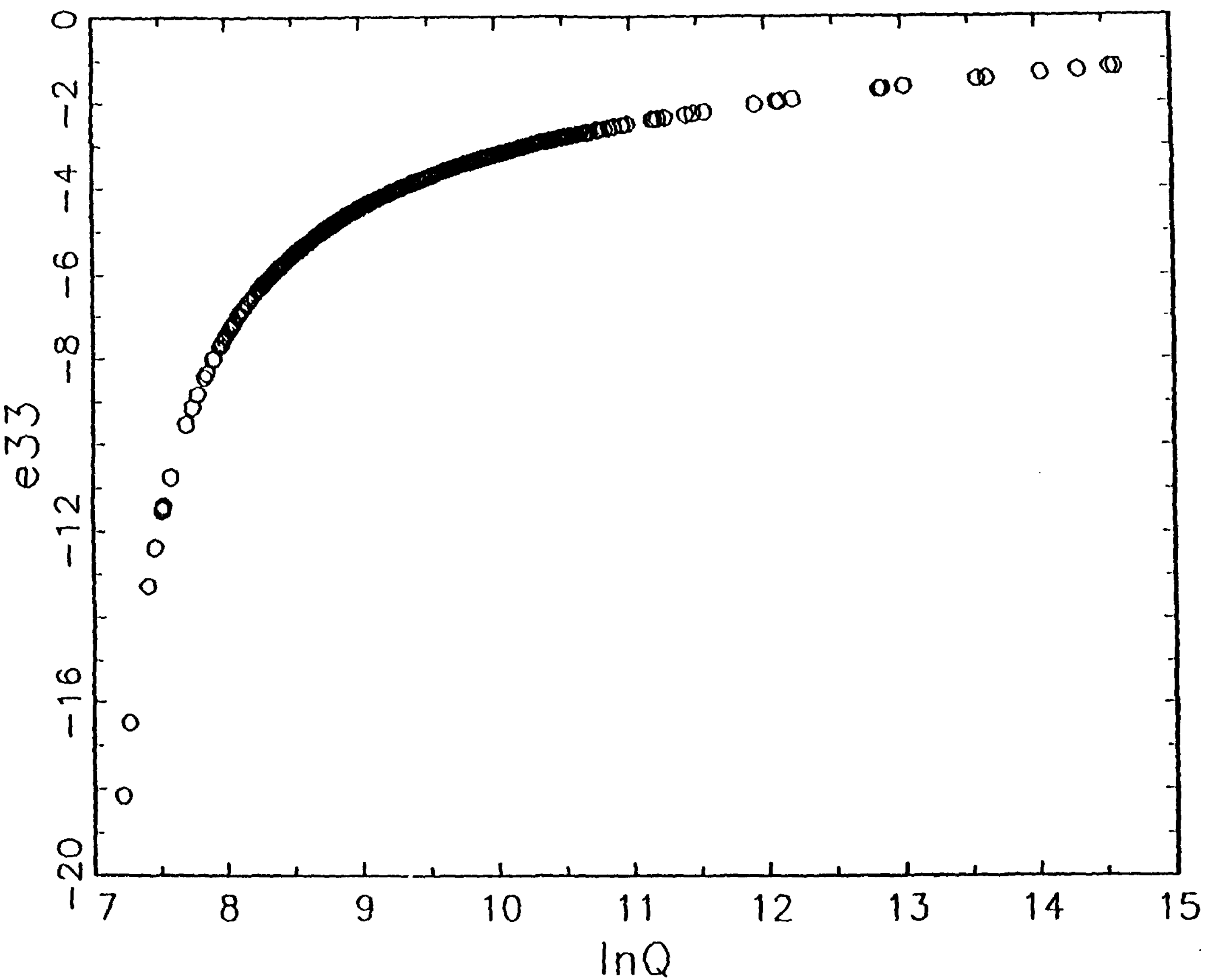

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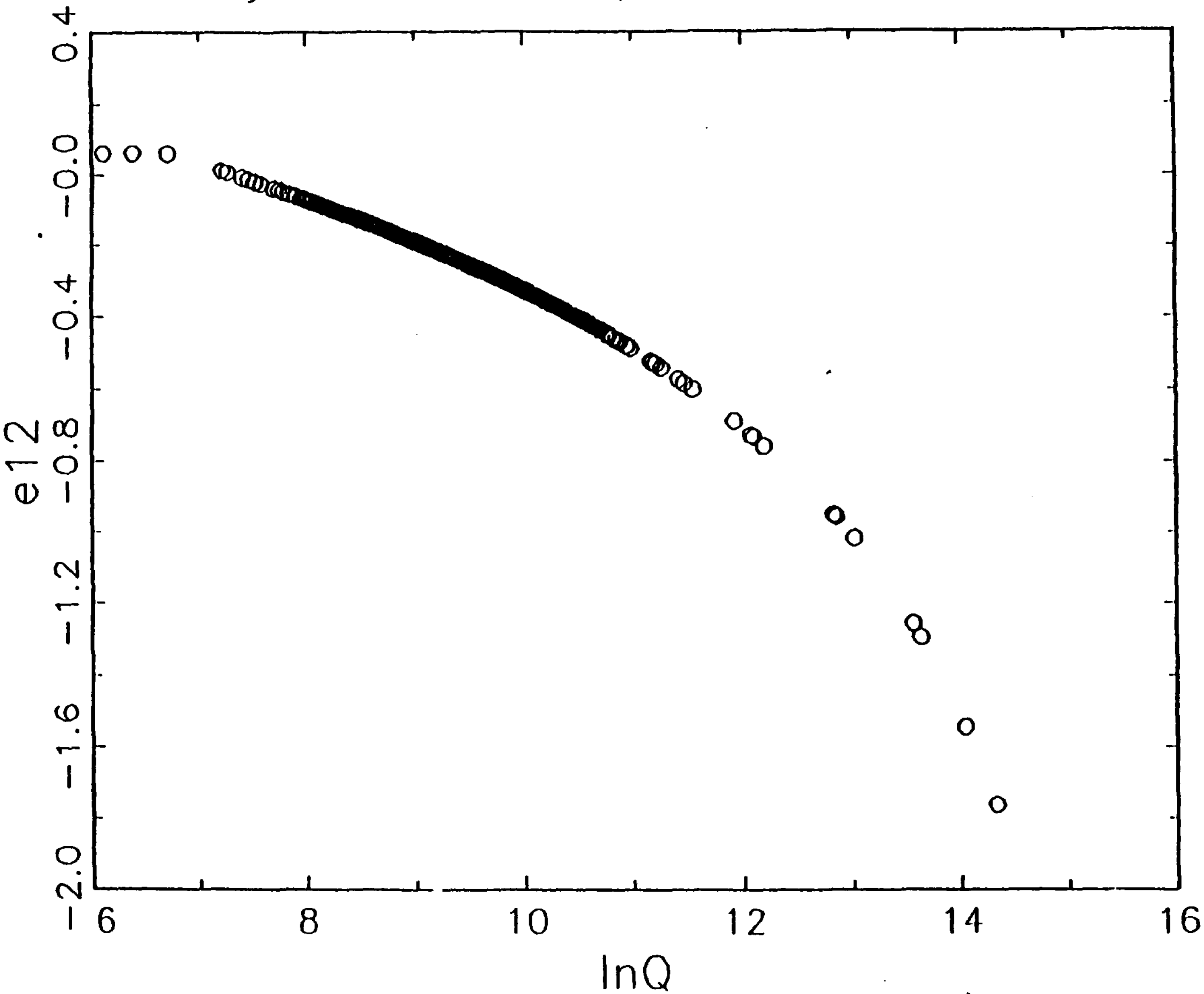

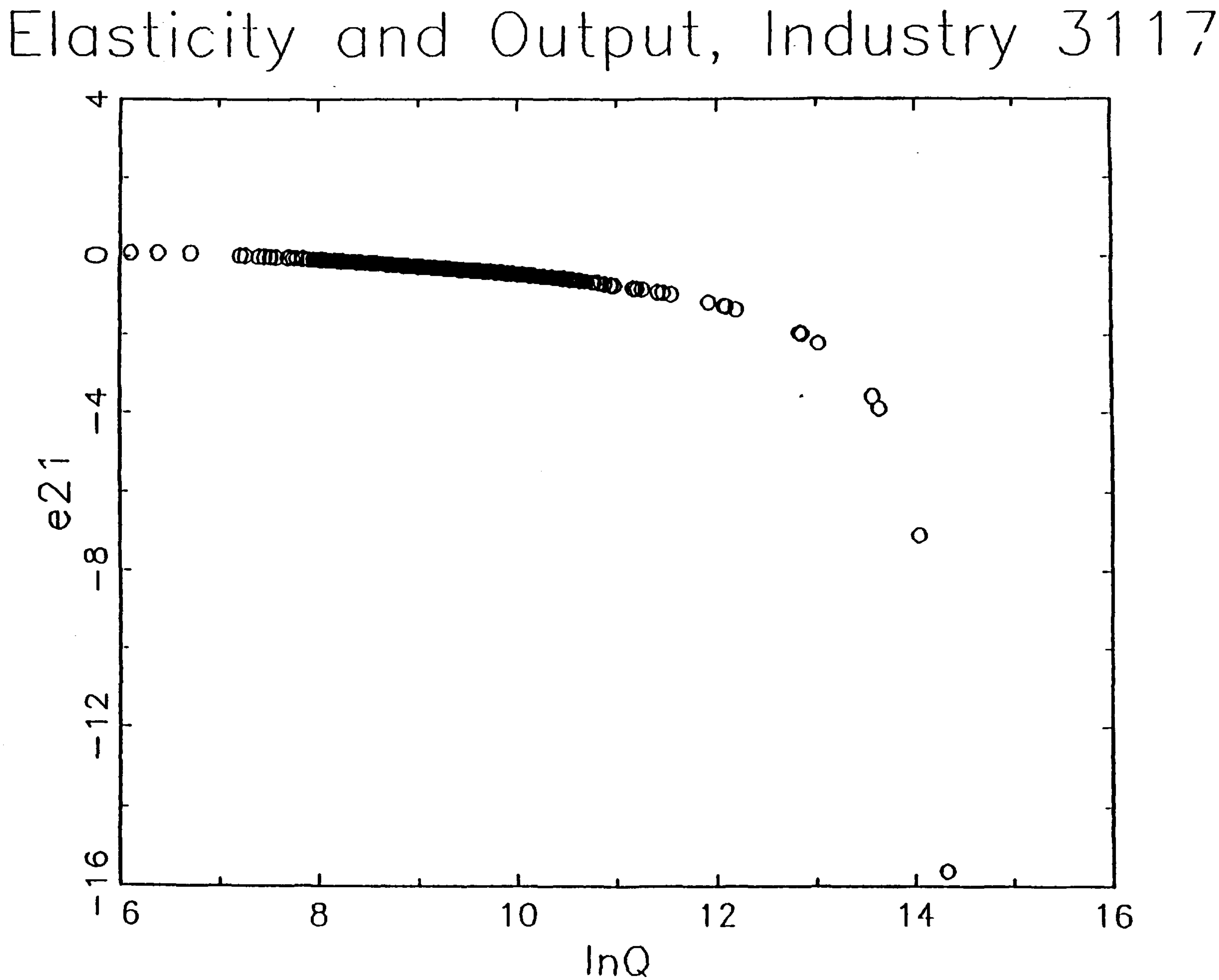
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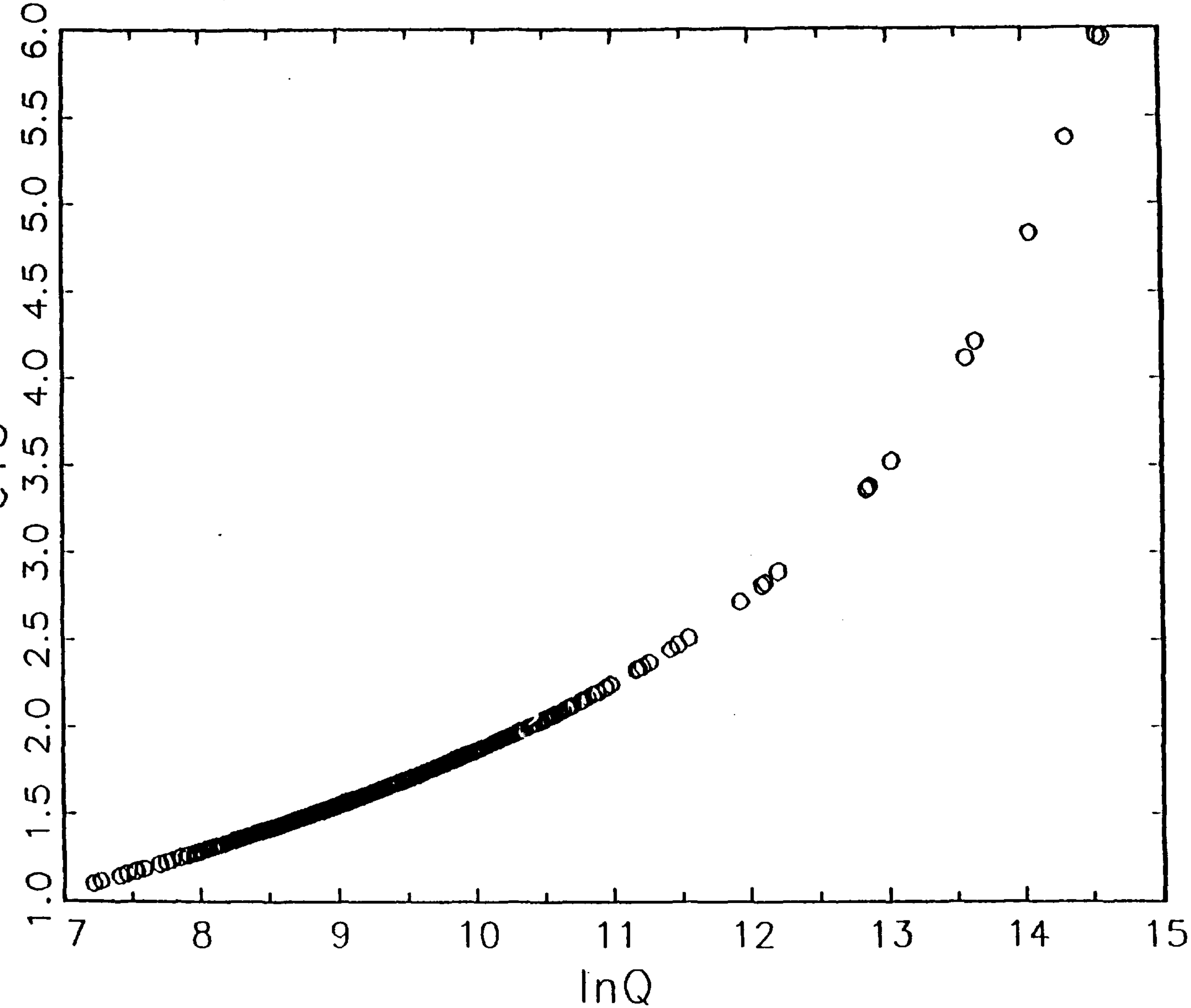

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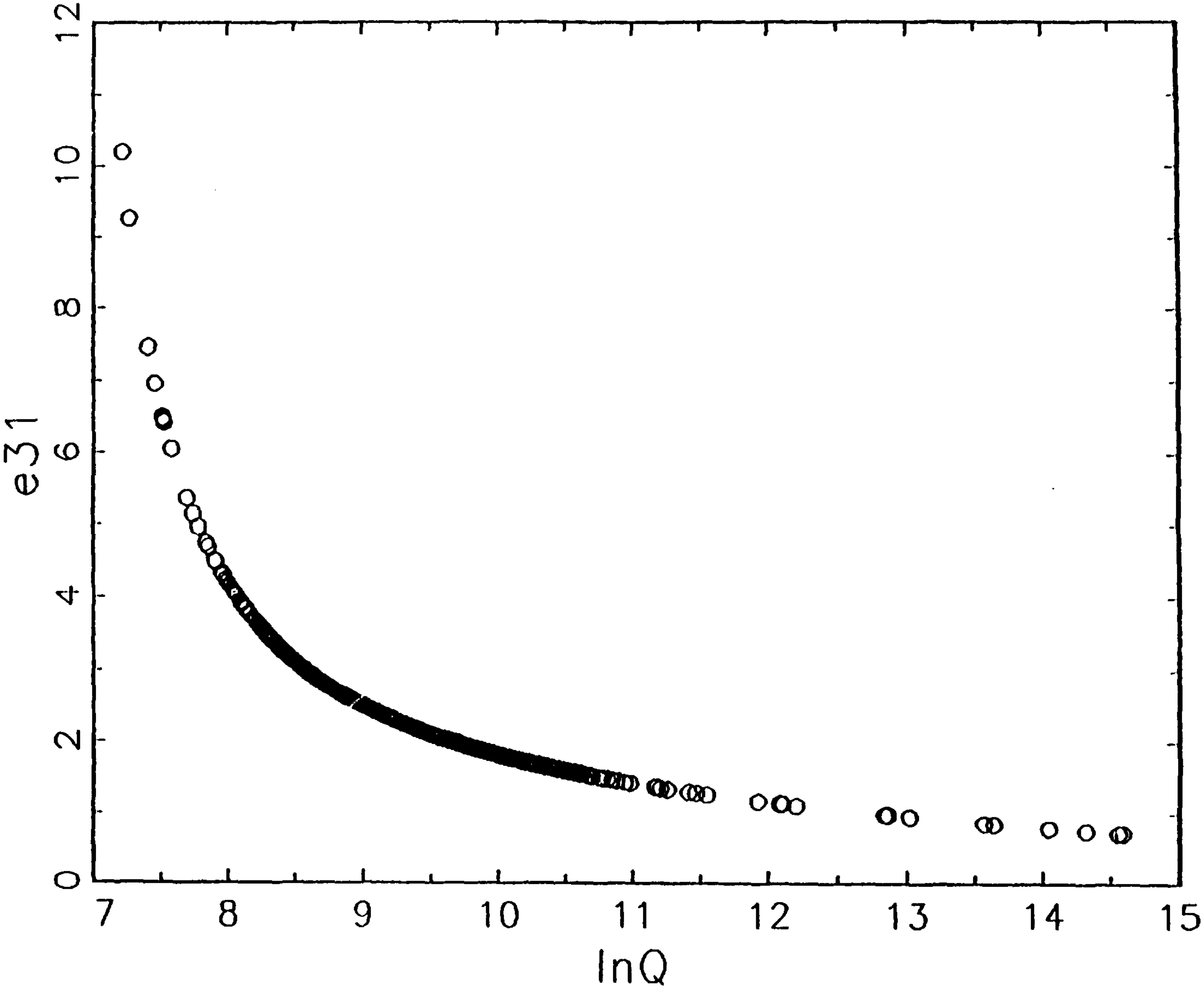

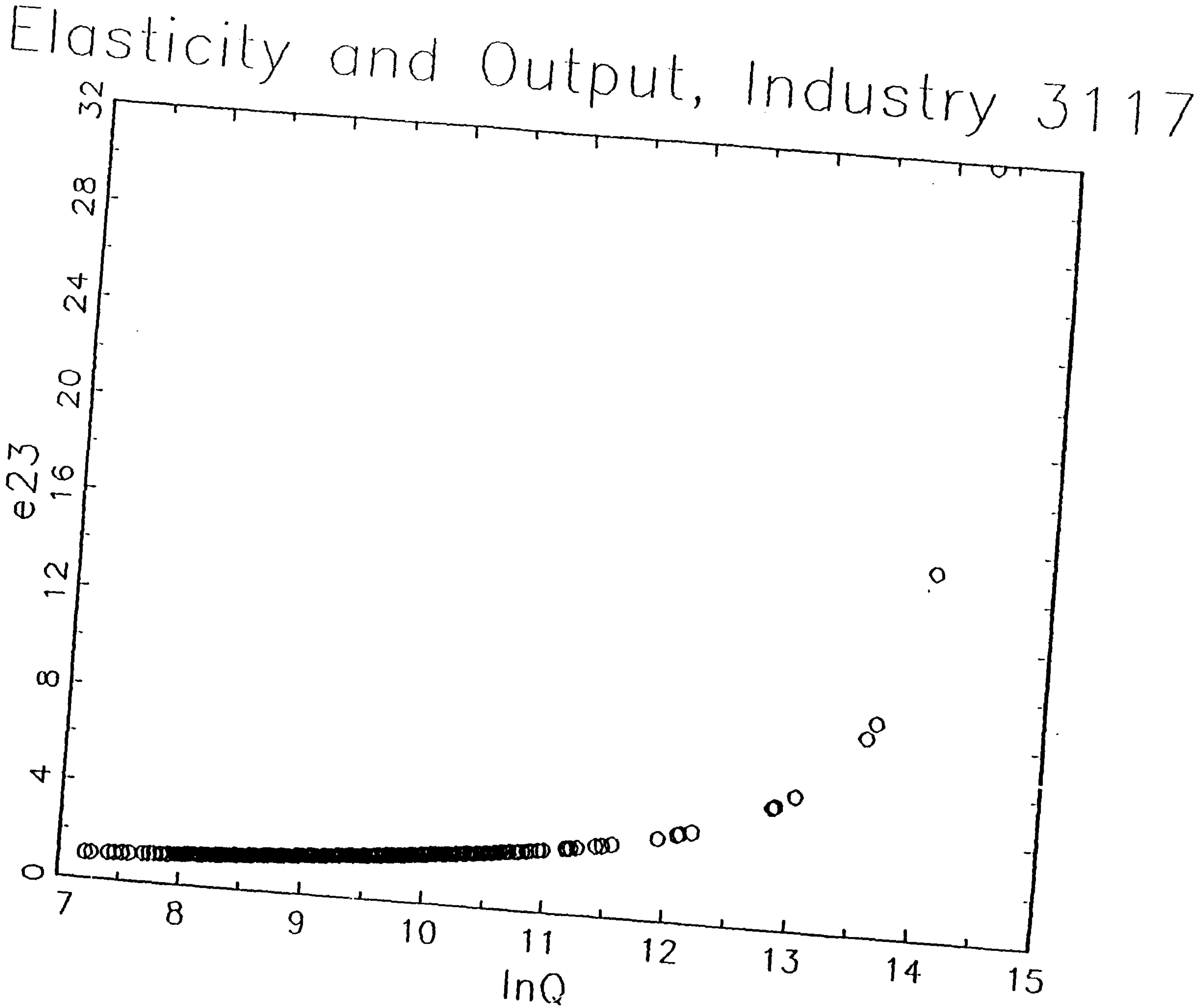
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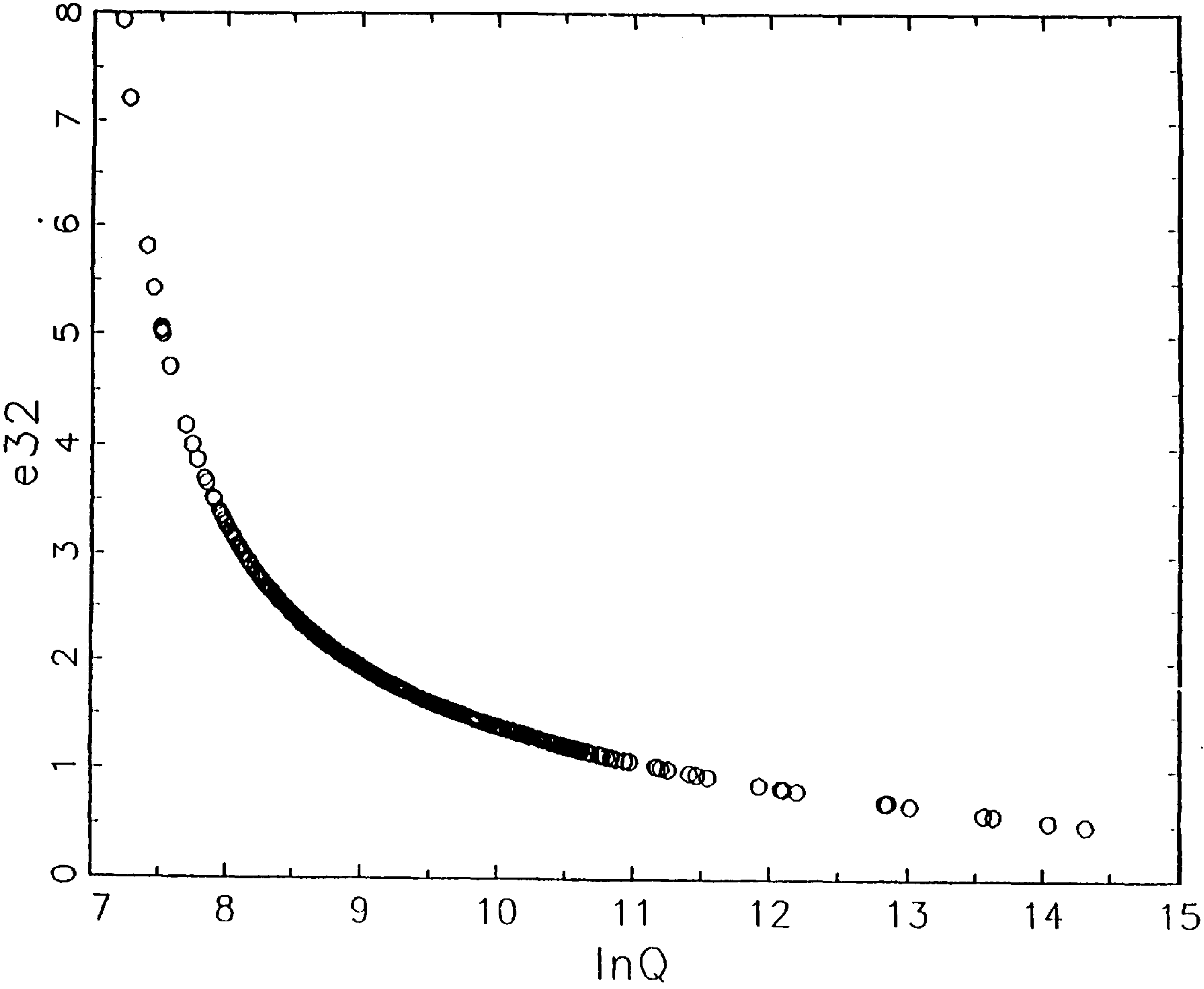

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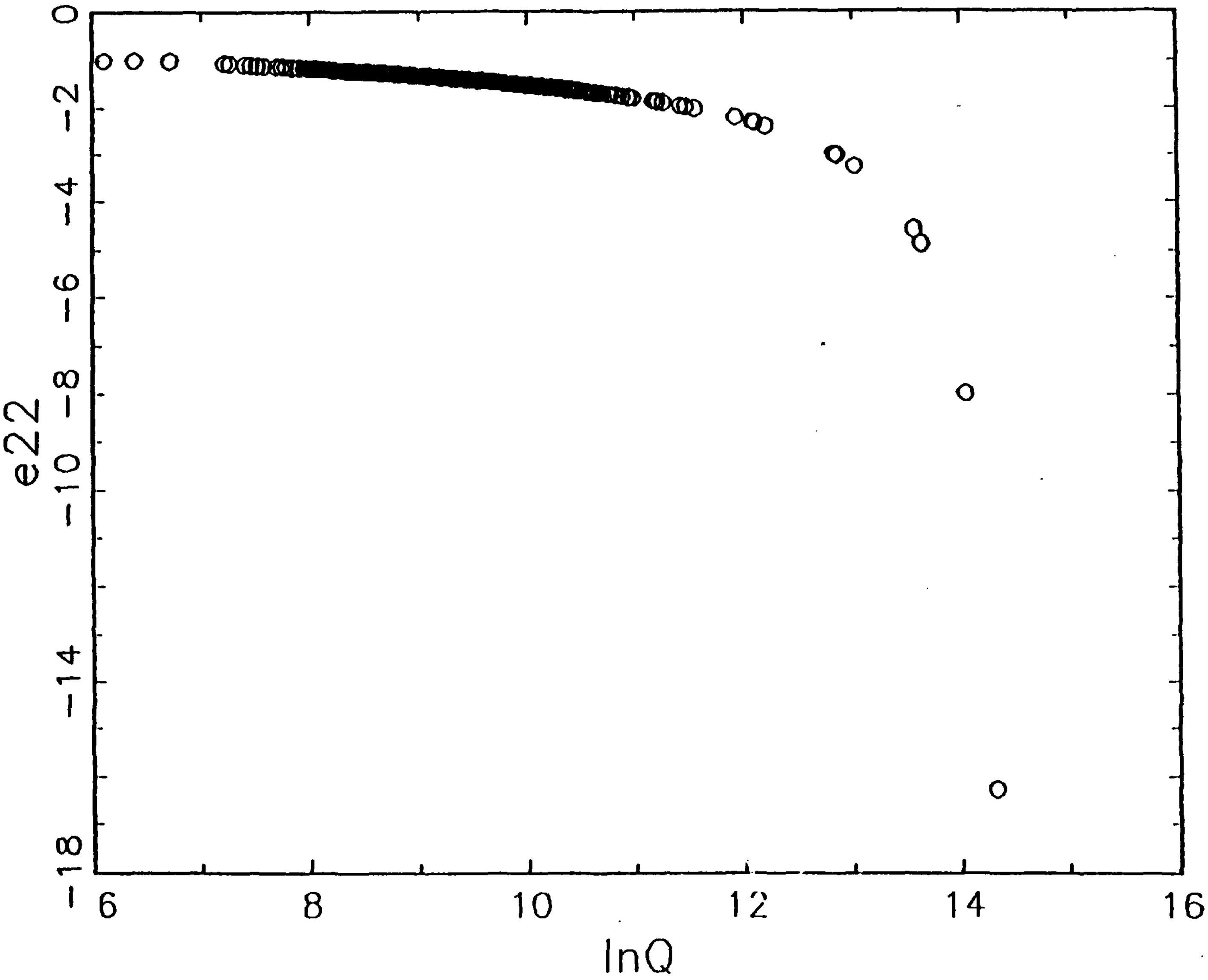

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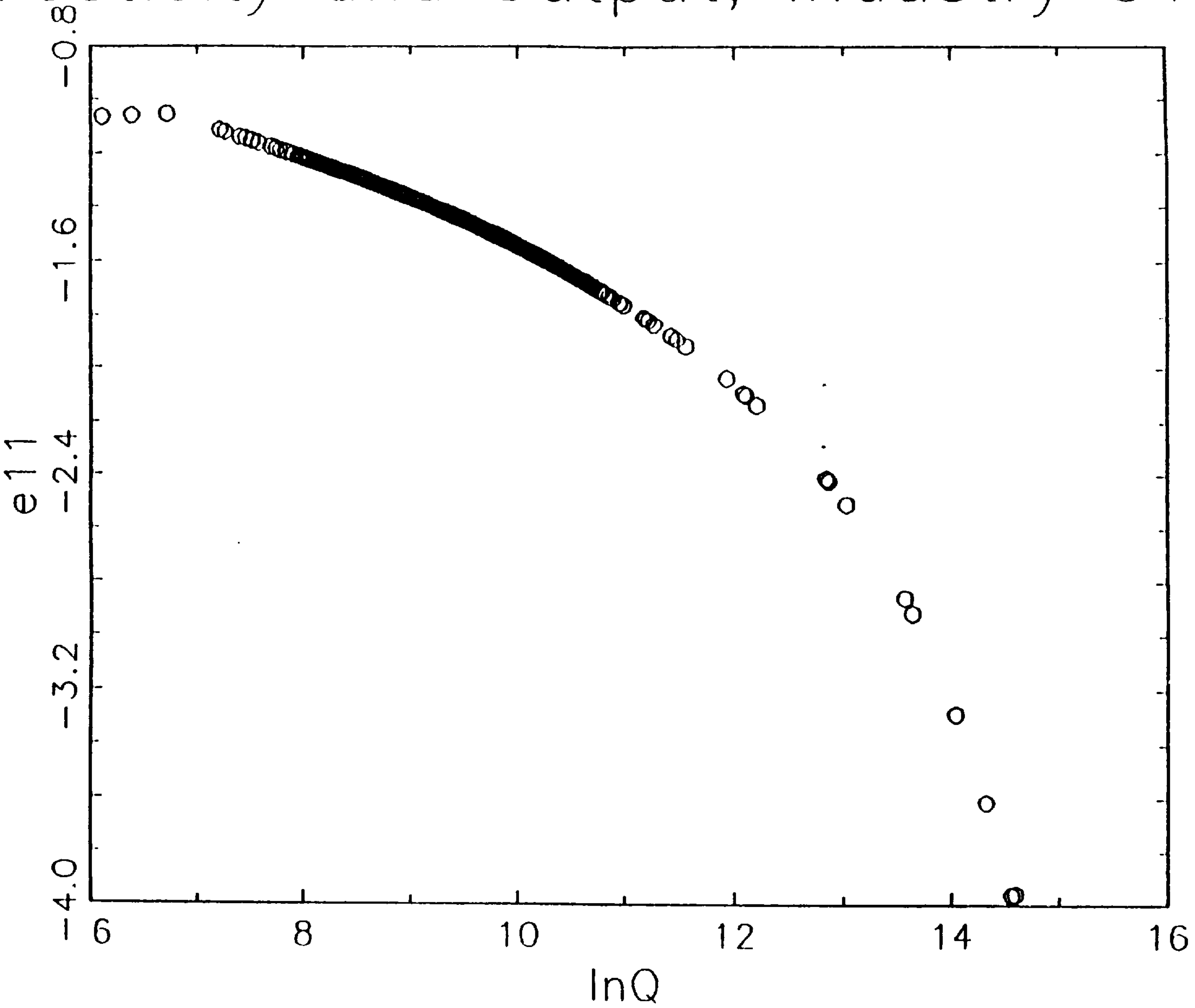

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