Does Industrial Concentration Raise Productivity in Food Industries?

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Abstract: This manuscript investigates the productivity-industrial concentration relationship in U.S. food industries. We identify a critical level of industrial concentration beyond which its relationship with productivity growth becomes negative. The welfare effects of an increase in concentration – productivity growth and deadweight loss- are computed. Welfare loss from increasing concentration is substantially offset by gains from productivity growth.

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I. Introduction

The purpose of this article is to investigate the effects of industrial concentration on innovation in the U.S. food processing industries. Increasing concentration, a characteristic of these industries in recent years, has often been cast in negative terms.[1] The exclusive focus on the welfare losses from imperfect competition has led to several investigations into the procurement and sales practices of food processors by the U.S. Departments of Agriculture and Justice. However, a number of studies have explored the theoretical possibility that the static welfare losses of increasing concentration can be offset by dynamic welfare gains such as a higher rate of innovation, the subject matter of this study (Peltzman, 1977; Grossman and Helpman, 1991; Scherer, 1999).[2] Specifically, we investigate (i) whether growth in concentration increases the rate of innovation in the U.S. food processing industry, and if so, (ii) can the welfare gains from a higher rate of innovation offset the deadweight loss from an increase in concentration.

The traditional reason for the effect of concentration on innovation is Schumpeter's "creative destruction," which suggests that a competitive market is perfectly suited for static resource allocation, but the large firm in a concentrated market is the source of long-run expansion of output. That is, extra profits from marking up prices over marginal costs provide resource for innovation. However, as Cohen and Levin (1989) note, market concentration is one source of innovation, while others such as the demand structure, technological opportunity and appropriability conditions are equally important. For instance, the existence of opportunities/production possibilities to translate research resources into new production techniques and the cost of imitation/copying by prospective competitors should be accounted for while investigating the effect of concentration on innovation.

Our study of the effect of industrial concentration on innovation differs from previous studies in several ways. First, the rate of innovation is represented by the rate of growth in total factor productivity (TFP). Growth in TFP embodies technological innovations, both product and process types (Scherer, 1999, p.30), while the analysis of it continues to remain useful and important in the development of new endogenous growth theories (Barro and Sala-I-Martin, 1995, p.352). Moreover, TFP growth is likely a better measure of the rate of innovation than patent counts or citations, which do not match the new product data in the case of the food industries (Hall, Jaffe and Trajtenberg, 2001; New Product News, 1998). Second, our focus is at the [food] industry level rather than at the firm level. Here, we search for a possible critical level of concentration, i.e., the inverted-U hypothesis (originally due to Scherer), beyond which its relationship with productivity can turn negative. Gisser (1982) also investigated the relationship between productivity and concentration at the industry level, but postulated a monotonic relationship between them. Furthermore, we estimate of the tradeoff between productivity growth and concentration in the presence of conditioning variables, and recognizing their simultaneity, unlike Gisser (1982) and other studies (Sexton, 2000).[3]

Data from the National Bureau of Economic Research (NBER) and the U.S. Department of Commerce (USDC) for the period 1964-92 are used for simultaneous estimation of TFP growth and concentration.[4] Consistent with prior research, we find that the conditioned productivity-industrial concentration relationship has an inverted-U shape. The critical level of concentration (ratio), where the relationship between growth rates of TFP and concentration turns negative, appears to be 62.3, a 24% increase from the current levels. Including welfare loss estimates and a mapping of the net gain from an increase in concentration suggests that current deadweight loss of $7.8 billion can be reduced to $2.8 billion with an increase in concentration by 18% from its current level.

II. Economic and Empirical Model of the Productivity-Concentration Relationship

Our investigation of the productivity-concentration relationship is based on some recent theoretical models of innovation-driven growth at the industry level (e.g., Peretto, 1996, and Smulders and van de Klundert, 1995). Since the basic models of this theory have been widely discussed, we provide in this section only rudimentary details and focus instead on the results. The reader is referred to Kamien and Schwartz (1982), Baldwin and Scott (1987), Cohen and Levin (1989), Scherer and Perlman (1992), and Sutton (1998) for a review of theory on market structure and technology, and empirical issues.

In the case of Peretto (1996), the economy's manufacturing sector is characterized as a differentiated oligopoly. Consumers maximize lifetime utility, where preferences are symmetric over the range of available differentiated goods. Firms' instantaneous demand schedules are of the Dixit and Stiglitz (1977) type. The manufacturing technology requires fixed costs and allows for knowledge cumulation and cost reduction. The maximization of the value of the firm involves allocating labor to physical and knowledge production and choosing the product price. All firms face the same production (and knowledge) technologies and demand schedules. A condition of symmetric industry equilibrium with free entry and exit is that the average rate of growth in cost reduction in an industry varies inversely with the number of firms, and directly with knowledge creation activities. In the case of Peretto (1996), for instance, the growth rate of innovation at the industry level (g) is given by:

$$g = \theta\left(\frac{1 + \gamma\,(N - 1)}{N}\right)L_Z,$$

where θ is the elasticity of cost reduction, N number of firms, 0<γ<1 captures access to competitor's knowledge, and L_Z is the aggregate industry R&D. Since R&D is assumed in-house, and there are increasing returns to scale in R&D, the presence of a larger number of firms causes "dispersion" of R&D resources and lower rates of innovation. This is countered by the effect of cumulative R&D, which is larger when there are more firms, to raise the rate of innovation.

In a similar setting, Smulders and van de Klundert (1995) derive short-run growth rate of innovation in an industry as a decreasing function of the number of firms, and an increasing function of the size of the economy (labor endowment) and the efficiency of knowledge creation. Here, the change in industrial concentration brings about four effects - scale effect, public knowledge effect, learning-by-watching effect, and monopolization effect – on the industry's rate of innovation. The tradeoffs among these effects suggest that increasing concentration is conducive to growth to some critical level, but excessive concentration depresses innovation.

Representing the rate of innovation in empirics, however, has been a subject of debate. As Griliches (1995) notes, there are three approaches to characterize and analyze innovation: case studies, event count (patent) analysis, and econometric studies of TFP. Case studies are interesting but few researchers have access to databases to trace the entire history of an innovation. Patents are counts of innovation but not of value of each innovation, and most process innovations are not patented (Hall, Jaffe and Trajtenberg, 2001). In the case of the food industry, the number of patents do not match the number of new products released every year, strongly suggesting the prevalence of process innovations (New Product News, 1998). That is, the underlying (unpatented) process innovations in the food industry has allowed for proliferation of new products/varieties. Moreover, patent citations data suffer from significant truncation and measurement problems. TFP growth accounts for growth in output that is not attributable to tangible inputs, and hence includes technical progress, improvements in technical efficiency, and learning-by-doing (Backus, Kehoe and Kehoe, 1992). It may also include scale economies and disequilibrium effects (Morrison-Paul, 2001), which can be controlled for using instrumental regression procedures. Moreover, analysis of TFP growth has served an important role in guiding policy (Scherer, 1999) and developing new growth theories (Barro and Sala-I-Martin, 1995). Given these trade-offs and the context (food industry), we choose TFP growth to represent the rate of innovation.

Empirical studies have used production or cost function as a starting point to derive TFP growth as function of industrial concentration and other factors.[5] Consistent with the theory and some recent empirical work (Nickell, 1996; Gort and Sung 1999), our initial specification of the productivity-industrial concentration relationship takes the following form:

$$dtfp_{it} = b_0 + b_1 cr_{it} + b_2 crsq_{it} + e_{it} \qquad (1)$$

where subscripts t and i denote time and industry, respectively, $dtfp_{it}$ is the annual growth rate of TFP, cr_{it} is the annual growth rate of concentration, and $crsq_{it}$ is the square of the annual growth rate of concentration, and ε_{it} captures all shocks to TFP growth.

The productivity-industrial concentration relationship as specified above is subject to endogeneity and specification problems. First, there is the case for reverse causality, i.e., innovation affects price-cost margins (Demsetz, 1973). Some authors have disagreed. For instance, Baldwin and Scott (1987), rephrasing Schumpeter, argue that large-scale innovation may not be attractive unless some sort of insurance is available to the potential entrepreneur. That is, an insurance against the failure of an innovation is the ability to engage in a price strategy, and thus monopolistic power in existing products markets may be a precondition for innovation (also see Gisser, 1986). However, our empirical investigation covers a fairly long time period and the possibility of TFP growth affecting concentration cannot be ignored.

Secondly all of the growth in productivity is not accounted for by concentration. As Cohen and Levin (1989) note, demand structure, technological opportunity and appropriability are additional factors impacting the rate of innovation in an industry. Since we focus exclusively on the food industries (four-digit Standard Industrial Classification, SIC, codes), demand differences are likely to be less important than factors such as research and development. Unfortunately, direct measures of R&D expenditures/stocks are not available at the level of our analysis, four-digit Standard Industrial Classification (SIC) codes. The R&D data available at the two-digit SIC (20) level together with growth in real factor prices faced by these industries are used to proxy technological opportunity and appropriability conditions.[6] The aggregate R&D represents the pool of knowledge available to these industries. When R&D is in-house, (creation of new products and/or processes is internal to a firm/industry) real growth in factor prices such as labor cost can capture its activity including learning-by-doing. Real increases in prices of intermediates and new capital goods are likely to reflect out-sourcing of technology (Levin, Cohen and Mowry, 1985; Grossman and Helpman, 1991). Hence, we augment the initial specification of the productivity-industrial concentration relationship to include a specification for growth in concentration:

$$dtfp_{it} = b_0 + b_1 cr_{it} + b_2 crsq_{it} + b_3 rd_t + b_4 pimat_{it} + b_5 piinv_{it} + b_6 wage_{it} + e_{it}, \quad \text{(2a)}$$

$$dcr_{it} = g_0 + g_1 dtfp_{it} + g_2 size_{it} + g_3 rd_t + m_{it}, \quad \text{(2b)}$$

where $pimat_{it}$, $piinv_{it}$, $wage_{it}$ are the annual growth rate in the real price of intermediates, investment, and labor (real wages), respectively, rd_t is the aggregate R&D, and $size_{it}$ is the average firm size in i-th industry at time t. The variable $size_{it}$ is included to capture the effect of scale economies, if any, on concentration (Morrison-Paul, 2001). Note that this specification can easily be obtained by differentiating an industry cost function (where some parameters are dependent on concentration) with respect to a technology index (Gort and Sung, 1999; along the same lines, Nickell 1996). Equation (2a) and 2(b) provide a simultaneous system albeit in a panel setting, which can be estimated using industry-level data on TFP, price indexes, concentration ratios and average firm size.

III. Data and Estimation Procedure

III.A Data: The primary source of 4-digit SIC level data is "Manufacturing Industry Database, 1958-96" from NBER. From this database we obtained (i) Five-factor TFP, (ii) investment deflator, (iii) materials cost (intermediates) deflator and (iv) total payroll ($) and employment ('000s), the ratio of which yielded the wage rate per employee per year. To convert the deflators and wages into real terms, we divided them by the consumer price index (CPI).

Data on industrial concentration take the form of four-firm concentration ratio, i.e., share of value of shipments accounted by the 4 largest companies in each food processing industry. Average firm size is represented as the ratio of real value of industry shipments to its number of companies (Bureau of the Census, USDC). Due to the availability of data for concentration ratio and number of firms at five-year intervals, we use grouped data (see Greene, 1997 for an exposition). We have 6 groups as follows: group1: 1964-1967 (group size: 4-year); group2: 1968-1972 (group size: 5-year); group3: 1973-1977 (group size: 5-year); group4: 1978-1982 (group size: 5-year); group5: 1983-1987 (group size: 5-year); group6: 1988-1992 (group size: 5-year). Thus, we compile one 4-year average and five 5-year average data.

The variables *dtfp*, *pimat*, *piinv*, *wage* and *rd* are generated by taking the difference between initial (I) and final (F) levels and solving for x in $(I+x)^{4 \text{ or } 5} = F$. The growth rate (x) is then premultiplied by the square root of the respective group size (4 or 5). Similarly, given concentration ratios and average firm size at 4- or 5-year intervals, the process above is repeated to derive their growth rates, which are then premultiplied by the respective group size. Note that Gisser (1982) uses grouped data for concentration variables, but does not account for the ensuing heteroskedasticity.

Our database has 6 (grouped) observations on each of the 36 out of the 48 food processing industries. The other 12 food processing industries are excluded since concentration ratios are not available for all census periods in our sample. Persistent negative growth rates of TFP, observed for a few industries, are likely whenever output growth is lower relative to growth of input, which can occur in highly protected industries such as the dairy processing and cane-sugar processing.

III.B Estimation Procedure: As noted earlier, equations (2a) and (2b) form a system of simultaneous equations in a panel setting. Advances have been made in deriving appropriate estimators and their properties in this context (Baltagi, Chapter 7, 1995). In line with prior applications of these procedures (e.g., Nguyen and Bernier, 1988; Kinal and Lahiri, 1993), we employ two-stage least squares (2SLS), which allows for fixed industry and time effects.[7] In the first stage growth rates of TFP and concentration are regressed on all exogenous variables, and industry and time dummies. Fitted values are obtained for both regressands using a one-way fixed effects specification based on a F-test. The respective specifications, as in equations (2a) and (2b), are estimated using the fitted values of TFP and concentration growth rates. Both one-way and two-way fixed effects models are estimated. The quadratic specification for TFP growth is compared with a linear specification as well. The objective and the log-likelihood values (F-test and Likelihood ratio test) are used to choose among the various specifications. The lowest (highest) objective (likelihood) value is obtained for a one-way specification with time dummies, the results of which are reported in table 1. The R^2 for the TFP and concentration equation are 39% and 22%, respectively, but note that the number of cross sections (36) exceeds that of the time series (6).

IV. Results

In this section, we first deal with the results of the relationship between productivity and concentration and vice versa. It is followed by the analysis of total welfare and the distributional impacts of a rise in concentration.

IV.1 Productivity and Concentration: The results from the estimation of equations (2a) and (2b) are reported in table 1. Consistent with conventional wisdom, regression of TFP growth on concentration and its square (fitted values), in the presence of conditioning variables, provide support for the inverted-U hypothesis. The coefficient on concentration and its square, 0.142 and –0.003, are significant at the 5% and 10% level, respectively. The magnitude of the estimates are similar to those obtained by Levin, Cohen and Mowery (1985). Figure 1 illustrates the effect of growth in concentration on TFP growth. A 1% growth in concentration brings about an initial 0.139% change in TFP growth, but the contribution declines with further increases in concentration. The peak suggests that a 24% growth in concentration, from existing levels, brings about the maximum benefits in the form of TFP growth at 1.687%. Concentration ratios ranged from a low of 22% (SIC 2026) to a high of 90% (SIC 2082) in 1992, and a simple unweighted average level of concentration in the food industry (SIC 20) is 50.2%. Hence, the results suggest that additional growth in TFP of about 1.687% can be achieved if concentration were to rise to 62.3% (=1.24*50.2). Note that the increase in concentration ratio by 24% need not occur in just one time period. A weighted average of concentration ratios as in Gisser (1982) does not change the qualitative interpretation of these results.

Evidence on technological opportunity or appropriability conditions is not strong. Although the aggregate R&D variable has the expected positive sign, it is not significant. The growth in the real price of capital has a negative and significant (10% level) effect on TFP growth, while the effect of real wages and real price of intermediates are insignificant. We suspect data limitations as the source of difficulty in modeling technological opportunity and appropriability conditions (Levin, Cohen and Mowry, 1985). Note that the R&D variable does not have cross-sectional variation.

The results of concentration growth equation (2b) are also reported in table 1. The effect of TFP growth (fitted values) is positive and significant suggesting that innovations increase concentration. Moreover, the effect of average firm size on concentration is significantly positive. That is, the larger the average size of firms in an industry the greater is the concentration, which is likely due to scale economies (Morrison-Paul, 2001). Similar to that of the TFP growth equation, R&D exerts an insignificant effect on growth in concentration.

<u>IV.2 Total Welfare Analysis:</u> Using the results from the TFP growth regression, we provide some insights into the tradeoff between productivity growth and industrial concentration. First, we assume a constant returns to scale (CRS) technology in food processing for computational convenience. In the cost function, the productivity paramter will be raised to the power of –1, if technology is of the CRS-type. Hence, a 1% increase in TFP lowers cost by 1%. Evidence suggests that a majority of the food processing industries exhibit increasing returns to scale, in which case the benefits from TFP growth are underestimated (Morrison-Paul, 2001; Bhuyan and Lopez, 1997). Given that the current level of gross output in the food processing industries is $514 billion (constant 1996 dollars, Bureau of Economic Analysis, USDC), a 1% reduction in cost leads to a welfare gain bounded by $5.14 billion, given the CRS assumption. In figure 2, we plot these welfare gains from TFP growth converted into cost reductions (billion $) for various rates of growth in concentration. Similar to the relation between concentration and TFP growth, we observe an inverted-U relationship between

concentration and cost reduction. Next, we derive the static welfare losses from market power that will offset the gains from increased concentration (TFP growth). The welfare loss estimates range from less than 0.2% to about 5.2% of gross output in the food processing industry (Azzam, 1997; Bhuyan and Lopez, 1997). Specifically, we derive welfare loss using a simple specification of the deadweight loss (DWL) per unit of sales as follows (Willner and Stahl, 1992):

$$\text{Cournot-Nash DWL} = \frac{CR_n{}^2}{2\,|e|\,n^2}$$

where CR_n denotes the n-firm (4) concentration ratio, and ϵ is the elasticity of demand.[8] Given an estimated demand elasticity of –0.514 (Bhuyan and Lopez, 1997), the latest average level of concentration in the food industry (50.2%) causes welfare loss of about $7.8 billion, which accounts for 1.52% of the shipment value. Note that the welfare loss rises monotonically with the concentration ratio. Figure 2 plots the welfare gains from TFP growth with the current concentration as the starting point along with the static welfare loss, and the net loss from increasing concentration. It is striking to note that the current net welfare loss of $7.8 billion declines to about $2.8 billion, when growth rate in concentration reaches 18%, but increases as growth in concentration exceeds this critical level. This result is qualitatively similar to that of Gisser (1982), who found that all of the deadweight and consumer losses are offset by a meager 6 percentage point rise in the concentration ratio (see also Azzam, 1997). In comparison, Sexton's simulation model on market-power and cost-efficiency tradeoff (using conjectural elasticities rather than concentration ratios) suggests a 30% cost reduction rate to offset both deadweight and consumer losses from market power. Gisser's (1982) and our study focuses only on oligopoly power rather than oligopsony or joint oligopoly and oligopsony power as in

Sexton. Note that even if losses from oligopsony are added to our welfare loss measure, the net loss may increase, but the possibility that it declines until a critical level of concentration continues to hold.

IV.3 Distributional Impacts: Thus far, we demonstrated that total welfare may improve when increases in concentration are accompanied by productivity growth. However, losses to consumers, not to the society, often are a guiding principle for antitrust policy. We can offer some insights into the distributional impact of the concentration-productivity relationship, albeit in a second-best world.

Note that the level of oligopoly output would lie somewhere between the competitive and monopoly output, given an inelastic demand structure. All else constant, the output level should shrink and the price should rise when concentration increases (static case). However, the marginal cost curve is not the same as before since there is a link between concentration and productivity. Hence, the shift (lowering) of the marginal cost curve results in new competitive and monopoly output levels, which are greater relative to the static case. As a result, oligopoly output can increase accompanied by a fall in the price when concentration increases up to a critical point. We showed in the previous section that the total welfare rises with concentration given current conditions. Given the possibility of increased output and lower prices as a result of an increase in concentration, consumer surplus can rise in a second-best world. That is, consumers are better-off than before although they are still farther from the "true" competitive equilibrium. With regard to producers' welfare, revenue and price vary inversely given the inelastic nature of the demand. However, they wouldn't have embarked on product/process innovations unless they are profitable.

V. Summary and Conclusions

In this study, we focused on the Schumpeterian hypothesis of "creative destruction," where industrial concentration can increase welfare by impacting innovation. We consider the productivity-industrial concentration relationship in the presence of other conditioning variables such as external and internal sources of knowledge, and industry-specific effects. In addition, we allow for a simultaneous determination of industrial concentration. Grouped data from public domain are used to provide empirical insights into this relationship. Our focus is a bit limited because R&D variables are available at aggregate levels and not at the level of our analysis.

We find that growth in concentration is an important determinant of TFP growth and vice versa. Consistent with prior studies, an inverted-U relationship is found between TFP growth and concentration. The critical growth rate of concentration is found to be 18%, where most of the static deadweight losses are offset by increases in TFP growth. Thus, total welfare improves and consumers are better-off given the second best scenario depicted here.

Future studies may continue to focus on evaluating the net welfare loss/gain from increasing concentration by adding static losses from concentration to the welfare gains from innovation and other sources (e.g., lower environmental externalities, reduced price variability). Thus, antitrust/regulation policies must take into consideration the dynamic welfare gains of industrial concentration.

Table 1: Parameter Estimates of the TFP and Concentration Growth Equations

Simultaneous Panel Model, 2SLS

Growth Rate of	**Parameter**	**t value**
TFP (Equation 2a)		
a) Concentration Ratio (fitted)	0.142[a]	2.601
b) Square of Concentration Ratio (fitted squares)	-0.003[b]	-1.645
c) R&D (SIC 20)	0.039	0.600
d) Real Price of Intermediates	-0.092	-0.965
e) Real Price of Capital	-0.481[b]	-1.635
f) Real Wages	0.047	0.389
Concentration (Equation 2b)		
g) TFP (fitted)	0.321[a]	3.596
h) Average Firm Size	0.231[a]	5.102
i) R&D (SIC 20)	-0.245	-0.267
No. of Observation/No. of Industries	216/36	

[a]significant at the 5% level; [b]significant at the 10% level.

Figure 1: Effect of Growth in Concentration on TFP Growth

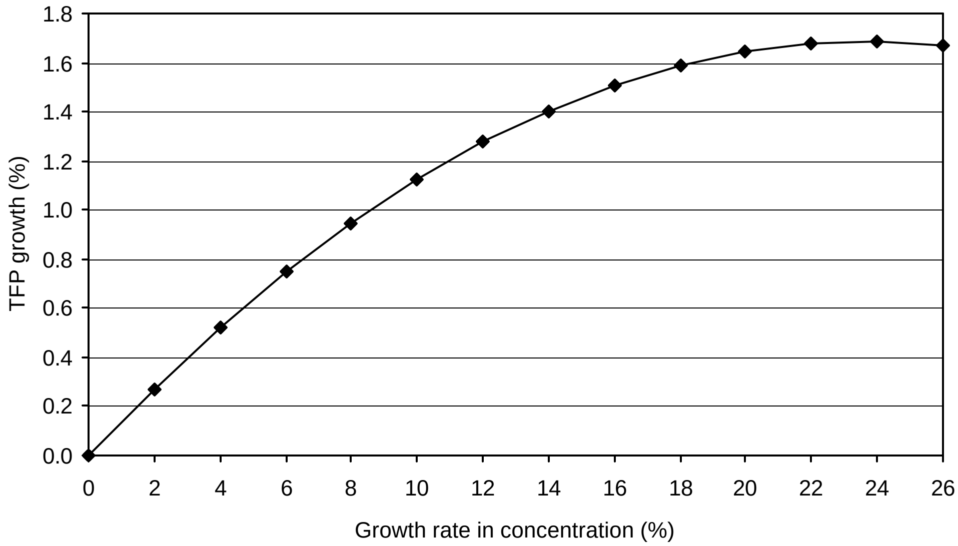
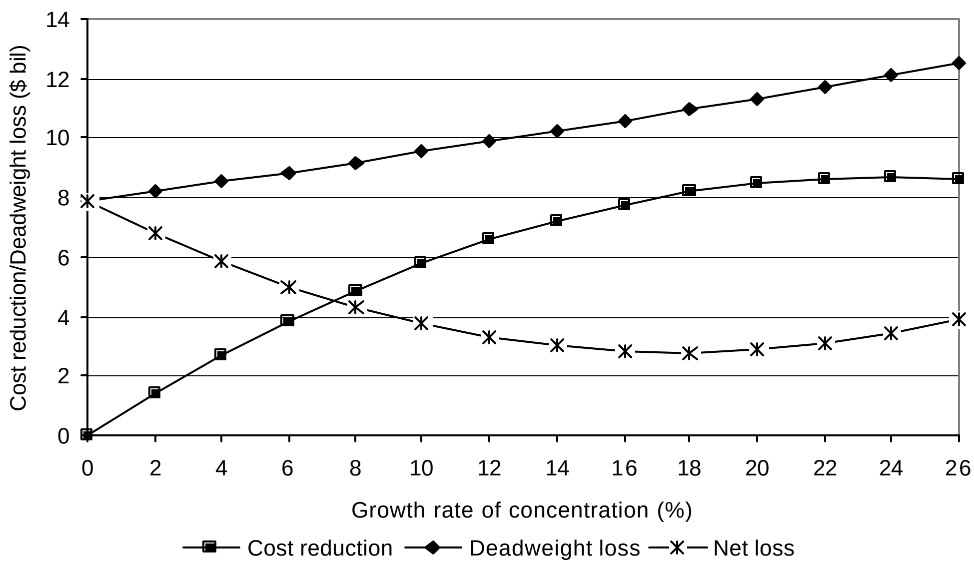


Figure 2: Cost Reductions and Deadweight Losses from Growth in Concentration



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[1]See Sheldon and Henderson (1991) for a survey of the new empirical industrial organization literature.

[2]Other sources of dynamic welfare gains include the protection of environment and natural resources (Baumol and Oates, 1975), and reduced price variability (Stigler, 1961).

[3] Azzam (1997) explores the market power and cost efficiency effects of concentration on output price.

[4]Data on four-firm concentration ratio for 1997 are not available at this time for inclusion into our analysis. In addition, the BEA uses a new system called North American Industrial Classification system for 1997 census, which does not necessarily have a one-to-one correspondence with the standard industrial classification system.

[5]For a survey of empirical studies at the firm level, see Cohen and Levin (1989).

[6]In line with prior empirical work, we let industry-specific dummies/error component to capture other missing effects.

[7]The implicit assumption in 2SLS is that the disturbances in our two equations are not contemporaneously correlated. Otherwise, three-stage least squares (3SLS) should be preferred. As Nguyen and Bernier (1988) note, the price that is paid for the use of 3SLS is that if the complete system is misspecified, all the estimates of the structural parameters will be affected, rather than, in the case of 2SLS, only the estimates of the structural parameters of one equation. Moreover, 2SLS continues to provide consistent estimators and as noted by Kinal and Lahiri (1993), the efficiency gains from 3SLS are modest.

[8]Willner and Stahl (1992) derive welfare losses under three different scenarios, Cournot-Nash, Stackelberg, and Collusive behavior and two types of demand specification. For the Stackelberg, and Collusive behavior, the computation of welfare losses is similar except that the denominators change to $[(2n-1)^2\ 2|\epsilon|]$ and $2|\epsilon|$, respectively.