Quality and Competition: An Empirical Analysis across Industries

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Abstract

This paper empirically explores the link between quality and concentration in a cross-section of manufactured goods. Using concentration data and product quality indicators, an ordered probit estimation explores the impact of concentration on quality that is defined as an index of quality characteristics. The results demonstrate that market concentration and quality are positively correlated across different industries. When industry concentration increases, the likelihood of the product being higher quality increases and the likelihood of observing a lower quality decreases.

Keywords: concentration, market structure, ordered probit, product differentiation, product quality.

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Introduction

This paper attempts to shed needed empirical light on the relationship between competition and quality. To say that the theoretical link between market competition and product quality is ambiguous is an understatement. Intuitively, should not increasing competition provide an incentive for a firm to increase product quality in order to garner the attention of consumers facing a large choice of products? On the other hand, is a more concentrated industry with firm market power necessary for economic profits to exist to cover fixed costs for higher quality? But, in that case, will the decline in competitive pressure end up reducing the incentives to satisfy consumers?

Economists have grappled with these questions for years, with no clear conclusion of the effect of market structure on quality. Spence (1975) first showed that a monopoly strategy where quality is determined via variable costs results in quality choices that are very different from those derived by a firm in a competitive market. A monopoly not only seeks to limit the quantity on offer but also may in some cases produce less than socially optimal quality. Spence shows how social welfare with regard to quality is maximized under perfect competition but that a monopoly considers only the marginal consumer's willingness to pay for quality. If the average consumer and the marginal consumer's willingness to pay for quality are very different, as they likely would be, the quality arising under the two market structures will differ as well.

Very early work on quality and market structure focused upon a specific dimension of product quality: durability (see the survey in Schmalensee, 1978). In these studies, researchers

mostly argued that the more concentrated the market, the lower the quality of the good. Swan (1970a,b) argued that such a conclusion was far from foregone and that quality choice itself may be shown to be independent of market structure. Since the time of Swan's publications, as Schmalensee (1978) discusses, researchers have sought to re-examine the theoretical issue with various adjustments to Swan's model and have reached different conclusions about the link between concentration and quality.

The economic analysis is trickier still when one considers quality choices based upon fixed costs. A large fixed cost such as a large research or advertising expenditure is perhaps more pertinent to the development of higher-quality products than are marginal costs. A large advertising expenditure can be crucial to product quality either as (i) a means for segmenting the market via product quality signals (e.g., Schmalensee, 1978), (ii) as a barrier to market entry to foster the economic profits necessary to undertake large investments in quality (e.g., Sutton, 1991), or (iii) as a component of perceived quality in its own right (e.g., Becker and Murphy, 1993). In any case, large fixed costs may be consonant with high concentration (Shaked and Sutton, 1981, 1983, and 1987), which leads back to the intrinsic question about firm incentives to increase quality in the face of higher concentration (see Sappington, 2005, for a recent survey).

Demsetz (1973) argued that a more concentrated market structure is likely to be related to a higher level of quality (and, relatedly, a higher price). The Demsetz "critique" of the link between competition and quality is essentially a "last man standing" argument that higher quality is consistent with a more concentrated market as only the firms whose products satisfy consumers remain in the market. Shaked and Sutton (1987) and Sutton (1991) reached similar conclusions, though for different reasons. Sutton showed that a firm tends to use fixed spending on advertising and R&D (e.g., endogenous sunk costs) to increase the quality of its products in

order to drive out competitors who cannot afford to compete on quality, hence increasing market concentration. One difference with this quality-concentration model from that of Demsetz is that while higher quality emerges on the market, there can also be a reduction in product variety such that overall social welfare is lost as some consumers would prefer low- or medium-quality products (at low or medium prices).

These studies are obviously just a sampling of the theoretical literature, but they are a representative sampling. Empirical studies of quality and market structure are fewer in number. Although they do not look precisely at this relationship, cross-sectional studies of multi-product quality agglomeration (Hjorth-Anderssen, 1988; Grunewald, Faulds, and McNulty, 1993) have shown that most industries tend to deliver products with good to very good quality. While reporting of such empirical regularities is useful, these studies neglect the question of whether the agglomeration is related to industry structure.

Recent papers have moved to examine the connection between quality and competition empirically, though on an industry-by-industry basis, in much the same spirit as structure-conduct-performance studies sought the relationship between competition and firm profits. Most of these studies examine service sector quality. For example, Dranove and White (1994) examine hospital service; Cotterill (1999) examines food retailing; Hamilton and Macauley (1999) examine car maintenance; Mazzeo (2002) examines motels; Mazzeo (2003) examines airline-flight delays, and Cohen and Mazzeo (2004) explore quality in the banking industry. The overall results from these studies provide evidence that more competition, in the form of *more* firms in an industry, increases quality.[1] To the extent that the premise of lower concentration means more

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[1] The data for these studies are typically either a cross-section of different geographic markets for one particular industry or a time series within a given market for a particular service.

competition, Demsetz's quality argument would seem to be rejected in these studies. Other empirical studies such as Robinson and Chang (1996), Berry and Waldfogel (2003), Dick (2004), and Ellickson (2006a,b) seem to validate Sutton's (1991) prediction about the positive correlation between concentration and advertising, R&D, and/or quality.

Given that agglomeration studies look at quality in a multi-industry setting but do not examine the relationship between concentration and quality, and that other studies that do look for such a relationship examine only one industry, what is missing thus far in the research on quality and concentration is a more general exploration that seeks a relationship in more than a single industry. Schmalensee (1985) has argued that cross-sectional studies, even with their obvious drawbacks, are useful for informing analysts about general statistical relationships even if theoretical underpinnings are more elusive.

The present paper provides a complementary insight into the previous studies by comparing the link between concentration and quality across different industries and consumer goods markets. Using data from the U.S. Bureau of Census and the magazine *Consumer Reports,* an ordered probit estimation explores the impact of concentration on quality while controlling for industry, firm, and product dimensions. Our statistical analysis generally supports a significant and positive relationship between market concentration and higher quality.

In the next section, we develop a stylized model that differs from previous theoretical approaches and allows us to underscore the absence of clear conclusions regarding the correlation of concentration and quality. Following that, we provide an empirical estimation of a cross-sectional model comparing quality and market concentration.

An Indefinite, Theoretical Relationship

We begin with a stylized framework that helps to introduce the empirical evaluation. We voluntarily abstract from dynamic aspects adopting a partial equilibrium framework. Using a very simple but intuitive model, we show why the discovery of a deductive relationship between quality choice and concentration is daunting and why current theoretical research may be in need of more inductive, empirical examinations to inform future analytical models.

Trade occurs in a single period with n (=1 or 2) seller(s) who offer products of high quality ($k+b$) or low quality (k), where b is the quality difference parameter with $0<b<k$. The seller's ability to offer high-quality products is dependent on the seller's effort but is also to some degree uncertain. This uncertainty could be for practical matters, such as the inability of a seller to strictly control all of the factors that determine quality (e.g., food manufacturers may have little control over production of the main ingredient); or uncertainty can arise, as there is never a one-to-one correspondence between the intrinsic quality of a product and consumers' perception of quality; or uncertainty can arise simply because the producer poorly forecasts public reaction to product features. For simplicity we let the producer's effort be equivalent to the probability of a high-quality product emerging (making the probability a function of the effort just adds a degree of complication that is unnecessary for the point we are trying to make in this section). With a probability $0 \leq \lambda_i \leq 1$, seller i offers high-quality products and with a probability $(1-\lambda_i)$ seller i offers low-quality products. We assume that the effort to produce high-quality products corresponds to a fixed cost equal to $f\lambda_i^2/2$ with $f \geq 0$. Finally, the marginal cost is zero whatever the quality for simplicity but also because Spence (1975) has already demonstrated the ambiguous quality outcome under variable costs.

For the quality that does emerge from firm i, k_i (equal to $(k+b)$ or (k)), a consumer has a willingness to pay equal to θk_i. A consumer who buys one unit of the product at a price of p_i has an indirect utility equal to $\theta k_i - p_i$ (see Mussa and Rosen, 1978, and Shaked and Sutton, 1983). The mass of those consumers is normalized at 1, with a uniformly distributed parameter $\theta \in$ [0,1].

The timing of this game is divided into two stages. In period 1, firms choose the level of effort $0 \leq \lambda_i \leq 1$ to produce high-quality products. In period 2, they compete in prices (Bertrand competition). The market equilibrium is described with 1 and 2 firms. The variation of this number is exogenous for simplicity.

A monopoly produces a product of quality k_i. In period 2, the consumer who is indifferent between either buying this product or buying nothing is $\underline{\theta} = p/k_i$ (coming from the equality $\theta k_i - p = 0$). As θ follows a uniform distribution, the demand is $1 - \underline{\theta}$. The gross profit (net of fixed cost) for the monopoly is $p(1 - \underline{\theta})$. The price that maximizes the gross profit is $p = k_i/2$, leading to a gross profit $\pi_m(k_i) = k_i/4$. In period 1, the effort determines the quality (high quality with a probability λ and low quality with a probability $(1 - \lambda)$) with expected profit of

$$\Pi_m(\lambda) = \lambda \pi_m(k+b) + (1-\lambda)\pi_m(k) - f\lambda^2/2. \tag{1}$$

The maximization of this profit (such that $d\Pi_m(\lambda_m,0)/d\lambda_i = 0$ for $\lambda_m < 1$ and $d\Pi_m(\lambda_m,0)/d\lambda_i > 0$ for $\lambda_m = 1$) leads to

$$\lambda_m = Min\left[1, \frac{\pi_m(k+b) - \pi_m(k)}{f}\right] = Min\left[1, \frac{b}{4f}\right]. \tag{2}$$

Thus, the optimal effort for a monopoly is $\lambda_m = 1$ if $f < f_1 = b/4$ and $\lambda_m < 1$ otherwise.

Under duopoly, a quality k_i is produced by seller i and a quality k_j is produced by seller j, with price competition in period 2. If the two sellers select the same level of quality, the price and profit are, of course, zero in this simple Bertrand game. When quality differs, namely, one seller with high-quality products of $k+b$ and the other with low-quality products of k, profits are positive. In this case, the demand is the following. A consumer indifferent between buying a high-quality (h) product and buying a low-quality (l) product is identified by the preference parameter $\hat{\theta} = (p_h - p_\ell)/b$ (such that $\theta(k+b) - p_h = \theta k - p_\ell$). A consumer indifferent between buying a low-quality product and buying nothing is identified by the preference parameter $\tilde{\theta} = p_\ell/k$ (such that $\theta k - p_\ell = 0$). The overall demand for high-quality product is $(1 - \hat{\theta})$ and the demand for low-quality product is $(\hat{\theta} - \tilde{\theta})$, with corresponding profits of $p_h(1 - \hat{\theta})$ and $p_\ell(\hat{\theta} - \tilde{\theta})$, respectively. The gross profits for the high-quality seller and the low-quality seller are equal to $\pi_d(k+b) = 4b(b+k)^2/(4b+3k)^2$ and $\pi_d(k) = bk(b+k)/(4b+3k)^2$, respectively.

In period 1, effort determines the quality levels. With a probability $\lambda_i \lambda_j$ (respectively, $(1-\lambda_i)(1-\lambda_j)$) both sellers offer the same quality, namely, high quality (respectively, low quality), leading to zero profits under Bertrand competition. With probabilities $\lambda_i(1-\lambda_j)$ or $(1-\lambda_i)\lambda_j$, both sellers offer differentiated products leading to positive profits. The expected profits for sellers i and j are

$$\begin{aligned}
\Pi_{d,i}(\lambda_i, \lambda_j) &= \lambda_i(1-\lambda_j)\pi_d(k+b) + (1-\lambda_i)\lambda_j\pi_d(k) - f\lambda_i^2/2 \\
\Pi_{d,j}(\lambda_j, \lambda_i) &= \lambda_j(1-\lambda_i)\pi_d(k+b) + (1-\lambda_j)\lambda_i\pi_d(k) - f\lambda_j^2/2
\end{aligned} \tag{3}$$

Regarding the choice of effort, multiple equilibria exist.[2]

First, there is a symmetric equilibrium where both sellers choose the same level of effort. The maximization of both profit functions ($\partial\Pi_{d,i}(\lambda_i^*,\lambda_j^*)/\partial\lambda_i = 0$ and $\partial\Pi_{d,j}(\lambda_i^*,\lambda_j^*)/\partial\lambda_j = 0$) leads to the optimal choice of effort

$$\lambda_i^* = \lambda_j^* = \lambda_d^* = \frac{\pi_d(k+b)}{f+\pi_d(k+b)+\pi_d(k)} = \frac{4b(b+k)^2}{4b^3+9fk^2+bk(24f+5k)+b^2(16f+9k)}, \qquad (4)$$

where $\lambda_d^* < 1, \ \forall f \geq 0$.

A second equilibrium that might arise is an asymmetric equilibrium. Here, sellers select different levels of effort, λ_1^{**} and λ_2^{**}, for maintaining maximum product differentiation. By using λ_d^* defined by (4), this second equilibrium satisfies the conditions

$\Pi_{d,i}(\lambda_1^{**},\lambda_2^{**}) > \Pi_{d,i}(\lambda_d^*,\lambda_d^*)$ and $\Pi_{d,j}(\lambda_1^{**},\lambda_2^{**}) > \Pi_{d,j}(\lambda_1^{**},\lambda_2^{**}+\varepsilon)$ $\forall\varepsilon > 0$.[3] These equations are satisfied for

$$\begin{aligned}\lambda_1^{**} &= 1 \\ \lambda_2^{**} &= 0\end{aligned}, \qquad (5)$$

when $f \leq f_2$, with f_2 determined by the equality $\Pi_{d,i}(1,0) = \Pi_{d,i}(\lambda_d^*,\lambda_d^*)$. In particular, the absence of effort by seller j is optimal, since the inequality $\Pi_{d,j}(1,0) > \Pi_{d,j}(1,\varepsilon)$ $\forall\varepsilon > 0$ is satisfied.

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[2] This is a result that has been overlooked by the quality choice literature under perfect information.

[3] For the first constraint, $\Pi_{d,i}(\lambda_d^*,\lambda_d^*)$ is the profit linked to the deviation of seller i. The reason is straightforward. Seller i chooses to deviate with a level of effort $\lambda_1^{**}-\varepsilon$ with $\varepsilon > 0$, expecting the effort of both sellers to converge toward λ_d^*. As soon as the effort of seller i is strictly lower than one, seller j has an incentive to make an effort

Thus, for $f \leq f_2$, multiple equilibria exist, with the effort defined by either equation (4) or by equations (5). For $f > f_2$ (corresponding to $\Pi_{d,i}(1,0) < \Pi_{d,i}(\lambda_d^*, \lambda_d^*)$), the choice defined by (5) is not an equilibrium since both sellers have an incentive to deviate. In this case, there is a unique equilibrium defined by (4).

Even with this extremely simple model, moving from a monopoly to a less concentrated (duopoly) market structure results in a variety of optimal quality choices. The key is the level of fixed cost. Figure 1 summarizes the above analysis with the cost parameter, f, located along the X-axis, and the effort level (equal to the probability of high quality) located along the Y-axis.

Figure 1. Quality, Effort, and Market Structure
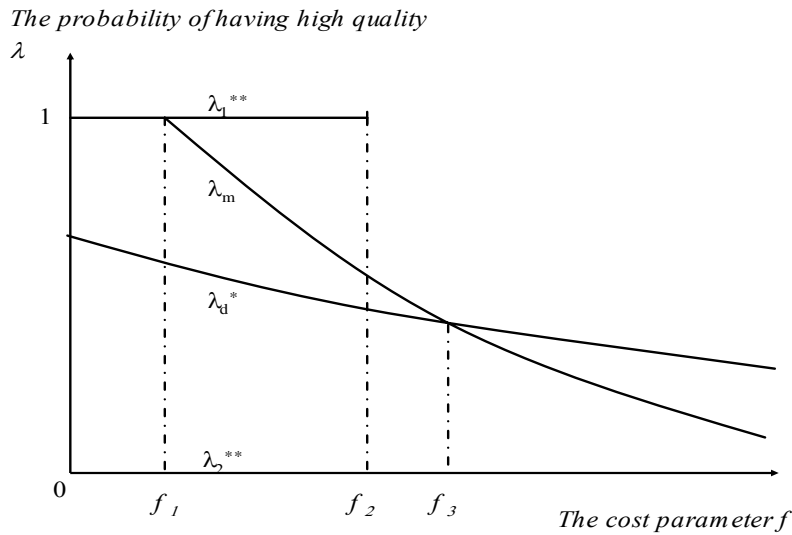
The incentive to produce higher quality depends on the fixed cost and the intensity of competition. A change in the competitive structure alters the quality incentives. Under

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$\lambda_j > 0$ satisfying $\Pi_{d,j}(\lambda_1^{**} - \varepsilon, \lambda_j) > \Pi_{d,j}(\lambda_1^{**} - \varepsilon, 0)$. Seller j has an incentive to deviate from the no-effort strategy. In this context, the level of effort of both sellers converges toward the value defined by (4).

monopoly, profits are larger than under duopoly but the incentive to increase quality declines as costs increase at a rate greater than that for the competitive market. Under duopoly, profits are zero if sellers have the same level of quality, bolstering the need for product differentiation, though such differentiation does not always arise.

The probability of observing high-quality products in the market is tricky because of the multiple equilibria arising under duopoly. Thus, compared with the monopoly situation (λ_m), the probability of observing a high-quality product in the market is lower under duopoly with a symmetric choice ($\lambda_d^* < 1$) until fixed costs become very high ($f > f_3$), at which point one is more likely to see higher quality in the competitive market. Under duopoly with an asymmetric choice ($\lambda_1^{**} = 1$), the probability of having a high-quality product on the market can either be equal to (for $f < f_1$) or higher than (for $f_1 < f < f_2$) the probability of high quality that emerges under monopoly; yet, for $f_2 < f < f_3$, the probability of observing high quality is greater under monopoly than under duopoly.

The previous analytical framework was admittedly simple. The following extensions could be easily integrated into our model. Instead of Bertrand, we could implement Cournot competition in stage 2. We could integrate a consumer cost for switching brands (see, e.g., Gehrig and Stenbacka, 2005) or a variable cost for quality. We could expand the number of products by increasing the number of firms in our market or introduce multi-product firms. However, such extensions, if anything, underscore rather than weaken our objective in this section: that the probability of observing a high-quality product is determined in a complicated way by both costs and market structure so that any theoretically derived comparative static is

likely to be ambiguous. Our next goal is simply to search for a general relationship in the data in the hopes of informing future theoretical and empirical work.

An Empirical Analysis

Though many aspects of quality are cardinally measurable, overall quality that is being compared among products across industries is more likely to be meaningful on an ordinal scale. Specifically, our interest is in the probability of observing quality of a particular ordinal rank, for example: $k = 0 =$ "poor"; $k = 1 =$ "fair"; $k = 2 =$ "good"; $k = 3 =$ "very good"; and $k = 4 =$ "excellent." Such rankings are common in popular product test magazines such as *Consumer Reports*, *Test,* or *Konsument*.

As shown above, there are many industry and firm-related factors that influence the quality of a product; the difficulty in a cross-sectional study is controlling for these effects. For this study, we propose the following ordered probability model of the likelihood that a product is of a particular ordinal quality, k:

$$\text{Prob}(\mathbf{y} = \mathbf{k}) = \lambda \mathbf{L} + \beta \mathbf{C} + \mathbf{D\delta} + \mathbf{F\varphi} + \mathbf{T\tau} + \mathbf{\varepsilon} . \tag{6}$$

Let *I* be the number of industries in the sample and N_i be the number of observations per industry, *i* with total observations denoted $N = \sum_{i=1}^{I} N_i$. In equation (6), $\mathbf{y}$ is an $N \times 1$ vector of observed, ordinal product quality rankings made up of industry group vectors ($\mathbf{y} = [\mathbf{y}_1, \mathbf{y}_2, \mathbf{y}_3, ...,\mathbf{y}_I]'$) such that each vector $\mathbf{y}_i$ contains N_i observations. $\mathbf{C} = [\mathbf{C}_1, \mathbf{C}_2, \mathbf{C}_3, ...,\mathbf{C}_I]'$ is an $N \times 1$ vector composed of an industry-level measure of concentration (e.g., an *n*-firm concentration ratio $CR(n)$, i.e., the combined market share of the *n* largest firms, or a Herfindahl-Hirschman index (HHI)). Our interest lies primarily in determining the relationship between $\mathbf{C}$ and the probability of observing a product of a particular quality while netting out the noise of industry,

firm, and product type effects that must differ in such a cross-sectional study. β is a scalar value to be estimated.

$\mathbf{D}$ is an $N \times I$ matrix of industry dummy vectors, $\mathbf{D} = [\mathbf{d}_1, \mathbf{d}_2, \mathbf{d}_3, ..., \mathbf{d}_I]$, where $\mathbf{d}_i$ equals one for observations corresponding to industry $i=1, ..., I$ and zero otherwise, and $\boldsymbol{\delta}$ is an I x 1 parameter vector. We are seeking to control for industry effects that might include such things as sunk costs that are particular to certain industries or regulatory standards that force a minimum level of quality on products in an industry. Sunk costs are likely unknown; to the extent that they do affect quality, the costs will be incorporated in part in the parameter vector $\boldsymbol{\delta}$. Equation (6) is, thus, a fixed effects model based upon the industry.

Likewise, we would like to account for firm effects such as the fixed costs per firm, but such data are likewise impractical to obtain, especially if firms are privately owned. In lieu of certainty over a firm's fixed costs, we incorporate $\mathbf{F}$ into the equation as a firm- or "brand"-level dummy matrix. For the N_F number of firms in the data set, we include $f = 1, 2, ..., N_F - 1$ dummy vectors such that $\mathbf{F} = [\mathbf{F}_1, \mathbf{F}_2, \mathbf{F}_3, ..., \mathbf{F}_{NF}\text{-}1]$ is an $N \times (N_F - 1)$ matrix. An individual vector $\mathbf{F}_f$ equals one to denote a particular firm and zero otherwise but is not limited to firms in a single industry. For example, an observation on vector $\mathbf{F}_f$ for Toyota would be a 0 for a non-Toyota product, a 1 if the observation were for a Toyota car, as well as a 1 if the observation were for a Toyota sports utility vehicle (SUV), even though cars and SUVs represent two different industries. $\boldsymbol{\varphi}$ is an $(N_F - 1) \times 1$ parameter vector. In this way, through $\mathbf{D}$ and $\mathbf{F}$, equation (6) controls for both the effects on quality related to a particular industry as well as for a particular firm.

The matrix $\mathbf{T}$ is made up of dummy vectors used to differentiate quality of product types within a particular product class. For example, vacuum cleaners have two basic model types,

upright and canister models, with overall quality possibly dependent on the design. We drop one type of dummy vector per industry. Let N_T^i denote the number of product types in industry i. $\mathbf{T}_i$ = $[\mathbf{T}_{i1}, \mathbf{T}_{i2}, \mathbf{T}_{i3}, ...]$ is an $N \times (N_T^i - 1)$ matrix and $\mathbf{T} = [\mathbf{T}_1, \mathbf{T}_2, \mathbf{T}_3, ..., \mathbf{T}_I]$ is an $N \times \sum_{i=1}^{I}(N_T^i - 1)$ matrix. An individual vector in $\mathbf{T}$ has an element equal to 1 for each particular product type within an industry and 0 otherwise. Being industry specific, these dummy vectors account for shifts in the probability of observing a particular quality at the industry level so that we can control for qualities of different types within an industry (e.g., sports cars versus sedans or regular versus light beer) as a difference in the industry intercept. $\boldsymbol{\tau}$ is an $\sum_{i=1}^{I}(N_T^i - 1) \times 1$ parameter vector. Following the discussion above concerning fixed costs, each of the dummy matrices ($\mathbf{D}$, $\mathbf{F}$, and $\mathbf{T}$) can be viewed as crude measures of fixed costs particular to an industry, firm, or product classification.

We also control for the retail prices of goods. $\mathbf{L}$ is an $N \times 1$ vector with individual observations equal to the percentage price differential for a product type. Specifically, at a particular observation, $L = 100 \cdot (P - Pmin)/P$, where P is the price of the observed product and *Pmin* is the lowest price for a product of type T in industry i (e.g., the price of a telephone with only basic features). $\mathbf{L}$ is a crude proxy for marginal cost differences as well as the heterogeneity in consumers' willingness to pay across quality and market power differences among sellers. It is included primarily because of Spence's work on the relationship between quality and variable costs. Finally, $\boldsymbol{\varepsilon}$ is a normally distributed, $N \times 1$ error vector.

Although our model is a probability model based upon quality, we note that equation (6) is very similar in spirit to Schmalensee's (1985) model of industry profits where a cross-industry, firm-level rate of return was modeled as a function of firm market shares, industry effects, and

firm effects. Nevertheless, we encounter a problem with estimating equation (6) given our data set. If **C** is invariant across observations within particular industry groups, as it is in our study, we run into a within-group multicollinearity problem (Schmalensee did not have this problem, as his profitability data contained firm-level, market share data). While our interest lies in the sign and magnitude of the parameter β, because the element of a vector $\mathbf{C}_i$ is the same for every observation in i, we have a within-group multicollinearity problem between the concentration measure and the industry-specific dummy variable. We could, of course, estimate equation (6) by dropping the industry dummies, but then our value of β would comprise both concentration and industry effects, and we need to net out industry effects in a model comparing product qualities across unrelated goods.

To separate both the concentration and industry effects, we rewrite equation (6) as

$$\text{Prob}(\mathbf{y} = \mathbf{k}) = \lambda \mathbf{L} + \mathbf{D}\boldsymbol{\gamma} + \mathbf{F}\boldsymbol{\varphi} + \mathbf{T}\boldsymbol{\tau} + \boldsymbol{\varepsilon}, \tag{7}$$

where $\boldsymbol{\gamma} = [\gamma_1, \gamma_2, ...,\gamma_I]' = \beta \mathbf{C} + \boldsymbol{\delta}$ is an $I \times 1$ vector (recall, industry observations of concentration, $\mathbf{C}_i$, are equal for all observations in i, so $\mathbf{C}$ in this equation is $I \times 1$). Doing so allows estimation in two stages.

At stage 1, we estimate the ordered probability equation (7) in order to obtain the I parameters, $\hat{\gamma}_i$. In the second stage we decompose $\hat{\gamma}_i$ into its industry and concentration effects by estimating equation (8), consisting of I observations for the industry and concentration levels:

$$\hat{\boldsymbol{\gamma}} = \beta \mathbf{C} + \boldsymbol{\delta}. \tag{8}$$

At the industry level, once we know the estimate, $\hat{\beta}$, we can determine the ith industry effect for equation (6) as $\hat{\gamma}_i - \hat{\beta}C_i = \hat{\delta}_i$. Note that each $\hat{\gamma}_i$ will have a variance as determined in the first stage but there is no reason why this variance would be equivalent across industries. As such, heteroskedasticity is possible.

Data

We compiled data from two sources. The measures of concentration are taken from the industry classifications in the 1997 Census of Manufacturers (the last year for which industry data have been reported) using the North American Industry Classification System (NAICS).[4] All of these reports classify industries by the percentage of output accounted for by the largest 4, 8, 20, and 50 companies, but only the manufacturing report includes another popular measure of concentration, the Herfindahl-Hirschman Index (HHI). Censuses of manufacturing industries are released every five years, and while a time-series component is of interest, the 2002 Census has yet to be released, and the previously published census (1992) used a different industry coding (SIC as opposed to the NAICS), making comparisons troublesome for certain industries we have chosen. We used two measures of concentration in our analysis: the four-firm concentration ratio ($CR(4)$) at the six-digit NAICS industry level (the most disaggregated level reported by the Census) and the six-digit industry HHI.

The measures of product quality roughly correspond to the Census year and are obtained from three years (1995-1997) of issues of the popular magazine *Consumer Reports*. *Consumer Reports* (CR) analyzes a variety of products in a product category in order to present what its researchers consider to be a representative sample of the category. CR investigators determine a quality level on various features as well as an overall quality score for each good. CR bases its choices of which products to examine on consumer surveys, popular features, prices, and nationwide availability in an attempt to scrutinize a representative sample of products available to American consumers. CR takes no advertising money and has no support from any firm. It

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[4] Details may be obtained from the U.S. Census Bureau website (2006).

buys each product that it examines and subjects its product to both guidelines set by the government (if applicable) as well as its own standards based upon consumer interests, desires, and/or concerns. Of course, the usage of a popular magazine's analysis of quality is not without problems, first and foremost being expert judgment bias (Wolinsky, 1993), but we do believe that CR provides an objective indicator of product quality. There have been a few studies comparing CR's product rankings with those of other product ratings and the results have shown a great deal of consistency. Friedman (1990), for example, determined statistically significant levels of agreement between *CR* and a similar journal, *Which?* (see also the study by Caves and Green, 1996). Greater discussion of how CR chooses products and undertakes its examination of product quality may be obtained from the CR website (http://www.consumerreports.org, last accessed December 2005).

We use CR's overall ranking for a product as our measure of product quality. Moreover, because the overall rating takes into account several characteristics (which Lancaster, 1966, argues is the true test of quality), our study is not a study of a single product dimension as others have been. However, as our study compares product quality across industries, we must be mindful of the limitations of comparing not simply apples to oranges, but, say, Apple computers to apple pies. This is why our econometric model attempts to net out industry, firm, and product-type effects so that the market concentration effect has meaning across industries.

Although CR utilizes both an ordinal scale of product quality ("poor," "fair," "good," "very good," and "excellent"), as well as a cardinal one (1-100), we think that it is not likely that a score of "71" for a vacuum cleaner is comparable to a score of "71" for an automobile. On the other hand, a quality score of "good" is arguably more meaningful across industries. Knowing whether "good" for one person means the same thing to another person is a problem in any

cross-sectional study, admittedly. Surveys, for example, must always contend with the problem of whether respondents' answers to Likert-type queries roughly correspond. If we were to undertake the quality determination ourselves, we might ask consumers to use the "poor" to "excellent" ratings on products across industries to verify our conjecture that the ordinal rankings have the same meaning across industries, but as CR does not do this, we note this as a shortcoming of this analysis but also point out that the research on quality agglomeration likewise performed cross-industry analyses using similar scales.

Even with its potential drawbacks, there are many positive features of CR's methodology. CR strives for objectivity, samples a wide and popular selection of each product category, uses more than one investigator, and bases its overall ranking on several product features. Another positive feature of CR's scoring is that a product's quality score is not relative to that of competing products. In other words, CR establishes the testing procedures first and does not rescale the results so that the highest quality product always earns a rank of "excellent" or the lowest earns a rank of "poor." If there were a re-scaling, we would not be able to perform the analysis because then our premise that "good" is comparable across industries would be invalid on its face. So, unlike a student graded on a curve, a product's overall score in the CR methodology is unaffected by the score earned by another good. In fact, several of the industries in our study contained products earning no score below "fair" while others contained products earning no score above "very good."

For our classification of product types (T in the above estimation discussion) we use CR's classifications. These varied from only one product type per examined product (e.g., chocolate cookies) to eight distinct product classes (for automobiles). For our control on firm or "brand" effects (F in the above discussion), we had to decide whether to treat a firm with several

divisions as a single entity or as multiple entities. As Sutton (1991) places much emphasis on the

fixed cost of advertising in his work, we decided to control for an individual brand or division

with its own firm-level dummy variable if the brand were promoted separately from the

corporation but to treat two goods with a single firm-level dummy otherwise. For example,

Lexus automobiles and Toyota automobiles each receive their own firm-level control variable

because Lexus and Toyota distinguish their brands through separate advertising even though

Lexus is a division of Toyota. However, General Electric telephones and General Electric

blenders use the same firm-level dummy in our analysis, as GE does a great deal of promotion of

GE as a generic brand name for all of its products. For our study, we have compiled 1,003

individual products representing 45 industries (*I*), 228 individual firms/brands (*F*), and 106

product types (*T*). No industry is represented by more than one product. Table 1 presents the

products, their industry code, the number of products and the number of product types per

industry, the concentration ratio for the industry they represent, and the mean of the CR ranking

(from 0 = "poor" to 4 = "excellent"). The average quality score across the 45 industries is 2.708.

For the 1,003 CR product rankings, there were only 7 observations of "poor," 54 observations of

"fair," 325 observations of "good," 496 observations of "very good," and 121 observations of

"excellent." Like studies of agglomeration that used other data sources (Hjorth-Anderssen, 1988;

Grunewald, Faulds, and McNulty, 1993), our data set indicates a skew toward better quality. The

data are available from the authors.

Table 1. Products and Industries

	Industries	Industry NAICS Code	Number of Products	Number of Product Types	Avg CR Score	St. Dev. CR Score	Industry CR(4)
1	Adult Breakfast Cereal	311230	35	1	2.257	0.505	82.9
2	Air Conditioners	333415	55	6	2.600	0.655	39.2
3	Baby Strollers	339932	12	1	2.917	0.515	42.7
4	Beer	312120	33	4	2.848	0.508	89.7
5	Blood Pressure Monitors	339112	17	3	2.765	1.033	31.4
6	Camping Tents	314912	20	3	2.950	0.686	10.4
7	Car Batteries	335911	18	3	2.611	0.850	52.0
8	Cars	336111	75	8	2.627	0.941	79.5
9	CD Players	334310	14	3	3.286	0.611	29.8
10	Ceiling Fans	335211	33	2	2.758	0.614	43.1
11	Cheese	311513	17	2	1.706	0.849	34.6
12	Children's Bicycles	336991	34	5	2.324	0.727	67.5
13	Chocolate Cookies	311821	7	1	2.429	0.535	59.9
14	Compact Cameras	333315	19	2	3.579	0.507	80.9
15	Computer Monitors	334119	12	2	3.167	0.718	45.3
16	Computers	334111	12	2	3.833	0.389	45.4
17	Corded Telephones	334210	26	2	2.731	0.724	54.4
18	Dish Washers	335228	19	1	3.105	0.658	56.6
19	Dishwashing Liquids	325611	21	1	2.762	0.625	65.6
20	Exercise Bikes	339920	19	3	2.526	0.697	21.4
21	Exercise Shoes	316211	19	2	3.000	0.471	54.6
22	Gas Ranges	335221	14	1	2.714	0.469	58.1
23	Home Entertainment Centers	337129	16	1	2.688	0.602	45.8
24	Hot Cocoa Mix	311320	12	2	1.917	0.515	79.5
25	Household Blenders	335211	12	1	2.750	0.866	65.1
26	Latex Wall Paint	325510	38	3	2.974	0.367	32.0
27	Luggage	316991	29	3	2.586	0.867	51.9
28	Men's Hiking Boots	316213	14	2	2.571	0.514	49.7
29	Men's Shirts	315223	17	1	2.412	1.004	42.9
30	Modems	334210	11	2	3.091	0.701	54.4
31	Pagers	334220	9	2	3.444	0.726	48.9
32	Pasta Sauces	311421	39	1	2.949	0.605	24.9
33	Photographic Film	325992	9	2	3.333	0.500	69.7
34	Pregnancy Test Kits	325413	15	2	3.000	0.926	62.5
35	Refrigerators	335222	31	6	3.097	0.597	81.5
36	Roofing Shingles	324122	34	1	2.265	0.864	47.2
37	SUVs	336112	13	2	2.308	1.182	99.3
38	Tires	326211	10	1	2.500	0.707	72.4
39	Tractors & Riding Mowers	333112	23	3	2.304	0.470	64.4
40	Vacuum Cleaners	335212	39	3	2.051	0.686	68.5
41	Washing Machines	335224	18	2	2.778	0.548	90.4
42	Wine	312130	57	4	2.439	0.655	43.2
43	Women's Hiking Boots	316214	13	2	2.462	0.519	49.5
44	Women's Shirts	315232	6	1	2.167	1.169	12.6
45	Yogurt	311511	7	1	2.286	0.756	21.3

Empirical Results on Quality and Market Concentration

For the first-stage probability estimation, we calculated the ordered probit model as in equation (7). The results are given in Table 2 along with some model summary statistics. The coefficients on the 227 firm (F) and 61 type (T)[5] control variables have been deleted to save space but are available from the authors. The coefficients on the 45 industry dummies, *D1* to *D45*, correspond to the $\hat{\gamma}_i$'s and comprise the observations for the dependent variable of the second-stage calculation. The coefficients denoted "Limit" are the estimated probability limits separating the distribution percentiles corresponding to the cutoffs between CR scores of 1 to 2 (Limit 1), scores 2 to 3 (Limit 2), and scores 3 to 4 (Limit 3), respectively (see Greene, 1990, p. 876). Each of these limit parameters is significant at the 1% level, suggesting the CR scores did represent relevant cutoff values (there is no reason to combine, e.g., "good" and "very good" into a single category).

Although fit for models such as this can be misleading, three standard measures of fit for these models are included and show that the estimated model predicts the probability of observing a particular level of quality fairly well. The McFadden LRI, the Veall-Zimmerman, and the McKelvey-Zavoina estimates are bounded between zero and one and are roughly comparable with a traditional R^2 value. Here, they range from a low of 0.46 (McFadden's LRI) to a high of 0.83 (McKelvey-Zavoina). The coefficients are mostly significant at traditional levels of significance for the variables of interest. Only the coefficients on the dummies for industries 24 (hot cocoa mix), 31 (telephone pagers) and 40 (vacuum cleaners) are insignificant at greater than a 10% level of significance. Because our interest in this first-stage regression primarily rests in obtaining the $\hat{\gamma}_i$ coefficients, discussion of marginal effects on the probability

of observing a particular quality ranking will be discussed later. We do note, however, that the gross industry effects on the 45 industry dummy variables are mostly positive and significant.[6]

We note that Schmalensee (1985) found that industry effects were also positively correlated with increased profits. To the extent that profit and quality are related, these two findings are consistent.

Table 3 provides four sets of results for the second-stage regression of equation (8). These estimations use either the four-firm concentration ratio ($CR(4)$) or the HHI as the measure of industry concentration. Results show both ordinary least squares (OLS) and a generalized least squares (GLS) correction for heteroskedasticity. As discussed, heteroskedasticity corrections may be needed, as the second-stage dependent variables have unequal variances.[7] However, as can be seen, the results using the correction are nearly identical to the OLS results.

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[5] There are 106 product types, but one type per industry was left out so that there are only 106-45=61 type dummies in the model.

[6] We also performed the estimations without the variable L, as markups might be industry-specific. The coefficient results on the remaining variables were only slightly altered from above, and the fit was somewhat poorer.

[7] There are various corrections for heteroskedasticity. Our correction follows that of Page (1995) whereby each observation in the second stage is weighted by the consistent estimator $\sqrt{\sigma_V^2 + \sigma_\gamma^2}$. σ_γ^2 is the estimated variance of each of the industry dummy coefficients from stage 1 and $\sigma_V^2 = \dfrac{\sum e^2 - \sum \sigma_\gamma^2}{s}$, where e^2 is the squared residual from the OLS estimation of the second stage. We also used a simple White correction for heteroskedasticity with results that were essentially unchanged from those above.

Table 2. Results from the Ordered Probit, First-Stage Model

Variable	Coefficient	Standard Error	t-Statistic	Variable	Coefficient	Standard Error	t-Statistic
L	0.019	0.003	5.90	D26	4.050	0.557	7.27
D1	3.157	0.426	7.41	D27	6.936	1.122	6.18
D2	3.009	0.786	3.83	D28	3.615	0.947	3.82
D3	4.055	0.622	6.52	D29	2.999	0.532	5.64
D4	5.383	0.818	6.58	D30	5.948	0.372	16.01
D5	-2.541	1.253	-2.03	D31	-0.607	5.389	-0.11
D6	4.783	0.527	9.08	D32	5.106	0.554	9.22
D7	2.639	0.652	4.05	D33	3.285	0.684	4.80
D8	5.408	0.691	7.83	D34	4.364	0.748	5.83
D9	6.383	0.621	10.28	D35	6.678	1.001	6.67
D10	3.963	0.748	5.30	D36	2.483	0.927	2.68
D11	1.634	0.885	1.85	D37	4.215	1.387	3.04
D12	4.850	1.013	4.79	D38	4.448	0.703	6.32
D13	4.298	0.687	6.26	D39	2.955	0.439	6.73
D14	6.882	0.653	10.54	D40	0.218	0.483	0.45
D15	5.863	0.470	12.48	D41	4.709	0.694	6.78
D16	13.375	0.943	14.18	D42	4.492	0.969	4.63
D17	4.007	0.816	4.91	D43	3.055	0.923	3.31
D18	5.491	0.857	6.41	D44	1.967	0.896	2.19
D19	3.956	0.454	8.72	D45	1.090	0.160	6.80
D20	2.552	1.118	2.28	Limit 1	2.181	0.321	6.80
D21	4.435	0.694	6.39	Limit 2	4.546	0.358	12.70
D22	4.075	0.766	5.32	Limit 3	7.349	0.395	18.61
D23	2.574	0.594	4.34				
D24	1.159	0.792	1.46				
D25	4.103	1.265	3.24				

N	1,003
Log-Likelihood	-633.844
McFadden's LRI	0.455
Veall-Zimmerman	0.735
McKelvey-Zavoina	0.831

Note: Approximately 300 coefficient estimates for firm and product type control variables are withdrawn for efficacy of presentation but are available from the authors.

Table 3. Second-Stage Results on Industry Concentration, with Dependent Variable $\hat{\gamma}$

	OLS				GLS			
	β	Standard Error	t-Statistic	R^2	β	Standard Error	t-Statistic	R^2
CR(4)	0.06645	0.00666	9.98	0.69	0.06713	0.00658	10.20	0.70
HHI	0.00252	0.00033	7.53	0.57	0.00252	0.00033	7.49	0.57

Note: HHI figures are unreported for two industries in the census, so the number of observations for those regressions is 43.

The results in Table 3 are interpreted as the effect of industry concentration on product quality after controlling for relative prices and industry, firm, and product type. Thus, the positive coefficient in each case indicates that as concentration increases in an industry, it positively influences the average industry's quality. Table 4 provides some sample statistics for each of the net industry effects, $\boldsymbol{\delta}$, from equation (8) and compares these with the simple averages of the industry effects of stage 1, $\boldsymbol{\gamma}$. What is important to notice here is that the first-stage, ordered probability model overstates the contribution to quality from each of the industries because it is composed of both industry and concentration effects.

Table 4. Comparison of Industry Effects on Quality

Parameter	N	Average	Std. Dev.	Min	Max
γ	45	3.945	2.398	-2.541	13.375
δ using *CR*(4)	45	0.330	2.555	-4.649	10.328
δ using *HHI*	43	1.031	2.876	-5.344	11.531

As the dependent variable, γ (the gross industry effect), is harder to interpret; one must look at the net marginal effect of concentration on the probability of observing a particular quality level. The marginal effect on the probability of observing a product of quality k from a change in the concentration variable is $\dfrac{\partial \text{Prob}(y = k)}{\partial C} = \dfrac{\partial \Omega}{\partial \gamma} \dfrac{\partial \gamma}{\partial C} = \dfrac{\partial \Omega}{\partial \gamma} \beta$, where Ω is the normal cumulative distribution function from the ordered probability model in the first stage, β is the parameter estimation from the second-stage regression, and the derivative $\dfrac{\partial \Omega}{\partial \gamma}$ takes into account

the estimated limit values for each quality index demarcation.[8] Table 5 shows the average

marginal effect, expressed in percentage terms, for each level of product quality, along with the

standard errors, obtained by calculating the marginal effect for each observation and then taking

the average. Table 5 provides the marginal effect from each concentration measure as well as the

effect from the relative price variable, L, calculated simply as $\frac{\partial \text{Prob}(y = k)}{\partial L} = \frac{\partial \Omega}{\partial L}$. All of the

marginal effects are significant at the 1% hypothesis level.

Table 5. Average Marginal Effects on Product Quality

	Poor	*Fair*	*Good*	*Very good*	*Excellent*
CR(4)	-0.0394%	-0.3716%	-0.9497%	0.7367%	0.6239%
	(0.2099%)	(0.6623%)	(1.2820%)	(1.5838%)	(0.8238%)
HHI	-0.0015%	-0.0140%	-0.0358%	0.0278%	0.0235%
	(0.0079%)	(0.0250%)	(0.0483%)	(0.0597%)	(0.0310%)
L	-0.0113%	-0.1071%	-0.2737%	0.2123%	0.1798%
	(0.0605%)	(0.1909%)	(0.3695%)	(0.4565%)	(0.2374%)

Notes: Standard deviations are in parentheses.

What Table 5 shows is that as either the level of industry concentration or the quality-

related price dispersion increases, the probability of observing a "poor," "fair," or "good,"

quality product goes down and the probability of observing a "very good" or "excellent" product

goes up. It is interesting that in terms of magnitude, the effect on the probability of observing a

particular quality from a 1% increase in the concentration ratio is greater than the effect from a

1% increase in price, although the magnitude of this result is weaker when using the HHI. As

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[8] See Greene (1990), p. 877.

such we cannot say whether competition or price dispersion has the greater correlation with quality.

We may also deduce the effect on average product quality from industry concentration. Based on Table 5, define average quality as $AQ = \sum_{k=0}^{4} pr_k.k$ where pr_k denotes the proportion of a particular quality level, k, in an industry. If the proportion of the five categories is invariant to an increase in concentration, the variation of the average quality depends on the variation of quality coming from a change in industry concentration, C, namely, $dAQ = \sum_{k=0}^{4} pr_k.\frac{\partial k}{\partial C} dC$. For example, if $pr_k = 1/5$, Table 5 would imply that a 1% increase in CR(4) leads to an increase in the average quality score by 0.004%. If, on the other hand, pr_k follows the distribution given by the 1,003 observations in our data set, then a 1% increase in the concentration ratio leads to an increase of 0.022% in average quality. To sum up, an increase in concentration leads to an increase in both the probability of observing a higher quality and an increase of the industry's average quality.

Conclusion

Dozens of theoretical studies have attempted to link market concentration and product quality, with conflicting conclusions. Likewise, empirical research of single industries, along a single dimension of quality, has shown both positive and negative correlations between concentration and quality. The contributions of this paper are twofold. First, the study provides a simple, theoretical model that displays the difficulty of deriving a uni-directional relationship between an industry's concentration and the probability of observing high quality in the industry because of

the intricate relationship between cost and product differentiation. Doing so provides an impetus for an inductive, empirical approach. Second, this paper is the first to examine empirically the relationship between quality and concentration with an overall product quality measure and using a cross-section of industries.

Using ordinal quality rankings from *Consumer Reports* and controlling for price dispersion, industry, firm, and product type effects, we find that, in general, as the level of concentration within an industry increases, the probability of observing a poor, fair, or good quality product decreases and the probability of observing a very good or excellent product increases. We remind readers of Schmalensee's call for cross-industry studies in 1985 (p. 341): "Cross-section data can yield interesting stylized facts to guide both general theorizing and empirical analysis of specific industries, even if they cannot easily support full-blown structural estimation." We feel that the positive relationship between concentration and quality should be taken as just such a stylized fact, and we hope this will prod further study to explain why it occurs.

Our results for manufacturing industries would appear to be a significant divergence from many of the previous findings in the empirical literature on service industries (recall Cotterill, 1999; Hamilton and Macauley, 1999; Mazzeo, 2002; Mazzeo, 2003; and Cohen and Mazzeo, 2004, as discussed in our introduction). Could there be a difference in quality outcomes depending on whether the industry is a service or a manufacturing one? As more census data are released, it will also be of interest to follow these 45 industries over time to observe how the results change. Extensions should consider a dynamic view using different time periods, other measures of quality, such as warranties, and whether agglomeration effects along multiple quality dimensions—as noted in previous studies—can be explained by industry concentration.

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