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I. Introduction

The performance characteristics of an industry are closely linked to the nature of entry and exit in the industry. If entry barriers are low, the threat of potential entry can effectively constrain the ability of incumbent firms to raise price above the competitive level. On the other hand, as entry barriers rise and the probability of entry diminishes, the potential for monopolistic practices increases. Prior empirical studies of entry have focused mainly on its determinants, emphasizing industry characteristics as entry barriers. Examples include McGuckin [19], Orr [21], McDonald [17], and Duetsch [7], which analyze the number of new entrants, and Berry [4], McDonald [17; 18], and Masson and Shannon [15; 16] which focus on the market share of entering firms.

Our study uses the model of Orr, and its later extension by Duetsch, as its initial reference point. Like the Orr-Duetsch studies we estimate a model for entry determinants across industries based on the number of new firms. Our contribution is two-fold. First, we analyze a new sample period, 1972–77. Second, we provide a methodological improvement over the logarithmic regression approaches of Orr and Duestch. Because the observations on entry are count data (non-negative integers), our model is developed from the premise that entry requires a statistical framework based on a discrete probability distribution. To meet this requirement, we specify and estimate an econometric model of entry based on the Poisson distribution. Our methodology is in the spirit of Hausman, Hall, and Griliches [11] who apply the Poisson distribution to count data on patent application across firms. Hausman, Hall and Griliches point out that the Poisson model offers an improved methodology for a wide range of economic applications that feature data in the form of repeated counts. This observation motivated our application of the Poisson distribution to the entry problem.\(^1\)

The Poisson approach admits a richer analysis of the entry data than the logarithmic regression approach in two ways. First, the logarithmic specification, while computationally convenient, provides a rather incomplete description of the entry data. The log of entry is only well defined

\(^1\) Other applications of the Poisson distribution to economic data can be found in Cameron and Triveda [5], and Mullaly [20].
for those industries showing positive entry; it is undefined for industries in which entry is absent. The flaw, of course, is that "zero entry" industries, which are not captured in the specification, are also important to the study of entry behavior. It is these industries that reveal the configurations of profits and other industry characteristics that preclude entry. If observations on the "zero entry" industries are deleted from the sample to facilitate the estimation, as is sometimes done in practice, then relevant information is lost. For the Poisson approach, in contrast, both types of observations (positive and zero entry) are natural outcomes of the specification; the Poisson approach incorporates all relevant information in a logically consistent manner.

The second limitation of the log specification, which is overcome by the Poisson, is that maximum likelihood estimation is precluded. Obviously, the error term for a logarithmic regression equation with a discrete dependent variable (the log of entry) cannot be normally distributed, which is required for the OLS estimates to coincide with the ML estimates. More generally, ML estimation is precluded for this specification because it is unclear what distributional assumptions are appropriate. In contrast, for the Poisson approach, which specifies the distribution of entry, ML estimation along with its well known desirable properties is readily available. ²

With the distribution of entry specified as Poisson we are also able to estimate the probabilities of entry across industries, and thus direct the study towards limit pricing in a new and interesting way. Indeed, the probability of entry has become a central feature of recent limit pricing models. In the classic static limit pricing model of Bain [2], dominant firms can either engage in limit pricing and deter all entry or they can set a short-run profit maximizing price that results in unimpeded entry. Entry barriers determine the optimal strategy; with high barriers, the price decrease needed to deter entry is likely to be small enough to make limit-pricing a viable alternative. The probability of entry is crucial to the recent extensions of Bain's work to a dynamic setting by Kamien and Schartz [13], Gaskins [9], Baron [3], and Flaherty [8]. In these models, firms face a continuum of pricing strategies linked to the probability of entry: as the price rises above that which completely blocks entry, the probability of entry gradually rises. In sum, dynamic limit-pricing models predict that pricing decisions across different market structures vary with the probability of entry across markets. Consequently, estimates of these probabilities are of interest for limit pricing.

Section II presents a general specification of entry based on the work of Orr [21] and Duetsch [7], and describes the Poisson estimation approach in more detail. Section III describes the data on the 330 four-digit SIC industries to be analyzed. Section IV presents the ML estimates of the Poisson model, and OLS estimates of log and linear entry models. These estimates are compared with each other and with those found in the literature. Finally, we present estimates of the probability of entry across industries.

II. A Poisson Model of Entry

The first task is to identify the relevant entry-variables. Our selection of variables was guided primarily by arguments given in Orr [21] and Duetsch [7] which we briefly summarize here.

2. In particular, under certain regularity conditions, the maximum likelihood estimator is the most efficient estimator in the sense that its asymptotic covariance matrix reaches the Cramer-Rao lower bound. Least squares estimators, on the other hand, share this property only if the error term in the equation is normally distributed. For further details, see, for example, Johnston [12, 274–9].
Having identified the relevant variables, we then turn to the problem of estimation, and introduce the Poisson model.

The relevant entry-variables follow from an assessment of the entry decision as a function of perceived benefits and costs. On the benefit side, entry is expected to be higher in industries in which incumbent firms earn relatively higher profits, and in large or growing markets. The costs of entry are captured by variables reflecting entry barriers. Three such variables traditionally emphasized are capital, advertising, and industry concentration. High capital requirements can discourage potential entrants, as can advertising expenditures by existing firms. The role of advertising expenditures, however, is somewhat ambiguous since entrants may use advertising as a vehicle for increasing the chances of successful entry. The level of industry concentration is negatively related to entry if potential entrants recognize the threat of collusive retaliation by dominant firms in concentrated markets.

Finally, entry conditions are related to production characteristics across markets. Large economies of scale in an industry can discourage entry: unless large scale entry is feasible, an entrant will produce at a higher cost than existing firms. Multiplant operations can also discourage entry. Duetsch [7] suggests two reasons for an entry-deterring effect. Multiplant operations may be caused by geographic or product segmentation of markets. A new entrant is likely to be at a cost disadvantage if it is only able to produce one product line or in one region. Established multiplant firms can also more readily initiate a price reduction in an individual market segment when entry occurs.

These considerations lead to the following specification:

\[ E_i = f(X_i), \quad \text{where} \]

\[ X_i = (PR_i, GR_i, VS_i, K_i, ASR_i, CR_i, SCAL_i, MULT_i), \]

\[ i = 1, 2, \ldots, n. \]

\( E_i \) denotes the number of new entrants in the \( i \)th industry; \( PR_i \) is a profit index; \( GR_i \) is industry growth; \( VS_i \) is the value of shipments in the industry; \( K_i \) is the capital requirement per plant; \( ASR_i \) is the advertising-sales ratio; \( CR_i \) is the industry concentration ratio; \( SCAL_i \) measures economies of scale; and \( MULT_i \) is an index of multiplant activity.

Orr [21] and Duetsch [7] base their estimations on logarithmic regression versions of the specification. The difficulty with this approach is that entry, \( E_i \), is an integer-valued count variable with a range that includes \( E_i = 0 \) (no entry). Thus, the problem arises of how to handle \( \log(E_i) \) for \( E_i = 0 \). If one wishes to retain the logarithmic specification there are two options, neither of which is completely satisfactory. The first option is to exclude the “zeroes” from the sample. However, a smaller and less informative sample means less efficient estimates. Alternatively, one can “solve” the zero value problem by adopting an ad hoc procedure such as setting the zeroes to one and adding a dummy variable to the equation as is done in Pakes and Griliches [22]. (Neither Orr nor Duetsch discuss the zero value problem, and thus it is not clear how they handle it.) Of course, the magnitude of the problem varies directly with the number of industries in the sample characterized by no entry. For our sample such industries are significant (38 percent), and consequently the zero value problem merits attention.

The necessity of ad hoc procedures or excluding observations brings into question the appropriateness of applying the logarithmic approach to the entry data. Recently, Hausman, Hall, and Griliches [11] address the problem of estimation with count data, and the related zero value
POISSON PROBABILITY MODEL OF ENTRY

Problem. As an alternative to the logarithmic regression approach, they propose modeling count data with the Poisson distribution, and obtaining the estimates by the method of maximum likelihood. Unlike the logarithmic regression specification, the Poisson explicitly reflects the integer nature of count data. The range of a Poisson random variable is the set of nonnegative integers, which obviously matches the possible values of \( E_i \). As a result, by specifying entry as a Poisson random variable, the zero problem, \( E_i = 0 \), becomes a natural outcome of the specification; there is no need to either exclude observations or incorporate ad hoc procedures into the estimation. For these reasons, this is the approach taken here.

The data on entry are assumed to be generated by the following Poisson distribution:

\[
Prob(E_i) = \mu_i E_i \exp(-\mu_i) / E_i!, \quad E_i = 0, 1, 2, \ldots
\]

where \( \mu_i \) is the first moment of the Poisson distribution, and thus is the expected value of entry in industry \( i \). The explanatory variables, \( X_i \), enter the model by specifying the Poisson parameter, \( \mu_i \), as a function of \( X_i \) and an unknown parameter vector, \( \beta \), to be estimated. Consequently, the Poisson model is analogous to the familiar regression specification in that \( E(E_i|X_i) = g(X_i, \beta) \), where \( g(X_i, \beta) = \mu_i \).

Following Hausman, Hall, and Griliches [11], we specify:

\[
\mu_i = \exp(Z_i \beta),
\]

where \( Z_i = (1, X_i) \). Augmenting the vector \( X_i \) with “1” allows for an intercept term.

To obtain the maximum likelihood estimate of \( \beta \) (and hence \( \mu_i \)), \( \beta \) is chosen to maximize the log likelihood of the sample of \( n \) industries:

\[
L(\beta) = \sum_{i=1}^{n} [E_i! - \exp(Z_i \beta) + E_i Z_i \beta].
\]

The maximum likelihood estimate, \( \hat{\beta} \), is obtained by solving the first order condition which takes the form:

\[
\sum[Z'_i(E_i - \exp(Z_i \beta))] = 0.
\]

Because \( \beta \) enters nonlinearly, a numerical algorithm such as Newton-Raphson is required to iterate to a solution. Hausman, Hall, and Griliches [11] point out that the likelihood function is globally concave which ensures convergence to a unique solution. This property follows from the negative-definite Hessian matrix of the likelihood:

\[
\sum[-(Z'_i Z_i) \exp(Z_i \beta)].
\]

Estimates of the asymptotic variances of the ML estimates, which are needed to compute \( t \)-statistics, are obtained from the negative inverse of this matrix evaluated at \( \hat{\beta} \).

As discussed in the introduction, the probability of entry is of interest to contemporary limit pricing theory. Once \( \hat{\beta} \) is obtained, estimates of these probabilities across industries can be easily generated from

\[
Prob(E_i > E_o) = 1 - \sum_{r=0}^{E_o} \mu_i^r \exp(-\mu_i) / r!.
\]
Table I. Variable Definitions and Means: 330 Four-digit Manufacturing Industries

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>Net entry of firms: number of firms in 1977 minus the number of firms in 1972</td>
<td>92.064</td>
<td>258</td>
</tr>
<tr>
<td>PR</td>
<td>Profit index: the residual of 1972 industry price-cost margins regressed on capital-sales ratios and advertising sales ratios</td>
<td>0.000</td>
<td>.073</td>
</tr>
<tr>
<td>VS</td>
<td>Value of 1972 shipments, millions of dollars</td>
<td>1705</td>
<td>3412</td>
</tr>
<tr>
<td>K</td>
<td>Average capital requirement per plant: Fixed assets in 1972 divided by number of plants in 1972 (million of dollars)</td>
<td>2.994</td>
<td>8.396</td>
</tr>
<tr>
<td>ASR</td>
<td>Advertising-sales ratio for 1972</td>
<td>.015</td>
<td>.027</td>
</tr>
<tr>
<td>CR4</td>
<td>1972 four firm concentration ratio</td>
<td>.397</td>
<td>.212</td>
</tr>
<tr>
<td>SCAL</td>
<td>Value-added per employee of the four-largest firms divided by value-added per employee of all smaller firms, 1972 values</td>
<td>1.393</td>
<td>.479</td>
</tr>
<tr>
<td>MULT</td>
<td>Number of plants in 1972 minus the number of firms in 1972 divided by the number of firms in 1972</td>
<td>.242</td>
<td>.366</td>
</tr>
</tbody>
</table>

III. Data Description

The sample to be analyzed consists of observations on 330 four-digit SIC industries for the years 1972 and 1977. Summary statistics and variable descriptions are given in Table I. Data on all variables except ASR are from the 1972 and 1977 census of manufacturers; data on the advertising variable, ASR, are from the 1972 Input-Output tables. 3

Following Orr and Duetsch we adopt “net entry” as an operational definition of $E$:

$$E_i = c_{i77} - c_{i72}, \text{ if } c_{i77} \geq c_{i72},$$

$$= 0, \text{ if otherwise;}$$

where, for example, $c_{i77}$ is the number of firms reported in the $i$th industry in 1977. For the reasons discussed in Duetsch [7, 480–1], net entry is likely to underestimate the number of entering

3. There are 450 four-digit SIC industries in manufacturing. Input-output tables provide data at the three digit level for a number of industries; these were deleted. The census of manufacturers does not provide data on concentration ratios in a few industries, resulting in their deletion also.

Our variables were generated from thirteen variables. The number of companies in 1972 and 1977, value of shipments in 1972 and 1977, value-added in 1972, total employment in 1972, number of plants in 1972; fixed assets in 1972, and total payroll in 1972 are from the four-digit industry tables entitled “Historical Statistics for the Industry: 1977 and Earlier Years,” in Volume II, Part 1, 2, and 3, Census of Manufactures. Fixed assets values were not available for 1972 for seventeen industries. In those cases the nearest ASM estimate was used. Values for the proportion of shipments, employment, and value-added accounted for by the four largest firms in each industry are from 1972 Census of Manufactures, Special Report Series, Concentration Ratios in Manufacturing, MCT2(SR)-2, Table 8. Values for advertising expenditures are from 1972 Input-Output Tables. A list of the SIC industries used is available on request.
firms. Ideally, one should measure \( E \) directly with data on gross entry; unfortunately, such data are unavailable.

Following Duetsch [7], the profit indices, \( PR \), are the residuals from regressing industry price-cost margins on capital-sales ratios and advertising-sales ratios. The reason for the adjustment is to obtain a measure of profitability more closely associated with the entry incentive. As Duetsch [7, 481] points out, high price-cost margins due to high advertising and capital intensity will be largely discounted by potential entrants.

For an index of scale economies in an industry, \( SCAL \), we use the productivity per worker of large firms relative to the productivity per worker of small firms. A similar index has been used by Allen [1], and Chappel and Cottle [6]. Descriptions of the remaining variables are left to Table I.

### IV. Empirical Results

For comparison purposes, three versions of the entry specification were estimated: a regression model with \( E \) as the dependent variable (the linear model), a log model (the Orr-Duetsch approach), and the Poisson model. The first two versions were estimated by OLS, and the Poisson by maximum likelihood. The log model excluded the "zero entry" industries from the sample, and thus was based on 203 observations. In contrast, estimation of the other two models used 330 observations. The likelihood function for the Poisson model was maximized by a SAS program written with "Proc Matrix". The program uses the Newton-Raphson algorithm. Our experience with maximizing the likelihood was similar to that reported by Hausman, Hall, and Griliches [11]; convergence to the global maximum was fairly rapid. The results are reported in Table II.

A comparison of the three columns of Table II reveals differences among the estimated models, and thus indicates the sensitivity of conclusions drawn from the entry-data to the econometric specification. In particular, as in Hausman, Hall, and Griliches [11], the estimated standard errors of the Poisson model are considerably smaller than those of the OLS estimates. While there are some similarities in results, there are also notable differences. Going from the linear to the Poisson model, the coefficients of \( PR \), \( ASR \), \( CR4 \), \( SCAL \), and \( MULT \) become significant. Going from the log to the Poisson model, the coefficient of \( ASR \) switches sign and becomes significant, and the coefficients of \( CR4 \) and \( SCAL \) become significant. We have argued that the most appropriate specification is the Poisson model. The remainder of the paper concentrates on the Poisson estimates.

The Poisson estimates are generally quite reasonable. All of the variables are statistically significant, and the signs of the coefficients for eight out of nine variables come out as predicted by theory. (The one exception, \( SCAL \), is discussed below.) We now turn to a discussion of the Poisson estimate for each variable individually, and draw comparisons with the results obtained by Orr and Duetsch. Interestingly, the Poisson estimates conform more closely, overall, to economic-theoretic predictions than do the results of either study.

Of the entry determinants in Table II, the estimates of the Orr and Duetsch studies agree on only market size, \( \ln VS \), and plant capital requirement, \( \ln K \). 4 The Poisson estimates also agree with these findings. Market size is positively and significantly related to entry, while the effect of plant capital requirements is negative and significant. The Orr-Duetsch estimates conflict for

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4. Both Orr and Duetsch use the average capital requirement of the largest plants in an industry as a measure of \( K \). We have used the average capital requirement of all plants in an industry with the same result.
three of the variables used in the Poisson model: \( PR \), \( ASR \), and \( CR4 \). Orr did not find profits, \( PR \), significantly related to entry, while Duetsch found it to be positive and significant. The Poisson estimate for \( PR \) agrees with Duetsch, and thus also conforms with the traditional notion that profits play a crucial role in the allocation of resources. Orr found both advertising, \( ASR \), and concentration, \( CR4 \), to be significant barriers to entry, but Duetsch’s results were insignificant. The Poisson estimates for \( ASR \) and \( CR4 \) agree with Orr, and thus with the roles typically assigned to advertising and concentration as entry barriers by economic theory.

There are three variables that are comparable only between the Duetsch study and the present study. Growth, \( GR \), is a positive and significant entry determinant in both studies. The Poisson estimate for multi-plant activity, \( MULT \), is negative and significant which corroborates Duetsch’s estimate and multi-plant hypothesis. Finally, the economies of scale proxy was insignificant in Duetsch, which contrasts with the positive and significant Poisson estimate for \( SCAL \). Thus, the sign of the Poisson estimate for \( SCAL \) is contrary to a priori expectations. This nontraditional result may indicate an aspect of the relationship between efficiency differentials of firms within an industry and entry that has generally been ignored. Recall that the proxy \( SCAL \) is the per worker

5. The scale proxy in Duetsch differs from the one used here. He used a measure of the cost disadvantage associated with operating sub-optimal plants; we use a productivity differential between large and small firms.

### Table II. Determinants of Entry*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Linear Model</th>
<th>Log Model</th>
<th>Poisson Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>(-454.296^a)</td>
<td>(-1.586^b)</td>
<td>(-1.509^a)</td>
</tr>
<tr>
<td></td>
<td>((-3.861))</td>
<td>((-2.299))</td>
<td>((-24.849))</td>
</tr>
<tr>
<td>(PR)</td>
<td>113.971</td>
<td>2.441</td>
<td>1.500</td>
</tr>
<tr>
<td></td>
<td>(.586)</td>
<td>(2.168)</td>
<td>(16.453)</td>
</tr>
<tr>
<td>(GR)</td>
<td>99.616</td>
<td>.621</td>
<td>1.255</td>
</tr>
<tr>
<td></td>
<td>(3.247)</td>
<td>(3.456)</td>
<td>(103.313)</td>
</tr>
<tr>
<td>(\ln VS)</td>
<td>67.922^a</td>
<td>.796^a</td>
<td>.783^a</td>
</tr>
<tr>
<td></td>
<td>(4.830)</td>
<td>(9.844)</td>
<td>(119.925)</td>
</tr>
<tr>
<td>(\ln K)</td>
<td>(-50.035^a)</td>
<td>(-.699^a)</td>
<td>(-.387^a)</td>
</tr>
<tr>
<td></td>
<td>((-2.960))</td>
<td>((-7.265))</td>
<td>((-39.603))</td>
</tr>
<tr>
<td>(ASR)</td>
<td>(-403.035)</td>
<td>.474</td>
<td>(-.755^a)</td>
</tr>
<tr>
<td></td>
<td>((-7.72))</td>
<td>(.159)</td>
<td>((-3.605))</td>
</tr>
<tr>
<td>(CR4)</td>
<td>(-115.047)</td>
<td>(-.750)</td>
<td>(-2.692^a)</td>
</tr>
<tr>
<td></td>
<td>((-1.144))</td>
<td>((-1.360))</td>
<td>((-49.792))</td>
</tr>
<tr>
<td>(SCAL)</td>
<td>48.899</td>
<td>(-.152)</td>
<td>(.300^a)</td>
</tr>
<tr>
<td></td>
<td>(1.495)</td>
<td>(.690)</td>
<td>(2.929)</td>
</tr>
<tr>
<td>(MULT)</td>
<td>(-15.551)</td>
<td>(-.558^b)</td>
<td>(-3.551^a)</td>
</tr>
<tr>
<td></td>
<td>((-.777))</td>
<td>((-2.312))</td>
<td>((-38.674))</td>
</tr>
</tbody>
</table>

*\(t\)-ratios are in parentheses. Following Orr [21] and Duetsch [7], the logarithmic values of \( VS \) and \( K \) are used in these regressions. The logarithmic model is estimated from 203 observations, while the other two models are estimated from 330 observations.

a. Significant at one percent level, two tail test.
b. Significant at five percent level, two tail test.
Table III. The Probability of Entry across Market Structures

ESTIMATED PROBABILITIES OF ENTRY:

<table>
<thead>
<tr>
<th>CR4</th>
<th>0</th>
<th>1</th>
<th>5</th>
<th>10</th>
<th>50</th>
<th>100</th>
<th>150</th>
<th>200</th>
<th>300</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;.20</td>
<td>1.00</td>
<td>.99</td>
<td>.99</td>
<td>.99</td>
<td>.83</td>
<td>.67</td>
<td>.56</td>
<td>.42</td>
<td>.25</td>
</tr>
<tr>
<td>.21-.30</td>
<td>.98</td>
<td>.97</td>
<td>.95</td>
<td>.93</td>
<td>.61</td>
<td>.34</td>
<td>.21</td>
<td>.13</td>
<td>.06</td>
</tr>
<tr>
<td>.31-.50</td>
<td>.98</td>
<td>.95</td>
<td>.83</td>
<td>.71</td>
<td>.29</td>
<td>.12</td>
<td>.05</td>
<td>.02</td>
<td>.01</td>
</tr>
<tr>
<td>.51-.70</td>
<td>.89</td>
<td>.84</td>
<td>.66</td>
<td>.49</td>
<td>.12</td>
<td>.05</td>
<td>.03</td>
<td>.02</td>
<td>.02</td>
</tr>
<tr>
<td>&gt;.71</td>
<td>.72</td>
<td>.57</td>
<td>.21</td>
<td>.10</td>
<td>.03</td>
<td>.00</td>
<td>.00</td>
<td>.00</td>
<td>.00</td>
</tr>
</tbody>
</table>

SAMPLE AVERAGES OF ACTUAL AND PREDICTED ENTRY:

<table>
<thead>
<tr>
<th>Concentration Ratio, CR4</th>
<th>Number of Industries</th>
<th>Actual Entry</th>
<th>Predicted Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;.20 mean = .13</td>
<td>71</td>
<td>257</td>
<td>250</td>
</tr>
<tr>
<td>.21-.30 mean = .24</td>
<td>61</td>
<td>86</td>
<td>99</td>
</tr>
<tr>
<td>.31-.50 mean = .40</td>
<td>102</td>
<td>40</td>
<td>43</td>
</tr>
<tr>
<td>.51-.70 mean = .57</td>
<td>63</td>
<td>38</td>
<td>30</td>
</tr>
<tr>
<td>&gt;.71 mean = .81</td>
<td>33</td>
<td>11</td>
<td>6</td>
</tr>
</tbody>
</table>

productivity differential between small and large firms. If there is a large difference between the productivity per worker of large and small firms, and hence a large value for SCAL, there are two possible effects on entry. To the extent that entering firms must compete with large, efficient firms, there is a negative effect on entry. This is the traditional interpretation. However, if there is a relatively inefficient fringe that entering firms are going to compete against, entry will be stimulated rather than suppressed. Our results suggest that when there is a significant cost difference among firms in an industry, there is a net positive effect on entry.

Next we consider the issue of limit pricing which was not addressed in the Orr-Duetsch studies. Limit pricing models are predicated on the assumption that dominant firms base their pricing decisions on the probability of entry. These models demonstrate that small probabilities of entry are suggestive of limit pricing. As mentioned earlier, an advantage of the Poisson model is that estimates of the probabilities of entry across industries can be computed from it. The estimated probabilities of entry are reported in Table III. Five market structures were created based on industry concentration levels. Actual and predicted entry (based on estimates of $\mu_i$) are also reported for each concentration group.

In the lowest concentration group (four-firm concentration less than or equal to 20 percent) the estimated probability of more than 10 and 50 firms entering is .99 and .83 respectively. This result is as expected: there is little basis for believing that limit pricing can occur in low concen-
tration industries. Similarly, the estimated probabilities of significant entry (more than 10 firms) are large for the next two groups: 21–30 percent and 31–50 percent concentration.

When concentration is greater than 50 percent, the results are more suggestive of limit pricing. In the 51–70 percent group, the estimated probability of entry by more than five firms is .66, drops to .49 for more than 10 firms entering, and is only .12 for more than 50 firms entering. The results for the highest concentration category (greater than 71 percent) indicate conditions amenable to limit pricing by dominant firms: the estimated probability of more than one firm entering is only .57 and the estimate dramatically drops to .21 for more than five firms entering.

V. Concluding Remarks

We have presented maximum likelihood estimates of an entry model based on the Poisson distribution. This methodology reflects the discrete nature of the dependent variable. The sample analyzed was for a more recent time period, and included considerably more industries than prior studies. The estimates generally conform to a priori expectations. We found profitability, growth, market size, and intra-firm efficiency differentials to be positively related to entry. Four indices of entry barriers were found to have a significant, negative impact: capital requirements, advertising, concentration, and multi-plant production. These results are especially important given the conflicting results of prior studies, most notably, those of Orr and Duetsch. Moreover, we presented the first estimates of the probability of entry across various market structures; a concept that is fundamental to contemporary limit pricing models.

References