Competition and Innovation: The Inverted-U Relationship Revisited*

Aamir R. Hashmi †

Departments of Economics,

National University of Singapore

and University of Toronto

August 18, 2005

Abstract

In this note we re-examine the inverted-U relationship between competition and innovation (originally modeled and tested by Aghion et al. [2005]) by using data from publicly traded manufacturing firms in the US. We find strong support for the inverted-U relationship. There is some suppport for the composition effect though it is much weaker than what Aghion et al. [2005] find in the UK data. Finally, there is no consistent evidence to support the claim that neck-and-neck industries innovate more than the unlevelled ones and that the escape-competition effect is stronger in more neck-and-neck industries.

JEL Classification Codes: L10; O30

*To be presented at the 20th Annual Congress of the European Economic Association to be held in Amsterdam on 24-27 August 2005.

†I thank Daniel Trefler for his guidance and Angelo Melino, Diego Restuccia, Carlos Rosell, Shouyong Shi, Johannes Van Bisiebroeck and seminar participants at University of Toronto for their comments. Special thanks are due to Rachel Griffith for sharing the data set used by Aghion et al. [2005]. The usual disclaimer applies.

1 Introduction

The question of the relationship between market structure and innovation is an old one. Since the publication of Schumpeter's *Capitalism, Socialism and Democracy* (Schumpeter [1950]), many theoretical and empirical studies have attempted to examine various aspects of this relationship.[1] Schumpeterian endogenous growth models pioneered by Aghion and Howitt [1992] offer a new theoretical foundation for this relationship. The original model (see Aghion and Howitt [1992]) predicts a negative monotone relationship between competition and innovation. The reason is that if it is the expectation of higher profit that drives the innovation then any increase in competition (that results in lower profits) will reduce innovation. However, empirical works of Nickell [1996], Blundell et al. [1999], Carlin et al. [2004] and Okada [2005] find a positive relationship between competition and productivity (or innovation). Aghion et al. [2005] (from here on, ABBGH) attempt to reconcile the theory with evidence. They develop a simple model in Schumpeterian tradition and derive an inverted-U relationship between competition and innovation.[2] They test the predictions of their model using data from manufacturing firms in the UK and find their predictions to accord well with the evidence.

In this short paper we re-test the theoretical predictions of their model using data from publicly traded manufacturing firms in the US. We find strong support for the inverted-U relationship and some weak support for the composition effect. However, there is no consistent evidence in favor of the claim that neck-and-neck industries innovate more than unlevelled ones and that the escape-competition effect is stronger in more neck-and-neck industries.

2 Theoretical Predictions

The theoretical predictions tested by ABBGH are the following:

A. There is an inverted-U relationship between product market competition and innovation. [Proposition 2, ABBGH p.715]

B. As competition increases, distribution of industries moves from neck-and-neck to unlevelled (the composition effect). In other words, the average degree of neck-and-neckness declines. [Proposition 4, ABBGH p.717]

[1] See Tirole [1988], chapter 10 sections 10.1 and 10.2, for a brief discussion of theoretical models and Cohen and Levin [1989], sections 3.2 and 3.3, for a survey of empirical studies of the Schumpeterian hypothesis. Kamien and Schwartz [1982] is a good survey of both theoretical and empirical literature up to the early 1980's.

[2] The idea of inverted-U relationship between competition and innovation goes at least as far back as Scherer [1967], who found an inverted-U relationship between market concentration and employment of scientists and engineers. In a recent paper, Mukoyama [2003] also finds an inverted-U relationship between competition and growth where growth is driven by innovations.

C. In more neck-and-neck industries, the peak of inverted-U is higher and occurs at a higher level of competition. [Proposition 5, ABBGH p.717]

In the following we shall empirically test these predictions. The next section describes our data set and compares it with the data set used by ABBGH.

3 Data

Our sample consists of manufacturing firms in the *Primary, Secondary and Tertiary File* of Standard & Poor's Compustat database. The sample period is 25 years from 1970 to 1994. We use SIC 1987 to classify industries and exclude industries with less than two firms in any year.[3] The final sample has 645 firms with 9882 observations. These firms are spread over 128 four-digit industries.

There are two types of data used in the study:1) accounting data; and 2) patent data. The accounting data are from Standard & Poor's Compustat database (from here on, Compustat) and the patent data are from Hall et al. [2001]. Of the 645 firms in the sample, 310 have at least one patent. These firms have 179,954 patents and 1,349,000 citations altogether during the sample period.

There are three key empirical variables: competition, innovation and technology gap. For all three we follow the definitions in ABBGH and results reported in the next section are based on industry-level variables.[4] Table 1 presents a summary of these variables in our sample vis-a-vis ABBGH's sample. Some observations are in order. The mean of our competition measure is 0.18 less than the mean of ABBGH's competition measure. This is not because the US firms are this much more profitable than the UK firms.[5] Instead, it is because of the following adjustment that we make in our data. When we compute lerner's index (LI) for our data, some 13% of the values are negative. If we set all negative LI's equal to zero (as ABBGH do), we have a huge spike at 0 in the distribution of LI's. To avoid this, we set lowest 3% of LI's equal to zero and readjust the rest such that the minimum is zero. The third percentile of our distribution of LI's is -0.1565, hence we add 0.1565 to all our LI's except the lowest 3% which are set equal to zero. The above adjustment notwithstanding, the US firms earn slightly higher profits than the UK firms but dispersion of their profits is also higher.

The second key empirical variable is innovation which we approximate by citation-weighted patents. The US firms patent a lot more (the mean is more than twice the mean for the UK

[3]This is done to ensure that there is at least one laggard in each industry.

[4]The results are broadly the same when firm-level variables are used. In case of industry-level variables, an observation represents an industry-year. Our sample has 2,481 such observations compared to 354 in ABBGH's sample.

[5]The median profit before tax as a percentage of sales is 9.14% for the US firms in our sample and 8.02% for the UK firms in ABBGH's sample.

firms in ABBGH's sample) and these patents are cited more (citations per patent in the US data are 7.50 compared to 3.33 in the UK data). However, dispersion of the US firms' patents is also much higher.

The third key variable is technological gap. The ABBGH data we received did not have the TFP included and quite a few observations of data on number of employees were missing. Hence, we could not compute TFP for all the firms in ABBGH's sample and as a result we have only 273 observations for TFP compared to 354 for other variables in ABBGH's data. This may partially explain why the technology gap statistics for ABBGH's sample as reported in table 1 are different from those reported in ABBGH [p.727]. Another reason could be the method used to compute TFP.[6] However, the statistics reported in table 1 for both ABBGH's and our sample have been computed using the same method and hence should be directly comparable. According to our computations, the US industries are more neck-and-neck (average technological gap is low) and dispersion of their technological gap is also lower as compared to the UK industries.

4 Empirical Methodology

Following ABBGH, we assume patents to follow a Poisson process. Patents generally do not satisfy the Poisson assumption of equal mean and variance.[7] To take care of this problem we augment the Poisson model to a negative binomial (NB) model.[8]

Let $\mathbf{x}_i$ be the vector of explanatory variables for an industry-year i and let y_i denote citation-weighted patents. Then the distribution of y_i is given by

$$f(y_i|\mathbf{x}_i, \nu_i) = \frac{e^{-\lambda_i \nu_i}(\lambda_i \nu_i)^{y_i}}{y_i!}, \tag{1}$$

where $\lambda_i = e^{\mathbf{x}_i \beta}$ is the conditinal mean and ν_i is the error term. We assume ν to follow a gamma distribution with mean 1 and variance α i.e.

$$g(\nu) = \frac{\nu^{\frac{1-\alpha}{\alpha}} e^{-\frac{\nu}{\alpha}}}{\alpha^{\frac{1}{\alpha}} \Gamma(\frac{1}{\alpha})} \tag{2}$$

[6]We compute TFP at the firm level as $(Y/L)/(K/L)^{\alpha}$, where Y is the output, K is the capital stock and L is the number of employees. We set α equal to 1/3. This measure of TFP is far from perfect. To test the credibility of our TFP estimates we compute simple average of firm-level TFP for each industry-year and compare the results with productivity estimates in NBER-CES Manufacturing Industry Database. The correlation between our estimates and NBER's 4-factor and 5-factor productivity estimates is around 0.2 and statistically significant at 1% level of significance.

[7]The unconditional mean and variance of patents in our sample are 18 and 5036, respectively.

[8] See Greene [2003] pp.744-5 and Cameron and Trivedi [1998] pp. 62-5 for some details on negative binomial model. The model we use is NB2 in Cameron-Trivedi terminology.

The conditional variance of y_i is assumed to depend on the conditional mean and is given by $\lambda_i(1+\alpha\lambda_i)$, which reduces to λ_i if $\alpha = 0$. α is the overdispersion parameter to be estimated alongwith other parameters of the model.[9] We estimate the parameters by maximum likelihood method. Under the above assumptions the command `nbreg` in Stata (S.E.) 8.0 produces the parameter estimates with standard errors and confidence intervals.

We use two specifications for conditional mean. Denoting citation-weighted patents by y, competition by c, technology gap by m and the vector of year dummies by $\mathbf{z}$, the log of conditional mean in the two models is:

$$\textbf{Model I}: ln(y_{jt}) = \alpha_0 + \alpha_1 c_{jt} + \alpha_2 c_{jt}^2 + \delta\mathbf{z} + \epsilon_{jt} \quad (3)$$

$$\textbf{Model II}: ln(y_{jt}) = \alpha_0 + \alpha_1 c_{jt} + \alpha_2 c_{jt}^2 + \beta_1(m \cdot c_{jt}) + \beta_2(m \cdot c_{jt}^2) + \delta\mathbf{z} + \epsilon_{jt} \quad (4)$$

Model I assumes a log-quadratic model in which technology gap does not play any role. Model II (which reduces to Model I if $\beta_1 = \beta_2 = 0$) assumes that the coefficients of c and c^2 vary with technology gap. To see this we can rewrite Model II as

$$ln(y_{jt}) = \alpha_0 + (\alpha_1 + \beta_1 m)c_{jt} + (\alpha_2 + \beta_2 m)c_{jt}^2 + \delta\mathbf{z} + \epsilon_{jt}. \quad (5)$$

If we further assume that technology gap depends on competition, the last equation simply says that competition affects innovation in two ways, one direct and another indirect. The direct effect is captured by α_1 and α_2, and the indirect effect, that operates through technology gap, is captured by β_1 and β_2.

To control for possible endogeneity of competition, we use one-year lagged values for competition.[10] The dependent variable in NB regressions is citation-weighted patents. We assume that an innovation takes place when a patent is applied and not when it is granted.

5 Results

5.1 Prediction A

We start with the main prediction of the model. We estimate models I and II using the entire sample. Table 2 reports the results. Both models fit the data well but highly significant LR-test statistic implies that model II is preferable. However, the predicted values from model II are almost identical to those from model I. These results confirm the existence of inverted-U

[9]For all the regressions that we report in the next section, we test the hypothesis that $\alpha = 0$. Invariably in all cases, it is rejected at 1% level of significance. This lends support to our choice of an NB model over a Poisson model.

[10]The correlation between c_t and c_{t-1} is around 0.81 and our conculsions remain the same whether we use c_t or c_{t-1}.

relationship between competition and innovation. They also show that the effect of technology gap on this relationship is small, though statistically significant.

In Figure 1 we show the scatter plot of citation-weighted patents (CWP's) against competition and superimpose the predicted values of CWP's from model II. To make it comparable to figure 1 in ABBGH [p.706], the scatter plot contains the observations that lie between tenth and ninetieth percentiles of citation-weighted patents. Figure 1 shows a clear inverted-U relationship and a comparison with figure 1 in ABBGH suggests that this relationship is robust to change in country.

To further test the robustness of this relationship we used R&D as the LHS variable and also tested the model using firm-level data. The inverted-U relationship remained robust to these changes. We conclude that there is strong support for the inverted-U relationship in the US data.

5.2 Prediction B

We test prediction B by means of linear and quadratic OLS regressions of competition on technology gap (m) and report the results in Table 3. We also run the same regressions for ABBGH's data set for easy comparison. Both linear and quadratic regressions do well to explain each data set, however, linear regression performs slightly better in case of ABBGH's data and quadratic performs better in case of the US data. It is notable that slope coefficient from linear regression using ABBGH's data set is about fifteen times larger than the slope coefficient from the same regression using the US data. To see this more clearly, in Figure 2 we scatter plot technology gap against competition for both data sets and superimpose the technology gap as predicted by the better fitting model in each case. The slope of the fitted line in case of the US data is very flat compared to the one for ABBGH's data. This shows that although technology gap varies positively with competition, the variation is much smaller in the US data.

As an additional test of this prediction, we divide the US data into n subgroups by the level of competition.[11] For each group we find the fraction of industries that have m greater than the median. The model predicts that this fraction should fall with competition. Figure 3 shows the fraction of low-gap industries against competition for $n = 50$ and 100. The graphs do not show any clear trend. We try other values of n but the results are very similar. The simple linear regressions (not shown in the graph) have negative but statistically insignificant coefficients.[12]

To sum up, although the evidence in support of composition effect in US data is not as

[11] We ignore a group if it has less than two observations.

[12] The slope coefficient when $n = 50$ is -0.55 with a p-value of 0.11. When $n = 100$ the slope coefficient is -0.27 and p-value is 0.45.

clear as in the UK data, we do find that average technology gap increases with competition. However, the magnitude of this increase is very small.

5.3 Prediction C

Before presenting our results for prediction C, we show in Figure 4 the inverted-U relationship as predicted by the model for three different values of h. We have set $\gamma = 1.135$. The figure shows visually what prediction C states in words: as the degree of neck-and-neckness increases (i.e. h increases), the peak of inverted U gets higher and moves to the right. So much so that for very high values of h, the relationship looks more positive than inverted U. It is important to recall the reason for this change: as degree of neck-and-neckness inceases, the escape competition effects gets stronger. This not only increases the overall innovation (the peak is higher) but also more than offsets the Schumpeterian effect over a greater range of competition and hence the peak moves to the right. In the extreme case, when h is 0.225, the escape-competition effect dominates the Schumpeterian effect for almost the entire range of competition and we see that the resulting relationship is almost positive throughout.[13]

Having understood prediction C better, we are ready to analyze our results. To test this prediction, first we follow ABBGH and split our sample in two groups by the level of technology gap. The 'low-gap' group consists of industries with technology gap less than the median and 'high-gap' group includes above-median industries. We fit models I and II to both groups and report the results in Table 4. For low-gap industries, model II fits better while for high-gap industries model I does a better job. Figure 5 shows the citation-weighted patents as predicted by the better fitting model for each group (compare it with figure 3 in ABBGH, p.720). The result is partially in line with prediction C in that the peak of inverted U is higher for low-gap (i.e. more neck-and-neck) industries. However, the peak in case of low-gap industries occurs at a lower level of competition while the model predicts it to occur at a higher level of competition. This observation suggests that although the escape-competition effect is stronger, the Schumpeterian effect dominates it quickly. This result suggests that this prediction warrants more testing. Hence we explore it a little further.

By virtue of a larger data set (we have 2481 industry-year observation compared with 354 in ABBGh's data set) we can break up our sample into more subgroups to see how the inverted-U relationship changes as we move towards more neck-and-neck industries. We do two such experiments. First, we divide the sample into four sub-samples according to the level of technology gap (m). The boundaries are set at three quartiles of m i.e. the first group contains industries with m less than the first quartile, the second with m between first and

[13]Proposition 2 in ABBGH stipulates the following condition for the inverted U pattern to hold: $\underline{x} < \tilde{x} < \bar{x}$. When $\gamma = 1.135$, this boils down to $h \in (0.0670, 0.2274)$. Since 0.225 is close to the upper limit on h, we call this an extreme case.

second quartiles, the third with m between second and third quartiles and the last with m greater than the third quartile. We fit both models I and II to each sub-sample and pick the model that performs better. Figure 6 plots the predicted citation-weighted patents for each of the four groups. To discuss the results we start with the least neck-and-neck group ($m > q_3$) and move gradually towards the most neck-and-neck group ($m < q_1$).

When we move from the least neck-and-neck group ($m > q_3$) to the next group ($q_2 < m < q_3$) in order of neck-and-neckness, we observe that the peak moves to the right (as predicted by the model) but is lower (which is opposite of what the model predicts). When we move further to the next group ($q_1 < m < q_2$), the peak is slightly higher and is to the right (both changes are in line with the model). Finally when we move to the most neck-and-neck group ($m < q_1$), the peak jumps to a very high level (as predicted) but moves to the left (which is again opposite to what the model predicts). These results cast doubt on prediction C as we do not see a consistent pattern.

To take this experiment a step further, we pick 10% of the most neck-and-neck industries and compare them with 10% of the least neck-and-neck industries and 10% of the industries from around the median. In other words now our groups are: industries with $m > p_{90}$; industries with $p_{45} < m < p_{55}$; and industries with $m < p_{10}$. Just like the last experiment we fit both models I and II to each group and pick the better fitting model. Figure 7 plots the predicted citation-weighted patents. When we move from least neck-and-neck group ($m > p_{90}$) to the group with m around the median ($p_{45} < m < p_{55}$), we see that the peak becomes slightly higher and moves to the right. In fact the relationship for the group with m around the median resembles what we saw in figure 4 when h was equal to 0.225. So far this experiment lends strong support to the model: as we increase the degree of neck-and-neckness the escape-competition effect has become very strong. However, when we move further to the most neck-and-neck group $m < p_{10}$, the reverse happens: the peak of inverted U is lower and occurs at a much lower level of competition. This is exactly opposite of what the model predicts. If we compare the least and the most neck-and-neck groups, we see that the peak of the inverted U is roughly the same for two groups and, contrary to prediction C, occurs at a lower level of competition for most neck-and-neck industries.

We conclude that there is no clear-cut evidence in the US data to support the claim that the peak of inverted U is higher and occurs at higher levels of competition for more neck-and-neck industries. In other words, there is no consistent evidence that as the degree of neck-and-neckness increases the escape-competition effect gets stronger relative to the Schumpeterian effect.

6 Concluding Remarks

We test the theoretical predictions in ABBGH by using data from publicly traded manufacturing firms in the US. We find strong support for the inverted-U relationship between competition and innovation. There is some support for the composition effect but it is weaker than what ABBGH find in the UK data. Finally, we find no clear support in favor of the claim that as the degree of neck-and-neckness increases the peak of inverted U becomes higher and occurs at higher levels of competition.

Our main conclusion is that although there is an inverted U relationship between competition and innovation, the nature of this relationship does not change systematically with change in technology gap. In other words, the average distance from technology frontier does not fully explain whether the escape-competition or the Schumpetrian effect will be dominant. Moreover, the technology gap also does not respond as much to competition in the US data as it does in the UK data.

Despite casting doubt on some of their predictions, our findings do not undermine ABBGH's contribution. They are the first to highlight the escape-competition effect and provide a model in which the interaction between escape-competition and Schumpeterian effects leads to the inverted U relationship. The data for both UK and US manufacturing firms provide overwhelming evidence that such a relationship exists and is robust to many variations. What is not so clear, however, is how the interaction bewteen these effects changes with the level of technology gap. Or whether the technology gap plays any role at all in explaining the inverted U relationship.

The last observation leaves room for some other explanation for the inverted U that does not depend on the technology gap. In other words, it is possible that the relationship between competition and innovation is inverted U regardless of the technology gap. One idea that we are currently pursuing is to use a partial equilibrium model on the lines of Ericson and Pakes [1995]. In that environment it can be shown that, under certain conditions, there is an inverted-U relationship between competition and innovation and this relationship does not depend on the technology gap. This is work in progress.

References

P. Aghion and P. Howitt. A Model of Growth through Creative Destruction. *Econometrica*, 60(2):323–351, 1992.

P. Aghion, N. Bloom, R. Blundell, R. Griffith, and P. Howitt. Competition and Innovation: An Inverted-U Relationship. *Quarterly Journal of Economics*, 120(2):701–728, 2005.

R. Blundell, R. Griffith, and J. V. Reenen. Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. *Review of Economic Studies*, 66(3):529–554, 1999.

A. C. Cameron and P. K. Trivedi. *Regression Analysis of Count Data*. Cambridge University Press, Cambridge, UK, 1998.

W. Carlin, M. Schaffer, and P. Seabright. A Minimum of Rivalry: Evidence from Transition Economies on the Importance of Competition for Innovation and Growth. *Contributions to Economic Analysis and Policy*, 3(1):1–43, 2004.

W. M. Cohen and R. C. Levin. Empirical Studies of Innovation and Market Structure. In R. Schmalensee and R. D. Willig, editors, *Handbook of Industrial Organization*, volume 2. Elsevier Science, Amesterdam: North-Holland, 1989.

R. Ericson and A. Pakes. Markov-perfect industry dynamics: A framework for empirical work. *Review of Economic Studies*, 62(1):53–82, 1995.

W. H. Greene. *Econometric Analysis*. Prentice Hall, New Jersey, 5 edition, 2003.

B. H. Hall, A. B. Jaffe, and M. Trajtenberg. Patent Citation Data File: Lessons, Insights and Methodological Tools. NBER Working Paper No.8498, 2001.

M. I. Kamien and N. L. Schwartz. *Market Structure and Innovation*. Cambridge University Press, Cambridge, UK, 1982.

T. Mukoyama. Innovation, Imitation and Growth with Cumulative Technology. *Journal of Monetary Economics*, 50(2):361–380, 2003.

S. J. Nickell. Competition and Corporate Performance. *Journal of Political Economy*, 104(4): 724–746, 1996.

Y. Okada. Competition and Productivity in Japanese Manufacturing Industries. NBER Working Paper No.11540, 2005.

F. M. Scherer. Market Structure and the Employment of Scientists and Engineers. *American Economic Review*, 57(3):524–531, 1967.

J. A. Schumpeter. *Capitalism, Socialism, and Democracy.* Harper, New York, 3 edition, 1950.

J. Tirole. *The Theory of Industrial Organization.* The MIT Press, Cambridge, Massachusetts, 3 edition, 1988.

Table 1: A Summary Comparison of US Data with ABBGH's Data

	ABBGH Data	US Data
Competition $= 1 - LI$		
Mean	0.9502	0.7740
S.D.	0.0230	0.0446
p_{10}	0.9184	0.7201
Median	0.9530	0.7735
p_{90}	0.9754	0.8289
Innovation = *Citation-weighted Patents*		
Mean	6.6158	16.6686
S.D.	8.4538	48.1890
p_{10}	0	0
Median	3.0000	2.8343
p_{90}	20.0000	36.4600
Technology Gap		
Mean	0.3494	0.2168
S.D.	0.1705	0.1418
p_{10}	0.1309	0.0522
Median	0.3375	0.1931
p_{90}	0.6000	0.4187

Table 2: Regression Results (Entire Sample)

Dep Var: Citation-weighted Patents		
Model	I	II
c	94.97^{***}	100.39^{***}
	(14.91)	(15.51)
c^2	-61.62^{***}	-66.10^{***}
	(9.71)	(10.27)
$m \cdot c$	–	-10.80^{*}
		(6.40)
$m \cdot c^2$	–	12.69
		(8.22)
LR-test	–	10.50^{***}

Notes: (1) Figures in the parenthesis are robust standard errors.

(2) ***, ** and * mean significance at 1, 5 and 10%, respectively.

Table 3: Prediction B

Dependent variable: m				
	ABBGH Data		US Data	
Model: OLS	Linear	Quadratic	Linear	Quadratic
c	3.08^{***}	21.49	0.20^{***}	2.47^{**}
	(0.44)	(28.79)	(0.06)	(1.09)
c^2	–	-9.70	–	-1.46^{**}
		(15.20)		(0.71)
F-stat	3.61^{***}	3.44^{***}	1.59^{**}	1.85^{***}

Notes: (1) Figures in the parenthesis are standard errors.

(2) ***, ** and * mean significance at 1, 5 and 10%, respectively.

Table 4: Regression Results (Low-gap and High-gap Industries)

Dependent variable: Citation-weighted Patents				
	Low-gap Industries		High-gap Industries	
Model	I	II	I	II
c	94.32***	99.65***	108.75***	93.67***
	(17.00)	(16.45)	(24.99)	(26.95)
c^2	−61.73***	−68.41***	−69.77***	−57.67***
	(11.17)	(10.89)	(16.10)	(18.07)
$m \cdot c$	–	−54.16***	–	14.03
		(18.52)		(11.33)
$m \cdot c^2$	–	64.02***	–	−17.12
		(23.64)		(14.50)
LR-test (I & II)	–	19.40***	–	2.23

Notes: (1) Figures in the parenthesis are robust standard errors.

(2) ***, ** and * mean significance at 1, 5 and 10%, respectively.

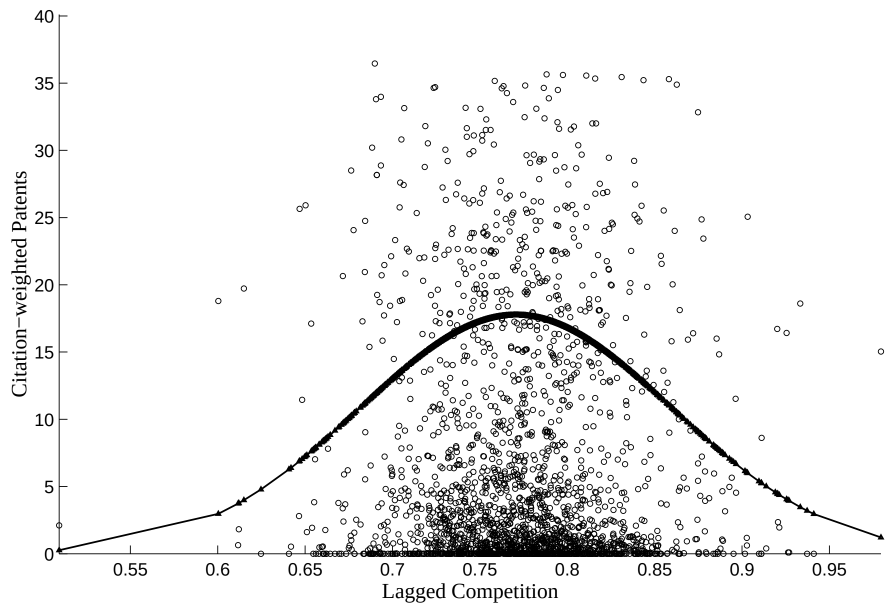

Figure 1: Competition and Citation-weighted Patents

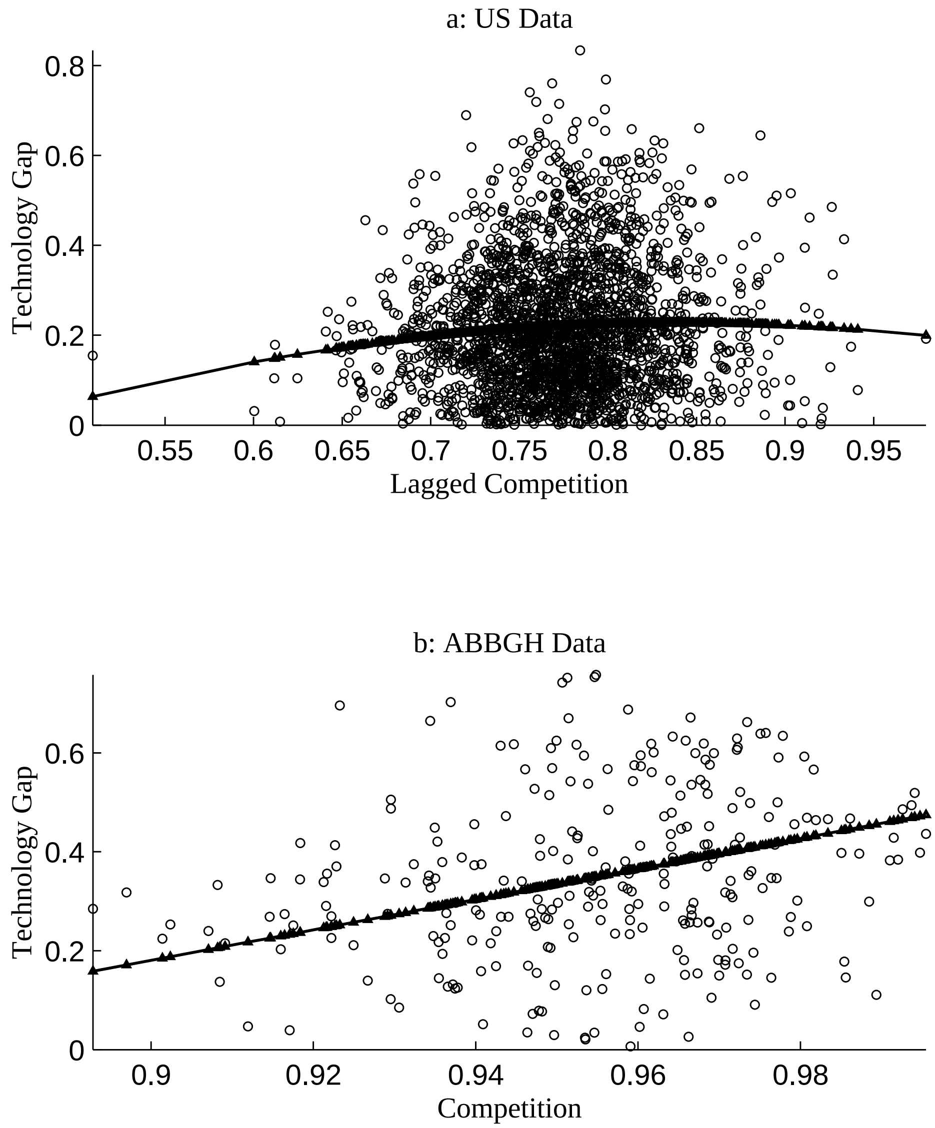

Figure 2: Competition and Technology Gap (m)

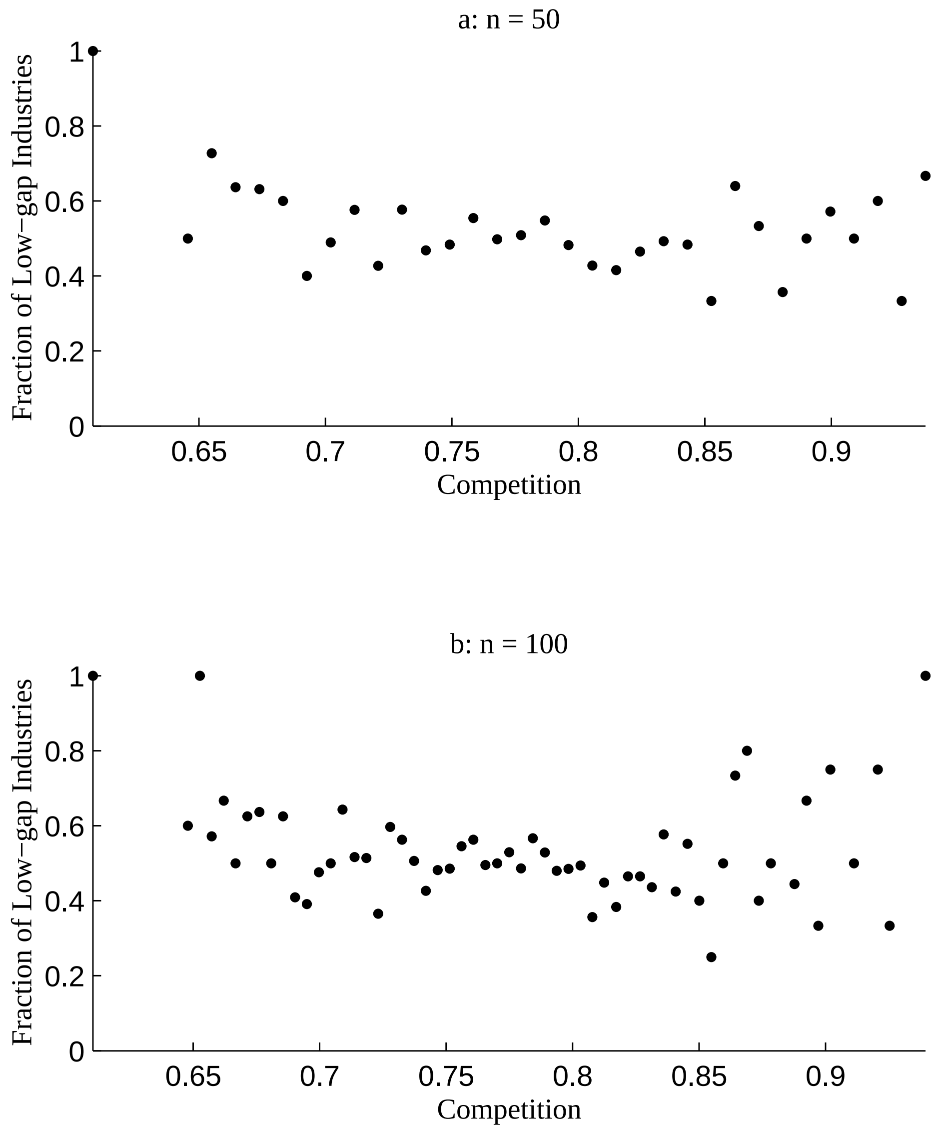

Figure 3: Competition and Fraction of Low-gap Industries

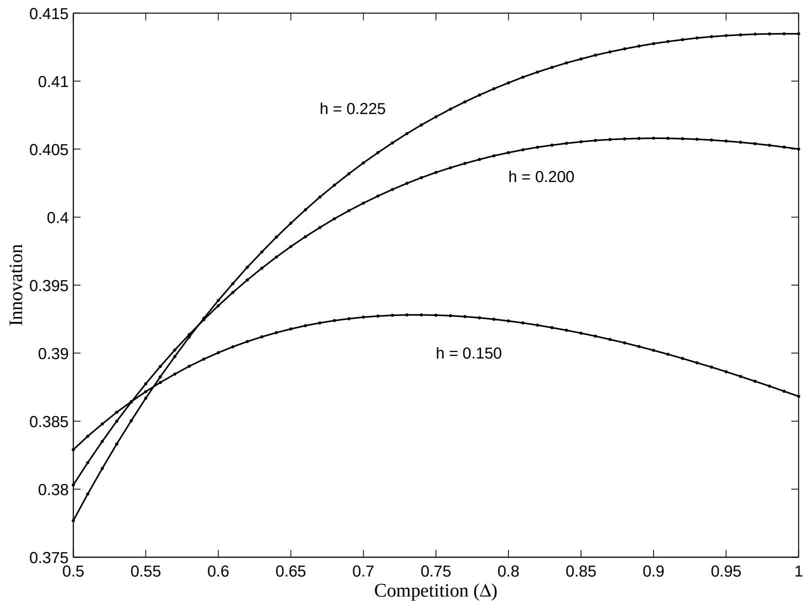

Figure 4: Competition and Innovation at Different Levels of Neck-and-neckness

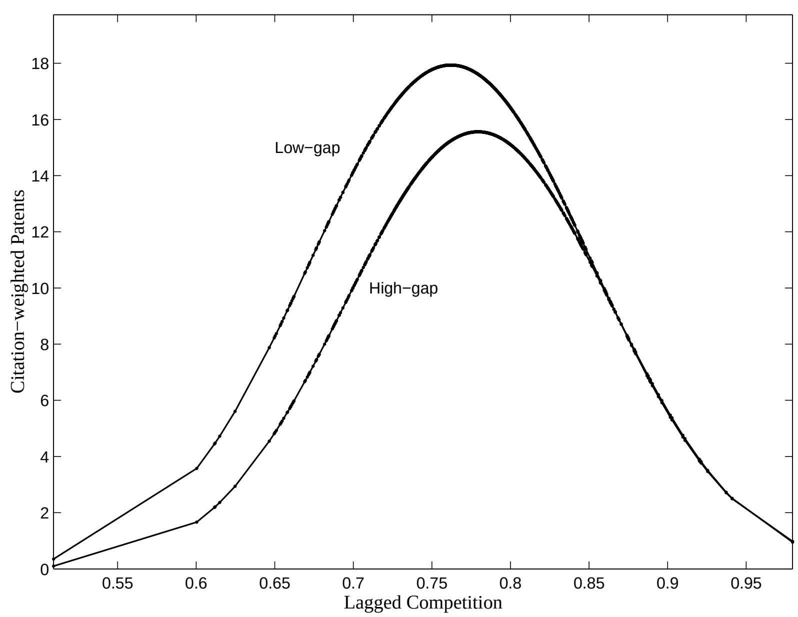

Figure 5: Comparison of Inverted U in Low- and High-gap Industries

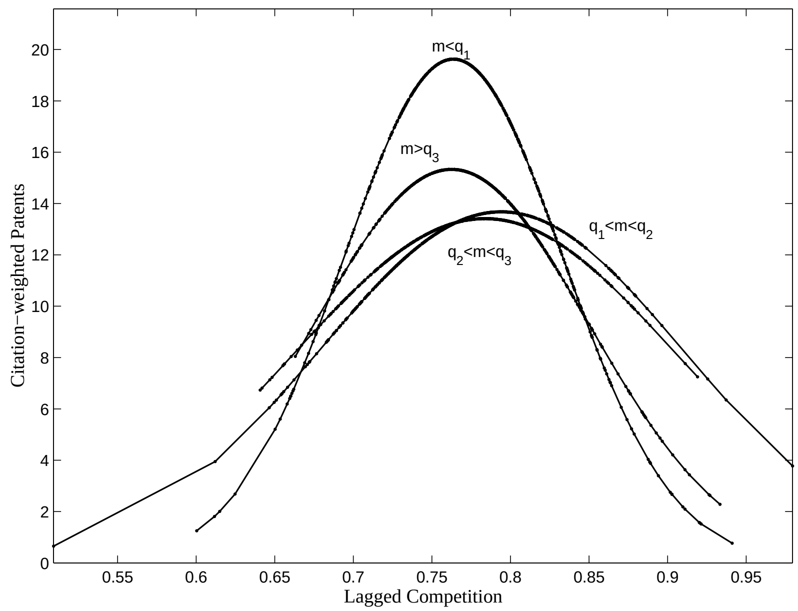

Figure 6: Comparison of Inverted U among Industry-groups with Different Technology Gaps

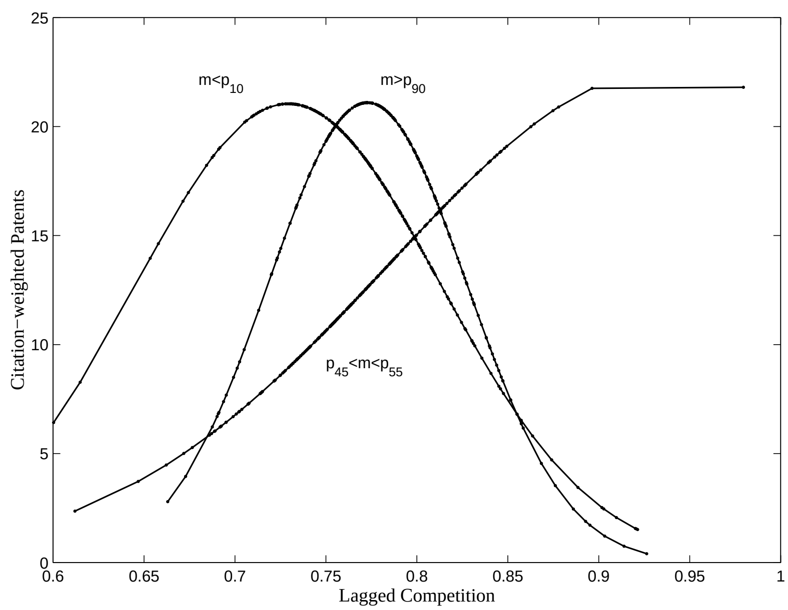

Figure 7: Comparison of Inverted U among Industry-groups with Different Technology Gaps