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Market structure and Schumpeterian growth

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Abstract

We present a discrete-time version of a Schumpeterian growth model. A natural R&D analogue to constant returns to scale implies a Poisson production function with diminishing marginal product.

Surprisingly, the industry demand for R&D inputs does not depend on the number of firms in the R&D sector if Bertrand competition ensues following ties. In contrast, demand is higher if ties result in collusion.

In general equilibrium, Bertrand competition leads to random switching between monopoly and competitive production. Under collusion, production is always at the monopoly level, but there is faster growth. Numerical simulations suggest that this leads to higher welfare.

JEL classification: L11; O31; O40

Keywords: Growth; Market structure

1. Introduction

Schumpeterian growth arises from the research and development (R&D) activities of innovators pursuing the monopoly rents that accrue to new proprietary technologies. There is a large and insightful literature on Schumpeterian growth, including early papers by Aghion and Howitt (1992), Grossman and Helpman (1991), and Segerstrom et al. (1990). However, the Schumpeterian growth literature has thus far ignored the effects of post-innovation market structure when several innovators can be successful at once, that is, when ties are possible. It is easy to understand why: in the continuous time models that dominate this literature, the probability of a tie is infinitesimal.

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Arguably, this ignores an important aspect of reality. R&D projects take time, and that time is naturally identified with the length of a discrete-time period. If the period length is substantial, then simultaneous (that is, same period) discoveries of similar innovations are likely to be common.[2]

Of course, whether the additional complexity of modeling ties is worthwhile depends on their empirical importance. Table 1, based on Phillips (1993), presents estimates of markups and average growth of Solow residuals along with the implied probability of success for 16 industries aggregated at the two-digit SIC level. If an industry grows in discrete jumps of size θ and the average growth rate over time is g, then the probability of success, ρ, solves $g = \rho(\theta - 1)$. The probability of a tie when an innovation occurs is reported in the last column of Table 1 for various numbers of R&D firms.[3] The results suggest that ties are likely to be empirically important for many industries.

The remainder of the paper explores a discrete-time, infinite-horizon model that is analogous to the continuous time Schumpeterian growth models. Sections 2–4, respectively, describe the three sectors of the model economy: innovators, producers, and consumers. Producers employ labor in the production of a consumption good using the current technology. In each period, J innovators come into existence and employ labor with the goal of discovering a labor-saving technology and supplanting the current producer or producers. For $J > 1$, we analyze two cases: the *Bertrand case*, where Bertrand competition in the product market follows R&D ties, and the *collusive case*, where successful innovators collectively maximize joint profits. We refer to $J = 1$ as the *monopoly case*. In discrete-time, an innovator's probability of success cannot exhibit constant returns to scale. We introduce a notion, called constant returns to duplication that is interpretable as having innovators decide how many independent experiments they are going to run simultaneously during the period.

Section 5 presents partial equilibrium analysis, assuming the industry is small enough to take wages and interest rates as given. Curiously, if ties result in (profit-dissipating) Bertrand behavior, then aggregate R&D is the same when $J > 1$ as when $J = 1$. The distribution of R&D across $J > 1$ innovators is indeterminate. Of course, such indeterminacies are common in constant-returns-to-scale models, but as noted above, ours is not such a model; so the source of the indeterminacy must lie elsewhere. In the Bertrand case, an additional experiment is of value to an innovator only if it succeeds when all other experiments fail. This is true whether the innovator or its competitors conduct the other experiments; indeed, it is true whether or not the innovator has competitors. Since the marginal value of an experiment depends only on the number of experiments and not on which innovators are running them, the equilibrium number of experiments is independent of the number of innovators. By contrast, if ties result in collusive behavior, or equivalently, if a monopoly is randomly granted to one of the successful (risk-neutral) firms, then the results differ from the Bertrand case. In the collusive case, an experiment has value whenever it is successful, so the aggregate number of experiments is higher than in the Bertrand case. Thus, if the number of innovators exceeds one, allowing collusion induces higher growth.

Section 6 extends the analysis of Section 5 with a simple general equilibrium model that makes wages and interest rates endogenous. If $J > 1$, the real wage depends on whether there was a tie

[2] A famous example of such a tie might be the simultaneous introduction of VHS and Beta video cassette recording technologies. Closer to home, readers of academic literature can probably think of numerous examples of similar ideas being published at about the same time.

[3] Note that Table 1 uses averages across two-digit SIC code aggregations of industries. A value of $J = 2$, for example, suggests that the average industry (for purposes of R&D races) within an SIC code has two R&D firms. It does not suggest that there are only two firms for the whole aggregation.