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Comment on: Strategic innovation and technology adoption in an evolving industry ☆

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1. The model

Models of firm dynamics usually take a very boring view of innovation. Firms innovate to become more productive. Productivity and size are related one-to-one: more productive firms have a higher marginal product (or lower marginal cost), and so they hire more inputs. In reality, innovation and the marketing or use of the product that results from innovation might be taken up by different firms entirely. Filson and Gretz contribute to our understanding of firm dynamics by showing how innovation and marketing might be allocated to different types of firms in equilibrium.

Filson and Gretz study a repeated racing model. The winner of the race has a choice: to market the product or license to another firm. Although firms do not differ in their abilities to produce, licensing may still be attractive. Firms with different portfolios of existing products have different pricing incentives on new products; a leader may be very interested in acquiring a license to a new technology, so that he can set the joint-profit maximizing price, rather than be forced to compete with a new firm. This same force affects the decision of how much to invest in innovation. Leaders are not eager for a new product to arrive, so they are less willing to innovate, especially to the extent that they can simply license the new product from the innovator once it does arrive.

The model is an appealing merger of the racing literature with the industry dynamics literature, allowing firms to specialize in innovation or in marketing.

☆ Comment on "Strategic Innovation and Technology Adoption in an Evolving Industry" by Darren Filson and Richard Gretz for the April 2003 Carnegie–Rochester Conference.

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Unfortunately, the model is sufficiently complicated that analytic results are not available. Fortunately, the authors deliver numerical solutions that are said to be robust, and that have intuitive appeal. The most important implications are for how young and old, leader and laggard firms vary in their innovative effort and their desire to license innovations.

Laggards are interested in innovating, since the arrival of a new product is not likely to reduce their profits as much as it would if they were a leader. Leaders, on the other hand, have an incentive to license innovations in order to keep competition low. The model has interesting and ambiguous predictions for the welfare effects of licensing: on the one hand, licensing makes innovations more valuable for laggards, since they can be sold to someone with a relatively high value. On the other hand, they may decrease the value of innovations for leaders, since leaders prefer the status quo and can license the innovations when they arrive. Since this is a racing model, innovation can be too high or too low in equilibrium, so the welfare effects of these countervailing effects on innovation are nontrivial. Moreover, licensing can have the usual effect that worries the Justice Department: they may decrease competition by allowing leaders to "buy off" products that might be competitors.

2. How should a model like this be taken to the data?

The authors relate the results of the model to data from the hard drive industry. The industry has a variety of features that make it well suited to the model, such as well defined product generations and useful quality measures.

The data approach that the authors take is common in the literature, but it lacks parsimony. They highlight some predictions of the model. In this case, those predictions come from simulations. Then, to compare these predictions to the data, they run regressions with proxies related to variables of interest in a variety of the hypotheses. The lack of parsimony comes from the fact that a variety of independent hypotheses are tested within the same regression, so that the regression coefficients have a conditional flavor that is not easy to interpret.

For instance, the probit regression of Table 10 is said to "test" Hypotheses 1–3. The hypotheses are statements about predictions of the model, such as when firms of various ages and technological sophistication are most likely to innovate. Other than the firm's technological level (Hypothesis 1), the age of the young generation (Hypothesis 2), and the relative quality of the young generation (Hypothesis 3), the statements are *unconditional*. The probit regression includes proxies for innovation by firms of various technological levels for various ages and qualities of the young generation. Since all of the proxies for the three hypotheses are in one regression, however, the coefficients are measuring *partial* correlations, where, in each case, conditioning variables from the other two hypotheses are being used to test the third. For instance, when the authors look to see whether laggard firms are more or less likely to innovate, they are implicitly "controlling" for the age of relative quality of the young product generation, since proxies for these are also regressors. However, Hypothesis 1 does not make the statement that if you *control* for age and quality of

the young generation you should observe a particular relationship between a firm's quality and the likelihood of innovation; it just makes a statement about the relationship between the firm's quality and the odds of an innovation arriving.

This inconsistency between the model's predictions and the regressions used to investigate the predictions is common in the industrial organization literature, but it is not easily justified, nor is it simply a technical issue. There is no reason to be assured that the sign of the unconditional correlations need line up with the results of a regression of this sort. While it might be arguable (but still questionable) to include in a regression controls for variables outside the model but relevant to the data, it is another matter to include variables accounted for by the model, but not included in the statement of the hypothesis to be tested.

Once the model's predictions become disconnected from the empirical implementation, one can easily fall down a slippery slope to the point of a fishing expedition, where the goal is to find some conditional statement in the data that seems to support, in a loose way, the model. Note that, for instance, it isn't obvious how these partial correlations would change if a right hand size variable was interchanged with a left hand size variable; in this case, the choice is obvious, but in some cases it might not be, further leading to the opportunities for fishing.

What is a better approach? The authors answer that question in several places, such as when they discuss new product generations. Here they report unconditional correlations from the data. Do pioneers tend to be spinouts? Do pioneers tend to be laggards? They show that, in the data, the number of pioneers who are spinouts or laggards is too high to be due to luck. It must be the case that something about spinouts and laggards make them pioneer new product generations; the model provides a rationale for the fact.

In order to be completely parsimonious, the authors could generate simulated data from their model (much as they generate simulated outcomes to form hypotheses from numerical outcomes) and compare the *same* statistics from the data and model. Regression output might be the relevant set of statistics for comparison, but to do the comparison we need to see the same conditional statistics from the model and the data.

The discussion of the role of licensing in the hard drive industry underscores the benefits to this sort of approach. Hypothesis 10 states that licensees are typically large. The authors report that large firms are statistically overrepresented in the sample of licensees; however, their overrepresentation is far short of the large firms' share of sales. Is this support for the hypothesis or not? It is hard to say. The model would predict that large firms are relatively intensive in licensing (which they are not), but at least they are doing more licensing than small firms. If we had comparable statistics from a parameterized version of the model, it would be easier to see to what extent these numbers represented a success or failure of the model.

Of course one parsimonious approach, one which is perhaps most preferable, would be structural estimation of the parameters of the model. Despite the lack of price data, the availability of both quality and quantity[1] data could be enough to

[1] Or at least total firm sales.

identify the parameters. Since a parameterized version of the model could be a useful policy tool, there seems to be value added in figuring out what parameters are identified. Moreover, some sort of parameterized model is going to be needed to answer quantitative questions. Taking the results in the paper as qualitatively supportive, we still do not know to what extent the forces introduced here can be quantitatively explained. The authors have taken an important first step, but additional steps will enhance the value of the authors' contribution.

3. Policy

The model is potentially well suited to studying policy questions: a parameterized version could be used to measure welfare implications of policies, such as limits to licensing, that are commonly used. Welfare implications are not obvious here, since the racing game can lead to too much or too little innovation, and licensing agreements impact both innovation and the subsequent degree of competition. However, in its current form, the authors do not have much to say about welfare, only innovation, since they are not willing to stand on any one particular parameterization. Moreover, the model as it stands seems ill suited to studying policies concerning covenants not to compete (CNCs) that the authors discuss. CNCs are a fundamentally ex-ante contract; they allow the employer to limit what the employee can do with future innovations. This is an uncomfortable fit with the model developed here, which relies on an inability of firms to write ex-ante agreements, such as ex-ante licensing agreements. Studying the implications of other contractual possibilities within the framework of this model might be an interesting topic for future study, and might make the model more appealing as a way to think about contractual arrangements like CNCs. Such a model is surely warranted, as the introduction of the racing aspect provides a new richness not present in state-of-the-art models of industry dynamics with worker mobility, such as Franco and Filson (2000).

In the long run, the development of models like this one is essential to a coherent discussion about innovation and licensing policy. Filson and Gretz have provided us with an empirically useful framework to use in that discussion.

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