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All Hail Large Firm Innovation: Reconciling the Firm Size and Innovation Debate

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Abstract
Since Schumpeter, there has been a long-standing debate regarding the optimal firm size for innovation. Empirical results have settled into a puzzle: studies consistently find that R&D spending increases with scale, however studies of R&D productivity indicate product and patent counts decrease with scale. Thus firms appear irrational: spending is decreasing in productivity. We propose the puzzle stems from measurement problems. Drawing on recent theory suggesting that size affects the type of R&D that firms conduct, we propose that product and patent counts undercount large firm innovation (incremental and process). To date we have had limited ability to test these more nuanced views because we lacked firm-level data on the type of R&D firms conduct. Additionally we lacked a universal measure of R&D productivity that could accommodate all types of R&D. Using recently available NSF BRDIS survey data to
solve the former problem and a recent measure of R&D productivity (RQ) to solve that latter problem, we find that both R&D spending and R&D productivity increase with scale. We further find that while large firms and small firms differ in the types of R&D they conduct, there is no type whose returns decrease in scale?there are merely types for which the small firm penalty is
less severe. This raises a new question: why do small firms conduct R&D? The answer appears to be they rely on spillovers. Thus not only do large firms provide the bulk of innovation in the economy, their spillovers subsidize small firms? innovation.

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Reconciling the Firm Size and Innovation Debate

By ANNE MARIE KNOTT AND CARL VIEREGGER*

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Since Schumpeter, there has been a long-standing debate regarding the optimal firm size for innovation. Empirical results have settled into a puzzle: studies consistently find that R&D spending increases with scale, however studies of R&D productivity indicate product and patent counts decrease with scale. Thus firms appear irrational: spending is decreasing in productivity. We propose the puzzle stems from measurement problems. Drawing on recent theory suggesting that size affects the type of R&D that firms conduct, we propose that product and patent counts undercount large firm innovation (incremental and process). To date we have had limited ability to test these more nuanced views because we lacked firm-level data on the type of R&D firms conduct. Additionally we lacked a universal measure of R&D productivity that could accommodate all types of R&D. Using recently available NSF BRDIS survey data to solve the former problem and a recent measure of R&D productivity (RQ) to solve that latter problem, we find that both R&D spending and R&D productivity increase with scale. We further find that while large firms and small firms differ in the types of R&D they conduct, there is no type whose returns decrease in scale—there are merely types for which the small firm penalty is less severe. This raises a new question: why do small firms conduct R&D? The answer appears to be they rely on spillovers. Thus not only do large firms provide the bulk of innovation in the economy, their spillovers subsidize small firms' innovation.

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I. Introduction

The firm size and R&D hypothesis is one of the two main hypotheses in innovation economics, the other being market structure. Both hypotheses are attributed to Schumpeter (1942) who asserted that large firms are the major engine of economic growth. The most important advantage of size is scale economies--at a minimum, larger scale amortizes the fixed cost per innovation over a larger number of units. Accordingly, the returns to innovation should be greater for large firms. This then is an argument about ability to exploit innovation.

A companion argument considers the impact of firm size on ability to conduct R&D. On one side of the argument, large firms are viewed to be more effective with their R&D. This could occur for a number of reasons. First, there may be minimum efficient scales for some R&D projects, e.g., there is only one super-collider. Second, R&D projects are known to be stochastic, Stevens and Burley (1997) report that on average for Industrial Research Institute member firms, it takes 125 funded projects to achieve one commercial success. Large firms are better able to pool risk because they can carry a broader portfolio of projects. Having a broad portfolio confers another advantage: technical diversity—typically more projects implies a broader set of problems and associated expertise (Nelson 1959). This increases the likelihood of having any required expertise in-house. Finally, large scale implies a broader set of product markets. Drawing again upon the stochastic nature of R&D, this increases the likelihood that projects that fail for a given application, might have other applications elsewhere in the firm.

On the flip side of the size debate are arguments suggesting small firms are more productive with their R&D. Indeed colloquially, people use the term "entrepreneurial" (conveying small start-up firms) to connote innovativeness. The small firm arguments typically rely on governance advantages. Fewer employees implies decision makers are closer both to the technology as well as the customer, thus they can better link technological possibilities to market needs. Relatedly, fewer employees also implies closer proximity between technical workers, which facilitates problem solving (Allen 1977). Finally, small firms have fewer levels of hierarchy, so decision-making can be more rapid.

Thus there appear to be compelling arguments for either size to be more effective in conducting R&D. This likely explains why both large and small firms conduct R&D. If either size had a substantial advantage, the other size would be unlikely to conduct R&D. Accordingly, more recent theories attempt to reconcile the co-existence of large firm and small firm R&D.

These theories suggest the two sizes differ in the type of R&D they conduct, and that the returns to type vary with firm size. In essence they argue that choice of R&D strategy is endogenous--firms choose the strategy most likely to be effective given their size. Rosen (1991) for example suggests that large firms do incremental innovation, while small firms do radical innovation. Cohen and Klepper (1996) suggest large firms do process innovation, while small firms do product innovation. Finally, Knott (2003) suggests that large firm innovation relies more heavily on firms' own R&D, while small firm innovation relies more heavily on spillovers.

There is a substantial empirical literature testing the size hypothesis (see Cohen 2010 for a summary). Tests of innovative behavior indicate that R&D investment increases with scale, e.g., Baldwin and Scott 1987, Scherer and Ross 1990. Assuming firm rationality, these results imply large firm R&D is more productive than small firm R&D. However, most studies of innovative outcomes find small firms are more productive, e.g., Scherer 1965, Pavitt et al 1987, Acs and Audretsch 1988, 1990. One limitation of these outcome studies is they rely on product counts or patent counts as the measure of R&D performance. However, if choice of R&D strategy is endogenously determined by firm size (as the more recent theories suggest), these tests will undercount large firm innovation, since theory expects it to be incremental and process. Moreover, these studies ignore the contributions of spillovers or rival R&D—thus overstate the contributions of own R&D.

Accordingly important questions in the firm size and innovation debate remain unresolved: 1) Why is investment behavior inconsistent with returns? 2) why if one size has higher returns, do we see both large firms and small firms conduct R&D? What's required to resolve these questions and the firm size debate, are empirical models that explicitly consider the endogenous choice of R&D strategy. This in turn requires data on R&D practices as well as a more comprehensive measure of productivity that captures all forms of R&D.

We exploit recently available NSF BRDIS survey data and a recent measure of R&D productivity (RQ) in an effort to resolve the firm size debate. We find that both R&D spending and R&D productivity increase with scale (thus resolving the first question of seemingly irrational behavior). We further find that while large firms and small firms differ in the types of R&D they conduct, there is no type whose returns decrease in scale—there are merely types for which the small firm penalty is less severe. This leads to the second question: why then do small firms conduct R&D? The answer appears to be they rely more heavily on spillovers. Thus not only do large firms provide the bulk of innovation in the economy, they provide the spillovers on which small firm innovation free-rides.

II. Empirical Approach

This study is an effort to resolve the firm size debate by testing the more nuanced theories of firm size and R&D. To do so we exploit recently collected data on firms' R&D practices from the National Science Foundation (NSF) Business R&D and Innovation Survey (BRDIS) as well as a recent measure of R&D effectiveness, RQ (short for research quotient) that captures all forms of R&D.

BRDIS Data

BRDIS is an annual survey of firms' R&D behavior conducted by the National Science Foundation (NSF) in conjunction with the U.S Census Bureau. BRDIS is a more expansive successor to the Survey of Industrial Research and Development (SIRD), which was conducted from fiscal years 1953 to 2007. Both surveys address the industry component of the NSF mandate "...to provide a central clearinghouse for the collection, interpretation, and analysis of data on scientific and engineering resources and to provide a source of information for policy formulation by other agencies of the Federal government."

The more expansive survey was deemed necessary because the bulk of R&D is now funded by industry, whereas in the 1950s, when the SIRD was created, the majority of R&D was funded by the US government. Thus greater insight into firm R&D behavior was warranted. In addition the new survey better matches the Community Innovation Survey (CIS) conducted by the EU countries. Accordingly, BRDIS data supports comparisons of innovative behavior between the US and other countries.

BRDIS is mailed annually to approximately 40,000 companies. The BRDIS sample is intended to represent the approximately 1.5 million for-profit companies in the United States with five or more domestic employees, both publicly or privately held. The overall response rate in the 2008 survey was 77.4%, and the response rate for the top 500 domestic R&D-performing companies was 92.6%. Of these responding firms, approximately 3% reported performing and/or funding R&D.

BRDIS gathers data on a number of R&D variables (see the full survey for 2010). However we focus attention on the variables related to firm size, firm R&D strategy, as well as financials required to derive firm RQ. With regard to the strategy variables, we examine the three R&D strategies hypothesized to affect or be affected by scale:

1) Portfolio horizon: "What percentage of R&D paid for and performed by your company was for:

   a. Basic research: planned, systematic pursuit of new knowledge without specific immediate commercial application
   b. Applied research: planned, systematic pursuit of new knowledge aimed at solving a specific problem or meeting a specific commercial objective
   c. Development: the systematic use of research and practical experience to produce new or significantly improved goods, services or processes".

2) Riskiness: "What percentage of this year's sales were from goods/services introduced in the past three years that were:

   a. New (or significantly improved) to your market
   b. New (or significantly improved) only to your company
   c. Unchanged or only marginally modified"

3) Form: "Did your company introduce any of the following in the prior three years:

   a. New (or significantly improved) goods
   b. New (or significantly improved) services
   c. New (or significantly improved) processes (methods of producing goods or services, distributions systems for inputs or outputs of your goods or services, support activities)"

RQ estimation

RQ is the firm-specific output elasticity of R&D in the firm's production function (Knott 2008). Thus it represents the percentage increase in revenues from a 1% increase in R&D, holding constant other inputs and their elasticities. Accordingly, RQ conforms with the most common means to measure returns to R&D (Hall, Mairesse and Mohnen 2010). Where RQ departs from prior measures of returns to R&D is that it captures them at the firm-level rather than at the industry or economy level. This departure stems from both the realization that there is substantial firm heterogeneity even within an industry (see Syverson 2011 for a review), and the availability of data and methods to estimate firm-level parameters.

The advantages of RQ over prior firm-based measures of R&D performance stem from universality, uniformity and reliability. Universality refers to the fact that RQ can be constructed for any firm conducting R&D. This stands in contrast to patent measures which can only be constructed for the 50% of firms who patent their R&D. Uniformity stems from the fact that RQ is unitless—it is essentially a nuanced ratio of revenues over R&D. This allows direct comparison of all forms of innovation. In contrast, patents have highly variable value—10% of patents account for 85% of the economic value of all patents (Scherer and Harhoff 2000). Finally reliability refers to the fact that RQ is empirically consistent with expectations from endogenous growth theory (Romer 1990, Thompson 1996, Lentz and Mortensen 2011). R&D investment, growth and market value all increase in RQ, while all three measures decrease in patent intensity (Knott and Vieregger 2014).

We derive RQ using random coefficients estimation of the firm's production function (Equation 1) in accordance with the general methodology described in Knott (2008) for Compustat data.[1] A random coefficients model (Longford 1993) represents a general functional form model which treats coefficients as being non-fixed (across members of a cross-section or over time) and potentially correlated with the error term. Random coefficient models are those in which each coefficient has two components: 1) the direct effect of the explanatory variable, $\beta_{\_}$ and 2) the random component that proxies for the effects of omitted variables, $\beta_{\_i}$. Accordingly, each firm's RQ is the sum $\beta_3 + \beta_{3i}$ in Equation 1.

Note that RC is a general functional form of which fixed effects is a restricted form where only the intercept is treated as a random coefficient. One complication with estimation using the BRDIS data is its input variables differ from those collected from firms'10-K filings (the source for Compustat data). While revenues and R&D expenditures are the same in both datasets, BRDIS collects capital expenditures rather than property, plant and equipment, and does not collect advertising. Accordingly we employ a model of the following form:

[1] Note this discussion follows closely with that in Knott 2008.

(1) $$\ln Y_{it} = (\beta_0 + \beta_{0i}) + (\beta_1 + \beta_{1i}) \ln K_{it} + (\beta_2 + \beta_{2i}) \ln L_{it} + (\beta_3 + \beta_{3i}) \ln R_{it\text{-}1} + (\beta_4 + \beta_{4i}) \ln S_{it\text{-}1} + \varepsilon_{it}$$

Firm level data items include (in \$MM unless otherwise stated): *revenues* (Y_{it}), *capital* expenditures (K_{it}), *labor* as full-time equivalent employees (1000)(L_{it}), and *R&D* (R_{it}). From these primary data, we derive a secondary measure: firm-specific *spillovers* (S_{it}) which is computed as the sum of the differences in knowledge between focal firm *i* and rival firm *j* for all firms in the four digit SIC industry with more knowledge (R&D) than the focal firm:

(7) $$S_{it} = \sum_{j \neq i} R_{jt} - R_{it} \; \forall \; R_{jt} \geq R_{it}$$

This construction mimics the spillover construct in endogenous growth models with heterogeneous firms, e.g., Jovanovic and MacDonald 1994. It is a density measure that takes into account the number of firms with superior knowledge as well as the amount of each firm's surfeit of knowledge relative to the focal firm. In essence it represents the likelihood and extent of discovering superior knowledge in a random encounter with a rival firm. Both R&D and spillovers are lagged one year. [2]

We validated the abbreviated RQ estimation with Compustat data using the full set of Compustat inputs as well as the restricted set of BRDIS inputs. That comparison indicates that RQs are 91.7% correlated across the two equations.

A second restriction of the BRDIS data is that is has only been released for years 2008-2011. Accordingly the maximum window size per RQ estimate is four-years, whereas prior estimates of RQ (Knott 2008, Knott and Vieregger 2014) used seven and ten-year windows. Accordingly, we tested the impact of window size using Compustat data, just as we tested the impact from a restricted set of inputs. Comparisons of RQs generated with Compustat data in a window surrounding the year 2000 indicate RQ estimates with a four-year window are 75.8% correlated with those estimated with seven-year window. Of these, 6.2% of RQs from the four-year window are significant, versus 17.7% for the seven-year window. Thus the shorter window will make it more difficult for us to obtain significant results. However if we do obtain significant results, the high correlation makes it likely results will hold and be more significant with the

[2] There is no significant difference between one and two year lags. This finding matches two empirical regularities: econometric equivalence between stock and flow models and econometric equivalence of models with different lags (Griliches and Mairesse 1984, Adams and Jaffe 1996).

longer window.

Firm Size Tests

Our firm size tests have three components: The main effects of scale, the choice and impact of R&D strategy, and treatment effects of strategy on outcomes.

Main Effects of scale. We begin firm size testing by examining the main effects of firm size on behavior (R&D spending) and performance (RQ). If as we expect, firm size drives R&D strategy, the coefficients on size will be biased in these estimations. Thus the main role of these tests is to generate results that can be compared to prior studies. Because we only have one observation for RQ (the 4 year mean), we form four-year averages of our scale variables, R&D as well as the practice variables. Because this leaves one observation per firm, we conduct cross-sectional tests using OLS.

Choice and Impact of R&D Strategy. To begin teasing apart how scale drives behavior and performance, we next examine R&D strategy. As mentioned previously, firm R&D strategy, as captured in the BRDIS data, has three components: portfolio horizon (basic, applied, development), riskiness (new to market, new to firm, incremental), and type (product, service, process). For each of the nine uni-dimensional strategies, we first test the impact of scale on choice of strategy. We then test the effect of the strategy on behavior (R&D spending) and performance (RQ), while controlling for scale. We allow strategy to have both a direct effect and an effect that varies with scale. The interaction allows us to examine whether certain strategies favor certain sizes, as both Rosen (1991) and Cohen and Klepper (1996) suggest. Again, if firm size affects choice of strategy, these estimates will be biased.

Treatment Effects. Given the bias concerns, our primary tests attempt to control for the endogenous impact of size on firm R&D strategy through two-stage selection models. Before conducting these tests however, we first examine whether firms' R&D strategies are better characterized as bundles rather than uni-dimensional decisions. We use cluster analysis to construct strategy "archetypes" for portfolio horizon, riskiness, and form.

Once we define the archetypes, we first replicate the tests of uni-dimensional strategies--examining the impact of firm size on choice of strategy Because we expect these analyses to indicate size drives choice of archetype, we then employ a two-stage treatment model, using Stata command, treatreg to determine if there are treatment effects from the strategy after controlling for the selection effects of size on archetype.

The treatment model comprises two stages: a first stage model of strategy choice, and a second stage model of outcomes. It is essentially a switching regression model that explicitly states there are two regimes: treatment and non-treatment. Accordingly, there are separate models for the outcome under each regime, both of which are estimated using maximum likelihood.

III. Results

Main Effects of Scale. Table 1 presents results for the impact of size on behavior (R&D spending) (Models 1-4) as well as performance (RQ) (models 5-6). For each test, we examine two alternative measures of firm scale (revenues and employees).

Insert Table 1 about here

Regarding the impact of scale on R&D investment, results indicate that scale is positive and highly significant. Indeed scale explains approximately 48% of intra-firm variance in R&D. The best fitting model is one using ln(employees) (Model 2). The coefficient estimate of 0.717 implies that a 10% increase in the number of employees increases R&D 7.2%. These results match stylized facts (Cohen 2010).

Because prior tests have examined R&D intensity (R&D/Sales) rather than R&D levels, we examine that as well (Models 3 and 4). Those tests indicate R&D intensity decreases with scale, also matching prior results.

Regarding the impact of scale on performance (RQ), we also find scale is positive and significant. Here however the best fitting model uses ln(revenues) rather than ln(employees). The coefficient estimate of 0.014 implies that a 10% increase in firm revenues increases R&D productivity (RQ) 0.14%. As with R&D investment, scale explains 41% of the variance in RQ. These results conflict with prior tests using patents (Bound et al 1984) and product counts (Acs and Audretsch 1988, 1990) as the measures of performance.

Thus our results using BRDIS data and the RQ measure yield firm behavior and performance that are consistent with one another: large firms have higher returns to R&D, and also invest more. While these results resolve our first question of prior inconsistency between behavior and returns, they leave open the second question of coexistence of large and small firm R&D. Accordingly we now examine the more nuanced theories regarding differential R&D strategies across firm size.

Impact of Scale on Uni-dimensional R&D Strategy. As noted previously, we would like to formally account for the impact of scale on choice of firm strategy via treatment models. However prior to estimating those models, we first conduct separate tests of the impact of scale on choice of uni-dimensional strategy and the impact of strategy on behavior and performance. Table 2 presents results for simple tests of size on R&D strategy; Table 3 presents results for simple tests of R&D strategy on R&D spending; and Table 4 presents results for simple tests of R&D strategy on RQ. Table 2 reveals there are a number of strategies that appear to be correlated with scale. In particular, scale increases the extent of basic research, the likelihood of product, service and process innovation and the extent of sales from incremental innovation. In contrast, scale decreases the extent of sales from new to market innovation.

The basic research result is consistent with expectations from Nelson (1959), the process innovation result is consistent with expectations and Cohen and Klepper (1996) and the incremental innovation result is consistent with Rosen (1991). Thus scale does indeed affect choice of R&D strategy in the manner suggested by theory.

Insert Tables 2-4 about here

Looking next at the impact of strategy on behavior (R&D investment), Table 3 reveals that R&D investment increases with scale for all strategies at about the same rate (combined coefficient for scale and scale*strategy are roughly 0.6 to 0.7 for all strategies.

Looking next at performance, Table 4 reveals that all R&D strategies have comparable returns to scale within class, e.g., for type, the coefficient is about 0.02, and for riskiness it's about 0.015. The exception is horizon: development (0.022) has about twice the returns of basic (0.014) and applied research (0.013). Most importantly, there is no strategy whose returns decrease in scale (the coefficient on scale is always positive). In other words, there is no strategy that favors small firms. There are merely strategies that penalize small firms less.

It is evident from Table 2 that firm strategy is substantially driven by firm size—thus the results in Tables 3 and 4 are likely biased. To account for that, we perform two stage selection tests. However before doing so, we rethink the strategy variables. Results in tables 2 through 4 implicitly assume that firms treat each uni-dimensional strategy as independent. It seems more likely strategies are complementary such that firms choose strategy bundles. We examine that possibility before proceeding.

R&D Strategy archetypes. We conduct cluster analysis of the three uni-dimensional strategies within each main strategy category (horizon, riskiness and form) to create strategy "archetypes". To generate the archetypes, we follow a two-step process. In the first step, we create nine separate groupings, ranging from a minimum of two clusters to a maximum of ten, and compare the Calińsky and Harabasz pseudo-F index across each grouping. Because the F-scores are similar across several groupings, in the second step we examine the content of each grouping in selecting our final cluster sizes. The objective of this second step is to ensure that the automatically-generated clusters also conform to observed strategic groupings in management practice. While our reported clusters are based on kmeans partition cluster analysis, we also test groupings based on kmedians, agglomerative hierarchical clustering methods, and the examination of dendograms, which produce qualitatively similar results. The analysis yields five archetypes for horizon, six for riskiness and seven for form. These archetypes are characterized in Table 5.

Insert Table 5 about here

Table 5a reveals that horizon clustered into five archetypes: BAD1 through BAD5. Each archetype has a fairly intuitive interpretation. BAD1: principally development, with some applied research; BAD2: applied/development balance; BAD3: exclusively development; BAD4: principally basic research; and BAD5: principally applied research. Note that BAD4 and BAD5 are rare, comprising 30 and 60 firms, respectively, while BAD3 is most prevalent (50% of firms).

Table 5b reveals that riskiness clustered into six archetypes: OWN1 through OWN6. As with horizon, each archetype has a fairly intuitive interpretation. OWN1: principally new to market; OWN2: principally new to firm; OWN3: new to market/incremental balance; OWN4: New to firm/incremental balance; OWN5: exclusively incremental; OWN6: principally incremental. OWN1 and OWN2 are relatively rare, comprising 90 and 70 firms, respectively, while OWN5 is most prevalent with 47% of firms.

Finally, Table 5c reveals that type clustered into seven archetypes: PSP1 through PSP6. As with horizon, each archetype has a fairly intuitive interpretation. PSP1: balance across all types; PSP2: exclusively product; PSP3: exclusively process; PSP4: exclusively service; PSP5: product/service balance; PSP6: product/process balance; PSP7: service/process balance. PSP3, 4, 6 and 7 are relatively rare, comprising 10, 20, 80 and 60 firms, respectively, while PSP1 is most prevalent with 52% of firms.

Having defined the strategy archetypes, we now estimate the two-stage treatment models to understand the extent to which strategy (rather than scale) is driving behavior and performance. We construct separate models for each of the eighteen archetypes. In each model, stage 1 captures the selection effects of scale (Sales) on choice of strategy archetype, and stage 2 captures the treatment effect of the strategy archetype on behavior and performance. We estimate each model using Stata command, treatreg. Results for the two-stage treatment tests are captured in Tables 6-8.

Insert Tables 6-8 about here

Table 6 presents the treatment model for the horizon archetypes. The results indicate that the only significant treatment effects are for BAD5 (principally applied). The stage 1 models indicate that likelihood of choosing BAD5 decreases with scale, and that it leads to lower R&D and lower RQ after taking into account the impact of firm size on choice of strategy. Moreover, BAD5 generates lower returns per dollar of R&D. Thus BAD5 appears to be a preferred strategy for small firms, and while it is associated with lower R&D investment (Model 5), it has lower returns per dollar of R&D (Model 15). While the results are not significant, the strategy with the highest RQ appears to be BAD2 (balance). Moreover, its likelihood increases with scale.

Table 7 presents the treatment model for the riskiness archetypes. The Stage 1 models indicate that scale increases the likelihood of choosing OWN5 (exclusively incremental). The stage 2 models indicate that OWN 5 has significantly higher returns even after controlling for the selection by larger firms. The stage 1 models also indicate small firms are more likely to follow new product archetypes (OWN1-3). The stage 2 models indicate these strategies have lower returns after controlling for selection by smaller firm size.

Table 8 presents the treatment model for the form archetypes. The Stage 1 models indicate that scale increases the likelihood of choosing PSP1 (balance across product, service and process innovation). The stage 2 models indicate that PSP1 has significantly higher returns even after controlling for the selection by larger firms. The stage 1 models also indicate small firms are more likely to follow product archetypes (PSP2, 5, 6), and that these strategies have lower returns after controlling for selection by smaller firm size.

Thus the treatment models reinforce results from the tests of main effects. Large firms choose strategies whose returns increase most with scale. Thus firms are rational in their choice of R&D strategy. The treatment models also indicate there are no strategies that favor small firms. Small firms choose strategies whose returns are lower even after accounting for their smaller size.

IV. Summary

Our main tests of firm size replicated prior results indicating R&D spending increases with size, but conflicted with prior results indicating small firms have higher R&D productivity. Our results indicate R&D productivity, like R&D spending, increases with firm size. Thus large firms are behaving rationally. The difference in our results versus prior results likely stem from use of RQ, an outcome measure that accommodates all forms of R&D, versus product/patent counts (which largely ignore process and incremental innovation). Accordingly our results resolve the first question of the seemingly irrational behavior of large firms.

This leaves the second question of why small firms conduct R&D. To understand that, we first turned to recent theory suggesting that small firms and large firms differ in their type of R&D, and that the returns to type might vary with size. Accordingly we examined choice of R&D strategy as well as the productivity of R&D strategies as a function of firm size. We indeed found that firm size affected choice of R&D strategy. In particular, scale increased the likelihood of incremental R&D (consistent with Rosen), 1991, process R&D (consistent with Cohen and Klepper, 1996) and balanced horizon (consistent with Nelson 1959). However we also found scale increased the likelihood of product and service R&D—indeed the most likely large firm "type" strategy was a balance across product/service/process. This result differs from Cohen and Klepper who found that small firms preferred product R&D. The difference likely stems from the fact that the BRDIS measures for type are fairly crude: "did you introduce an innovation (of the given type) in past three years?" In contrast Cohen and Klepper measure the extent of product and process R&D.

Somewhat surprisingly each of these strategies had higher returns even after controlling for selection effects. Thus while Rosen and Cohen and Klepper are correct that small firms choose different strategies, it is not the case these strategies favor small firms. Rather the strategies appear to be ones for which the small firm penalty is less severe.

Thus we are still left with the question of why small firms conduct R&D. Theory offers one additional insight—spillovers. Spence (1984) presented a theory of spillovers as a substitute for R&D. However his model and much of the subsequent empirics have assumed the spillover pool is shared equally by all firms in the industry—both the size of the pool (excluding the focal firm), and the ability to exploit knowledge in the pool. If correct, then spillovers won't compensate for the small firm disadvantage.

However more recent work, motivated by macro models of heterogeneous firms, e.g., Jovanovic and MacDonald 1994, has proposed that spillover pools are asymmetric (Knott 2003). In this view, flows are directional, such that firms at the frontier have no one to learn from, while small firms can learn from almost the entire industry. In addition to work proposing spillovers are asymmetric, is work proposing firms differ in their ability to exploit spillover pools (Cohen and Levinthal 1989, Acs, Audretsch and Feldman 1994, Knott 2003). Empirical work supports both hypotheses (Knott, Posen and Wu 2009). Given that, we next test the extent to which spillovers compensate for small firm disadvantages with their own R&D.

Table 9 mimics Table 1, but examines the spillover pool (ln(uppersum) and SQ rather than own R&D and RQ). SQ (short for spillover quotient) is the estimated firm-specific output elasticity of spillovers (the sum of ($\beta 4 + \beta 4i$) in equation 1. Thus it is the percentage increase in output associated with a 1% increase in spillovers. Table 9 indicates the coefficient on scale in the spillover pool regression is negative and significant. This is largely due to the manner in which spillover pools are constructed. Thus the role of the regression is principally to define expected pool size as a function of scale. In contrast, the coefficient on scale in the SQ regression is positive and significant. The combination of results indicates that while the size of the spillover pool decreases with size that the ability to exploit the pool increases with size. Looking across all our results, the spillover pool is the only variable whose effect decreases with scale. Thus spillovers are the only "strategy" of those tested, that favors small firms. Accordingly, spillovers can partially explain why small firms conduct R&D despite their scale disadvantages.

Insert Table 9 about here

V. Conclusion

There has been a long-standing debate regarding the impact of firm size on innovation. Stylized facts indicate R&D spending increases with size, while R&D productivity decreases with size. This creates a puzzle of large firm irrationality. One possible explanation for the puzzle is that firm size affects the type of R&D firms conduct, and that the productivity of types differs with firm size. Until recently, we have been unable to comprehensively test these views because we lacked firm-level data on the type of R&D firms conduct, and because the most common measures of R&D outcomes (product and patent counts) embed type.

We exploited recent developments to test these more nuanced views of innovation and firm size. In particular, we utilized a recently created dataset (BRDIS) to solve the data availability problem and a recent measure of R&D productivity (RQ) to solve the measurement problem. The BRDIS data and the RQ measure allowed us to conduct a series of tests examining the relationship between firm size, R&D strategy, R&D investment and R&D performance (RQ).

We found first that R&D spending and R&D productivity both increase with firm size. This reconciles the puzzle of large firm irrationality. While the spending result is consistent with prior studies, the productivity result conflicts with them. We believe the conflict stems from the fact that prior results rely upon "type-specific" (product and patent count) measures of R&D productivity that undercount the types of R&D done by large firms.

We found second that firm size does indeed affect choice of R&D strategy as expected in theories proposed by Nelson, Rosen and Cohen & Klepper. All three theories correctly predicted the strategies preferred by large firms. However the unexpected finding was that no strategy favored small firms, there were merely strategies that penalized their scale less. This left the question, "why do small firms conduct R&D?"

Given there was no strategy favoring small firms, we could identify only one other factor that might account for small firms conducting R&D—that they benefit disproportionately from spillovers. We explored that possibility by characterizing the impact of scale on both the size of a firm's spillover pool and the elasticity of output with respect to that spillover pool. We found that the size of the spillover pool decreases with scale, but that the elasticity of the pool increases with scale. Thus small firms do appear to have one advantage relative to large firms—larger spillover pools.

Beyond reconciling the first puzzle of irrational large firms, and providing insight into the second puzzle of why small firms conduct R&D, our results offer a broader implication: that large firms are the chief engine of innovation (and accordingly economic growth). Thus Schumpeter (1942) was correct. Not only do large firms (using the US Small Business Association definition of greater than 500 employees) conduct 5.75 more R&D in aggregate than small firms, they have 13% higher productivity with that R&D. However this merely captures their private returns to R&D. Perhaps an even greater benefit of large firm R&D is that it generates the spillovers upon which small firm innovation free-rides.

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TABLE 0. Data Summary
Observations=2030

Variable	Mean	Std. Dev.
Sales (4-year average, log)	11.803	2.137
Employees (4-year average, log)	6.193	1.900
R&D (4-year average, log)	8.595	1.951
spillover (log)	12.450	4.570
R&D Intensity (4-year average)	0.259	2.993
RQ (4-year average)	0.264	0.048
SQ (4-year average)	-0.024	0.016
Development R&D (4-year average, percent)	4.198	9.074
Applied R&D (4-year average, percent)	14.711	17.811
Basic R&D (4-year average, percent)	81.091	20.826
Process R&D (4-year average, percent)	0.582	0.370
Product R&D (4-year average, percent)	0.771	0.322
Service R&D (4-year average, percent)	0.330	0.368
R&D Incremental (4-year average, percent)	76.879	25.613
R&D New-to-Market (4-year average, percent)	12.022	19.079
R&D New-to-Firm (4-year average, percent)	11.099	17.382

TABLE 1. Main Effects of Firm Size

	Dependent Variable					
	ln(R&D)	ln(R&D)	ln(R&D /Sales)	ln(R&D /Sales)	RQ	RQ
ln(Sales)	**0.621**		**-0.374**		**0.014**	
	0.019		0.019		0.001	
ln(Employees)		**0.717**		**-0.325**		**0.009**
		0.018		0.019		0.001
Constant	**1.263**	**4.152**	**1.081**	**-1.318**	**0.094**	**0.210**
	0.219	0.111	0.217	0.124	0.006	0.004
R-squared	0.463	0.488	0.239	0.143	0.412	0.120
N	2030	2030	2030	2030	2030	2030

All variables are four year (2008-2011) means

TABLE 2. Main Effects Of Firm Size On Uni-Dimensional R&D Strategy

	Dependent Variable																	
	%basic	%basic	% applied	% applied	% Develo pment	% Develo pment	prob: product	prob: product	prob: service	prob: service	prob: process	prob: process	New to market- %sales	New to market- %sales	New to firm- %sales	New to firm- %sales	incre mental- %sales	incre mental- %sales
ln(Sales)	**0.760**		0.221		-0.338		**0.086**		**0.177**		**0.219**		**-1.047**		-0.329		**1.624**	
SE	0.177		0.242		0.275		0.043		0.022		0.032		0.264		0.249		0.306	
ln(Employees)		**0.909**		0.280		-0.445		0.069		**0.229**		**0.278**		**-0.756**		-0.280		**1.336**
SE		0.199		0.272		0.310		0.048		0.026		0.038		0.299		0.279		0.345
Constant	**-11.704**	**-8.364**	**8.386**	**9.248**	**88.680**	**87.447**	**1.614**	**2.187**	**-1.802**	**-1.129**	**-0.865**	**0.010**	**19.629**	**11.940**	**10.441**	**8.283**	**59.359**	**70.256**
SE	2.177	1.346	2.917	1.779	3.321	2.024	0.503	0.302	0.266	0.162	0.364	0.220	3.177	1.940	3.000	1.815	3.667	2.231
R2	0.002	0.002	0.000	0.000	0.000	0.000	0.004	0.002	0.024	0.031	0.029	0.034	0.001	0.000	0.000	0.000	0.002	0.001
observations	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030

TABLE 3. Impact Of Uni-dimensional R&D Strategy On R&D Spending

Dependent variable=ln(R&D)

	strategy								
	%basic	% applied	% Development	P(product)	P(service)	P(process)	New to market-%sales	New to firm-%sales	incremental-%sales
strategy	0.007	**0.048**	**-0.038**	**-4.047**	**-2.050**	**-2.889**	**0.027**	**-0.021**	**-0.015**
	0.017	0.009	0.008	0.556	0.479	0.510	0.007	0.010	0.006
strategy*ln(sales)	0.000	**-0.003**	**0.003**	**0.337**	**0.210**	**0.218**	-0.001	**0.002**	0.000
	0.001	0.001	0.001	0.047	0.039	0.043	0.001	0.001	0.001
ln(sales)	**0.609**	**0.672**	**0.373**	**0.346**	**0.506**	**0.478**	**0.639**	**0.583**	**0.614**
	0.017	0.020	0.056	0.040	0.022	0.032	0.018	0.018	0.041
constant	**1.337**	0.563	**4.316**	**4.487**	**2.390**	**3.043**	**0.780**	**1.558**	**2.323**
	0.203	0.241	0.659	0.467	0.261	0.367	0.217	0.218	0.469
R-squared	0.431	0.439	0.437	0.446	0.446	0.442	0.461	0.438	0.461

TABLE 4. Impact Of Uni-dimensional R&D Strategy On RQ

Dependent variable=RQ

	strategy								
	%basic	% applied	% Development	P(product)	P(service)	P(process)	New to market- %sales	New to firm- %sales	incremental- %sales
strategy	-0.00060	**-0.00130**	**0.00100**	**0.08500**	**0.06100**	**0.07200**	**-0.00100**	**0.00060**	**0.00060**
	0.00040	0.00020	0.00020	0.01400	0.01200	0.01300	0.00010	0.00025	0.00010
strategy*ln(sales)	0.00004	**0.00010**	**-0.00009**	**-0.00700**	**-0.00700**	**-0.00700**	**0.00007**	**-0.00007**	**-0.00003**
	0.00004	0.00002	0.00002	0.00100	0.00090	0.00100	0.00001	0.00002	0.00001
ln(sales)	**0.014**	**0.013**	**0.022**	**0.020**	**0.018**	**0.019**	**0.013**	**0.015**	**0.016**
	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.001
constant	**0.097**	**0.116**	0.008	**0.028**	**0.062**	**0.047**	**0.114**	**0.088**	**0.052**
	0.005	0.006	0.016	0.011	0.006	0.009	0.005	0.005	0.012
R-squared	0.412	0.421	0.420	0.423	0.442	0.423	0.434	0.417	0.430

Table 5. Strategy Archetypes

		CLUSTER MEANS (*STDEV*)		
	Firms	BASIC %	APPLIED %	DEVELOP MENT %
BAD1	630	5.13	16.96	77.91
		6.75	*6.26*	*6.32*
BAD2	290	8.12	37.42	54.46
		8.60	*9.65*	*8.64*
BAD3	1020	0.89	2.85	96.27
		2.31	*3.60*	*4.37*
BAD4	30	51.17	14.53	34.30
		23.91	*13.78*	*19.89*
BAD5	60	5.57	79.79	14.63
		8.27	*15.29*	*12.09*
TOTAL	2030	4.20	14.71	81.09
		9.07	*17.81*	*20.83*

		CLUSTER MEANS (*STDEV*)		
	Firms	NEW TO MARKET %	NEW TO FIRM %	INCRE-MENTAL %
OWN1	90	81.01	6.08	12.91
		13.93	*9.80*	*11.15*
OWN2	70	12.31	78.94	8.75
		17.19	*20.16*	*11.10*
OWN3	160	39.77	14.29	45.94
		9.90	*12.96*	*12.53*
OWN4	180	8.70	33.54	57.76
		8.04	*10.14*	*10.35*
OWN5	960	2.17	2.48	95.35
		2.92	*3.19*	*4.10*
OWN6	570	11.25	9.82	78.93
		7.94	*6.85*	*5.76*
TOTAL	2030	12.02	11.10	76.88
		19.08	*17.38*	*25.61*

		CLUSTER MEANS (*STDEV*)		
	Firms	PRODUCT	SERVICE	PROCESS
PSP1	1050	0.81	0.70	0.56
		0.29	*0.32*	*0.32*
PSP2	190	0.73	0.00	0.00
		0.30	*0.00*	*0.00*
PSP3	10	0.00	0.00	0.50
		0.00	*0.00*	*0.30*
PSP4	20	0.00	0.47	0.00
		0.00	*0.26*	*0.00*
PSP5	620	0.84	0.64	0.00
		0.24	*0.30*	*0.00*
PSP6	80	0.69	0.00	0.49
		0.31	*0.00*	*0.28*
PSP7	60	0.00	0.67	0.68
		0.00	*0.28*	*0.32*
TOTAL	2030	0.77	0.33	0.58
		0.32	0.37	0.37

TABLE 6. Two Stage Treatment Test Of Horizon Archetypes

	Dependent Variable														
	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	RQ	RQ	RQ	RQ	RQ
Ibad_1	69.341					-40.789					1.574				
	36.998					*21.906*					*0.842*				
Ibad_2		246.277					-148.801					5.745			
		364.497					*220.004*					*8.492*			
Ibad_3			-97.356					58.594					-2.254		
			79.222					*47.861*					*1.837*		
Ibad_4				-253.149					171.390					-6.473	
				165.130					*111.402*					*4.207*	
Ibad_5					**-80.589**					**69.709**					**-2.569**
					24.919					*21.396*					*0.788*
Constant	-12.912	-26.622	57.273	12.715	11.059	9.322	17.949	-32.626	-6.118	-5.460	-0.224	-0.558	1.391	0.369	0.342
	11.497	*52.158*	*39.626*	*2.780*	*0.823*	*6.807*	*31.481*	*23.939*	*1.876*	*0.707*	*0.262*	*1.215*	*0.919*	*0.071*	*0.026*
Treatment – ln(Sales)	0.025	0.009	-0.016	-0.025	**-0.052**	0.025	0.009	-0.016	-0.025	**-0.052**	0.025	0.009	-0.016	-0.025	**-0.052**
	0.014	*0.016*	*0.013*	*0.032*	*0.027*	*0.014*	*0.016*	*0.013*	*0.032*	*0.027*	*0.014*	*0.016*	*0.013*	*0.032*	*0.027*
Constant	**-0.788**	**-1.179**	**0.189**	**-1.849**	**-1.273**	**-0.788**	**-1.179**	**0.189**	**-1.849**	**-1.273**	**-0.788**	**-1.179**	**0.189**	**-1.849**	**-1.273**
	0.163	*0.192*	*0.156*	*0.382*	*0.309*	*0.163*	*0.192*	*0.156*	*0.382*	*0.309*	*0.163*	*0.192*	*0.156*	*0.382*	*0.309*
lambda	-41.951	-133.730	60.918	100.029	**34.780**	24.792	80.698	-36.776	-67.415	-29.878	-0.955	-3.115	1.412	2.549	**1.104**
	22.434	*197.836*	*49.644*	*65.136*	*10.712*	*13.283*	*119.410*	*29.992*	*43.942*	*9.198*	*0.511*	*4.609*	*1.151*	*1.659*	*0.339*
rho	-1.000	-1.000	1.000	1.000	1.000	1.000	1.000	-1.000	-1.000	-1.000	-1.000	-1.000	1.000	1.000	1.000
sigma	32.017	86.260	48.617	32.120	14.014	18.957	52.065	29.371	21.669	12.033	0.729	2.010	1.127	0.818	0.443
Prob>chi2	0.061	0.499	0.219	0.125	0.001	0.063	0.499	0.221	0.124	0.001	0.062	0.499	0.220	0.124	0.001
N	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030

TABLE 7. Two Stage Treatment Test Of Riskiness Archetypes

	Dependent Vaariable																	
	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	RQ	RQ	RQ	RQ	RQ	RQ
Iown_1	**-36.84**						**26.75**						**-1.07**					
	6.18						4.23						0.17					
Iown_2		**-91.85**						**59.62**						**-2.25**				
		29.65						19.00						0.72				
Iown_3			**-65.16**						**42.87**						**-1.63**			
			21.05						13.68						0.52			
Iown_4				-988.35						519.94						-20.56		
				4614.19						2425.38						95.91		
Iown_5					**31.17**						**-18.63**						**0.72**	
					8.23						4.75						0.18	
Iown_6						-2505.41						1458.84						-56.14
						46932.04						27328.10						1051.61
Constant	**10.16**	**11.81**	**13.80**	**96.81**	**-6.08**	**716.48**	**-4.46**	**-5.42**	**-6.75**	-49.73	**5.44**	-415.52	**0.31**	**0.34**	**0.39**	2.10	-0.07	16.13
	0.31	1.11	1.73	411.87	3.89	13260.41	0.22	0.71	1.12	216.49	2.25	7721.41	0.01	0.03	0.04	8.56	0.09	297.13
Treatment – ln(Sales)	**-0.08**	**-0.05**	**-0.05**	0.00	**0.05**	0.00	**-0.08**	**-0.05**	**-0.05**	0.00	**0.05**	0.00	**-0.08**	**-0.05**	**-0.05**	0.00	**0.05**	0.00
	0.02	0.03	0.02	0.02	0.01	0.01	0.02	0.03	0.02	0.02	0.01	0.01	0.02	0.03	0.02	0.02	0.01	0.01
Constant	**-0.75**	**-1.21**	**-0.84**	**-1.31**	**-0.67**	**-0.57**	**-0.75**	**-1.21**	**-0.84**	**-1.31**	**-0.67**	**-0.57**	**-0.75**	**-1.21**	**-0.84**	**-1.31**	**-0.67**	**-0.57**
	0.27	0.30	0.23	0.22	0.16	0.17	0.27	0.30	0.23	0.22	0.16	0.17	0.27	0.30	0.23	0.22	0.16	0.17
lambda	**17.21**	**40.54**	**32.50**	497.93	**-19.80**	1502.15	**-11.59**	**-25.85**	**-21.04**	-261.72	**11.35**	-874.69	**0.47**	**0.98**	**0.81**	10.35	**-0.44**	33.66
	2.79	12.99	10.44	2324.06	5.15	28139.10	1.91	8.32	6.78	1221.61	2.98	16385.14	0.08	0.31	0.26	48.31	0.12	630.52
rho	1.00	1.00	1.00	1.00	-1.00	1.00	-1.00	-1.00	-1.00	-1.00	1.00	-1.00	1.00	1.00	1.00	1.00	-1.00	1.00
sigma	7.82	17.06	17.82	281.86	15.81	1128.01	5.35	10.93	11.58	148.15	9.13	656.83	0.21	0.41	0.44	5.86	0.35	25.28
Prob>chi2	0.00	0.00	0.00	0.83	0.00	0.96	0.00	0.00	0.00	0.83	0.00	0.96	0.00	0.00	0.00	0.83	0.00	0.96
N	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030	2030

TABLE 8. Two Stage Treatment Test Of Form Archetypes

Dependent Variable

	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)
Ipsp_1	**12.9149**						
	1.3749						
Ipsp_2		**-28.2084**					
		4.4254					
Ipsp_3			-747.7068				
			765.0867				
Ipsp_4				-287.0797			
				178.2907			
Ipsp_5					**-27.4149**		
					5.8354		
Ipsp_6						**-54.1700**	
						11.5176	
Ipsp_7							-257.1411
							217.2868
Constant	**1.9149**	**11.1685**	**12.6508**	**11.9926**	**16.9630**	**10.8390**	**15.6958**
	0.7249	*0.4432*	*4.3255*	*2.2196*	*1.8023*	*0.5354*	*6.0728*
Treatment – ln(Sales)	**0.1252**	**-0.1146**	-0.0301	-0.0362	**-0.0644**	**-0.0961**	-0.0184
	0.0137	*0.0209*	*0.0531*	*0.0389*	*0.0142*	*0.0267*	*0.0265*
Constant	**-1.4302**	-0.0192	**-2.1975**	**-1.8420**	0.2459	**-0.6349**	**-1.7018**
	0.1632	*0.2385*	*0.6198*	*0.4542*	*0.1684*	*0.3036*	*0.3147*
lambda	**-7.8300**	**14.4034**	259.8887	108.8053	**16.2697**	**24.6228**	108.8401
	0.8606	2.2553	265.8792	67.6862	3.5327	5.2040	91.8959
rho	-1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
sigma	6.3304	8.2396	54.9463	31.0286	12.4189	10.9431	42.1954
Prob>chi2	0.0000	0.0000	0.3284	0.1074	0.0000	0.0000	0.2366
N	2030	2030	2030	2030	2030	2030	2030

	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)	ln(R&D /Sales)
Ipsp_1	**-7.8622**						
	0.9178						
Ipsp_2		**20.7518**					
		3.2454					
Ipsp_3			510.9059				
			522.6124				
Ipsp_4				221.7198			
				138.2809			
Ipsp_5					**17.2780**		
					3.8820		
Ipsp_6						**40.4271**	
						8.4941	
Ipsp_7							185.3555
							156.3688
Constant	**0.7376**	**-5.2222**	**-6.1004**	**-5.9531**	**-8.6029**	**-5.0037**	**-8.4475**
	0.4839	*0.3250*	*2.9547*	*1.7215*	*1.1990*	*0.3948*	*4.3702*
Treatment – ln(Sales)	**0.1252**	**-0.1146**	-0.0301	-0.0362	**-0.0644**	**-0.0961**	-0.0184
	0.0137	*0.0209*	*0.0531*	*0.0389*	*0.0142*	*0.0267*	*0.0265*
Constant	**-1.4302**	-0.0192	**-2.1975**	**-1.8420**	0.2459	**-0.6349**	**-1.7018**
	0.1632	*0.2385*	*0.6198*	*0.4542*	*0.1684*	*0.3036*	*0.3147*
lambda	**5.0558**	**-10.4702**	-177.4676	-84.3608	**-10.7405**	**-18.0763**	-78.2965
	0.5745	1.6540	181.6157	52.4969	2.3501	3.8379	66.1322
rho	1.0000	-1.0000	-1.0000	-1.0000	-1.0000	-1.0000	-1.0000
sigma	4.2259	6.0426	37.5325	24.0655	8.2616	8.0705	30.3656
Prob>chi2	0.0000	0.0000	0.3283	0.1088	0.0000	0.0000	0.2359
N	2030	2030	2030	2030	2030	2030	2030

	RQ	RQ	RQ	RQ	RQ	RQ	RQ
Ipsp_1	**0.3006**						
	0.0336						
Ipsp_2		**-0.7734**					
		0.1209					
Ipsp_3			-18.8561				
			19.2832				
Ipsp_4				-7.8591			
				4.8850			
Ipsp_5					**-0.6623**		
					0.1457		
Ipsp_6						**-1.4898**	
						0.3128	
Ipsp_7							-6.4863
							5.4649
Constant	**0.1084**	**0.3345**	**0.3662**	**0.3569**	**0.4660**	**0.3256**	**0.4430**
	0.0177	*0.0121*	*0.1090*	*0.0608*	*0.0450*	*0.0145*	*0.1527*
Treatment – ln(Sales)	**0.1252**	**-0.1146**	-0.0301	-0.0362	**-0.0644**	**-0.0961**	-0.0184
	0.0137	*0.0209*	*0.0531*	*0.0389*	*0.0142*	*0.0267*	*0.0265*
Constant	**-1.4302**	-0.0192	**-2.1975**	**-1.8420**	0.2459	**-0.6349**	**-1.7018**
	0.1632	*0.2385*	*0.6198*	*0.4542*	*0.1684*	*0.3036*	*0.3147*
lambda	**-0.1911**	**0.3958**	6.5504	2.9823	**0.4063**	**0.6708**	2.7376
	0.0211	0.0616	6.7012	1.8545	0.0882	0.1413	2.3113
rho	-1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
sigma	0.1549	0.2252	1.3849	0.8501	0.3101	0.2972	1.0612
Prob>chi2	0.0000	0.0000	0.3281	0.1076	0.0000	0.0000	0.2353
N	2030	2030	2030	2030	2030	2030	2030

TABLE 9. Main Effects Of Scale On Spillovers And SQ

	Dependent Variable			
	ln(uppersum)	ln(uppersum)	SQ	SQ
ln(Sales)	**-0.652**		**0.004**	
SE	0.045		0.000	
ln(Employees)		**-0.743**		**0.003**
SE		0.051		0.000
Constant	**20.144**	**17.056**	**-0.074**	**-0.040**
SE	0.543	0.329	0.002	0.001
R2	0.093	0.095	0.319	0.095
N	2030	2030	2030	2030