Reconciling the Firm Size and Innovation Puzzle

by

Anne Marie Knott
Washington University

Carl Vieregger
Drake University

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Abstract

There is a prevailing view in both the academic literature and the popular press that firms need to behave more entrepreneurially. This view is reinforced by a stylized fact in the innovation literature that R&D productivity decreases with size. However, there is a second stylized fact in the innovation literature that R&D investment increases with size. Taken together, these stylized facts create a puzzle of seemingly irrational behavior by large firms—they are increasing spending despite decreasing returns. This paper is an effort to resolve that puzzle. We propose and test two alternative resolutions: 1) that it arises from mismeasurement of R&D productivity, and 2) that firm size endogenously drives R&D strategy, and that the returns to R&D strategies depend on scale. We are able to resolve the puzzle under the first tack—using a recent measure of R&D productivity, RQ, we find that both R&D spending and R&D productivity increase with scale. We had less success with the second tack—while firm size affects R&D strategy in the manners expected by theory, there is no strategy whose returns decrease in scale. Taken together, our results are consistent with the Schumpeter view that large firms are the major engine of growth, they both spend more in aggregate than small firms, and are more productive with that spending. Moreover the prescription that firms should behave more entrepreneurially, should be treated with caution—one small firm strategy has lower returns to scale than its large firm counterpart.

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* Knott: Washington University, One Brookings Drive, Campus Box 1156, St Louis, MO 63130 (email: knott@wustl.edu), Vieregger: Drake University, 360 Aliber Hall, 2847 University Ave, Des Moines, IA 50311 (email: carl.vieregger@drake.edu). We gratefully acknowledge support under NSF Award 1246893: The Impact of R&D Practices on R&D Effectiveness.

DISCLAIMERS: Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. One author has a financial interest in amkANALYTICS, a subscription database of firm RQs.
A common prescription in both the academic literature (e.g., Eshima and Anderson 2017) and the popular press (e.g., Shapiro 2011) is that firms should behave more entrepreneurially. Inherent in the prescription is the view that the optimal size for innovation is small firms. This view is so widespread that Sarah Williamson, CEO of FCLT Global, an organization co-founded in 2016 by BlackRock, CPPIB, Dow Chemical, McKinsey, and Tata Sons to encourage a longer-term focus in business and investment decision-making, said that a current ethos among FCLT members (both institutional investors and corporations) is that companies shouldn’t do R&D, because they can later acquire (smaller) firms who have the needed technology. If this view is wrong, and instead Schumpeter (1942) is correct that large firms are the major engine of economic growth, the view itself presents a tremendous risk to that engine.

Accordingly, the question of the optimal firm size for innovation has been one of the most examined in the innovation literature. Arguments favoring large firms begin with Schumpeter’s economies of scale: larger scale amortizes the fixed cost per innovation over more units of output. Other arguments favoring large firms point to the fact they are more effective conducting R&D. 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 (IRI) member firms, it takes 125 funded projects to achieve one commercial success. Large firms are better able to absorb this risk because they can pool it over a broader portfolio of projects. Fourth, having a broad portfolio confers another advantage: technical diversity—typically more projects imply 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 failing for a given application, might have applications elsewhere in the firm.

Arguments favoring small firms typically rely on governance advantages. One such advantage is that small firm compensation systems are better able to align employee behavior with company goals. First, because there are fewer employees it is easier to observe employee behavior directly, and thus design compensation systems tied to behavior. Second, often there is only one group or department in the company, so compensation tied to company-level outcomes
is aligned with group performance. These compensation advantages translate into better ability to both attract and motivate high caliber employees. Indeed Zenger (1994) found that small companies in Silicon Valley were able to attract higher caliber (based on GPA, degrees, awards, publications and patents) employees, and those employees worked more hours than employees in large companies. Beyond hiring and retention advantages, small companies have communication advantages: 1) decision makers are closer both to the technology as well as the customer, so can better link technological possibilities to market needs, 2) there are fewer hierarchical levels, so decision making is more rapid, 3) engineers are in closer proximity to one another, so communicate more frequently, and therefore solve problems more quickly. While this final advantage was first documented by Allen (1977), a more recent study finds it still holds even though researchers now have email and the internet (Liu 2016).

Given compelling arguments for either size to be more effective in conducting R&D, the issue of firm size and innovation became an empirical matter. The consensus from that literature, summarized in Cohen (2010) and elsewhere is that: 1) R&D rises proportionally with firm size, and 2) R&D productivity (innovation per unit of R&D) declines with firm size. Thus, not only has the empirical literature been unable to resolve the firm size debate, it has arrived at a puzzle of seemingly irrational behavior of large firms. This is perhaps best captured by Cohen and Klepper (1996):

“No has been repeatedly found that within many industries, firm R&D effort varies proportionally with firm size. If large firms have no advantage in R&D competition, though, why do they spend proportionally more on R&D than smaller firms? Furthermore, if they generate fewer innovations per dollar of R&D than smaller firms, as has been found repeatedly, why do larger firms conduct proportionally more R&D than smaller firms? Even more fundamentally, how can large firms survive and prosper, especially in R&D intensive industries, if they conduct proportionally more R&D than smaller firms but get less out of their R&D than smaller firms?” (1996:926)

Accordingly, new theories have emerged to explain the empirical puzzle. These “size contingent” theories don’t advocate for a particular firm size. Rather they suggest the two sizes

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1 While it seems awkward to convert continuous size into two discrete classes (large vs small), this follows convention in the theoretical literature, and has an empirical incarnation—the Small Business Administration (SBA)
differ in the type of R&D they conduct, and that the returns to type of R&D 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.

The first of the size contingent theories is that large firms are more likely to conduct basic research. Nelson (1959) argues this is due to a broader technological base, as well as a wider range of products firms are willing to produce if the research identifies opportunities. The second of the size contingent theories addresses the observation that radical innovation tends to decrease with firm size (Mansfield 1981). Rosen (1991) develops a model in which firms separately choose project riskiness and project scale. Because the scale of their output is greater, large firms prefer safer innovation that enhances their existing product lines. In contrast, precisely because they lack scale, small firms require riskier projects that have the potential for greater price premia. The final size contingent theory addresses the observation that process R&D tends to increase with firm size (Link 1982, Scherer 1991). Cohen and Klepper (1996) argue that because process innovation provides lower cost good/services to existing customers, the returns to process innovation increase in ex ante output. In contrast, because the returns to product innovation stem from licensing or sales to new customers, they are independent of ex ante output. Accordingly, large firms favor process innovation, while small firms favor product innovation. Cohen and Klepper (1996) test their model using FTC Line of Business data, and confirm that process share of R&D increases with firm size.

Thus, while empirics have been able to demonstrate that firm R&D strategy conforms to these size contingent strategies, they’ve been unable to show the theories resolve the puzzle. This is because the R&D productivity measures haven’t been closely matched to the theories. As Acs and Audretsch (1987) note: “Virtually all of empirical studies testing the Schumpeterian hypotheses ... have had to rely on deficient measures of innovative activity...or else a proxy measure of innovative output such as patented innovations...measures of patents suffer because not all patented inventions prove to be innovations and many innovations are never patented” (1987:567).

Thus one explanation for the empirical puzzle (the one proffered by the size contingent theories), is that firm size determines the type of R&D firms conduct, and type of R&D determines returns. An alternative explanation for the empirical puzzle is that it is an artifact of threshold of 500 firms, as used by Acs and Audretsch (1988) as well as others.
mismeasurement. R&D productivity in the theories of large firm innovation advantage, e.g., Schumpeter (1942), Rosen (1991) and Cohen and Klepper (1996), pertains to the financial returns to R&D—amortizing the fixed cost of R&D over a greater scale of output. In contrast, the R&D productivity measures used to date to test the theories (innovation counts/R&D) capture something different—the efficiency of generating innovations. If innovations mapped cleanly onto returns, this wouldn’t be a problem, but patents and products have highly variable values. Scherer and Harhoff (2000) report that 10% of patents comprise 80% of the economic value of all patents.

Beyond the concern that count measures are mismatched to theory, is an additional concern that they miss a good deal of large firm innovation. This is because process and incremental innovation (the two forms favored by large firms) don’t show up in trade journals (the source of innovation count measures) and are less likely to be patented. Indeed, Cohen and Klepper (1996) state they don’t examine R&D productivity in their study of product versus product R&D, precisely because process R&D is less likely to be patented.

Note that scholars have acknowledged these concerns, but until now have had no alternative measures (as evidenced by the earlier Acs and Audretsch quote). However, a recent firm-level measure of R&D productivity appears to match the construct in Schumpeter (1942), Rosen (1991) and Cohen and Klepper (1996). RQ (short for research quotient), which we discuss in greater detail in the next section, is the firm-specific output elasticity of R&D (Knott, 2008). Thus, it is the firm-level equivalent of the most common means to measure industry-wide returns to R&D (Hall, Mairesse, & Mohnen, 2010).

We hope to shed new light on the firm size puzzle by using RQ to retest the Schumpeter hypothesis itself—"do large firms have higher returns to R&D?”, as well as to test each of the three size contingent theories. We examine not only whether firm size drives R&D strategy in the manner proposed by each theory (replicating prior tests), but also whether and how size and R&D strategy interact to affect R&D productivity—"do any of the theories resolve the puzzle?”

We find that the Schumpeter hypothesis is upheld when using RQ as the measure of R&D productivity: R&D spending and RQ both increase with scale. With regard to the size contingent theories, our results confirm that firm R&D behavior matches each theory: basic research, process innovation and incremental innovation all increase with scale. However, there were no strategies for which RQ decreased in scale—there were merely strategies for which the
small firm penalty was less severe. Taken together, the results suggest that large firms are rational in their R&D investment, as we would expect. Moreover the results suggest the prior empirical puzzle of irrational large firms was an artifact of mismeasurement, rather than failure to account for the impact of firm size on R&D strategy.

Beyond offering a resolution to the puzzle of irrational large firms, which is important for theory, our results also offer implications for practice. At the policy level, our results suggest it is large firms, rather than small firms, who disproportionately drive innovation (and accordingly economic growth), as anticipated by Schumpeter. 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, our results indicate they have 13% higher productivity with that R&D. Thus they comprise 87% of the economic contribution of industrial R&D. Given that, anti-trust policy may want to consider tradeoffs between the anti-competitive effects of large scale against the innovative benefits of large scale. This is a variant of the Williamson (1968) argument that the efficiency benefits of large firms may outweigh their anti-competitive effects.

Our results also hold implications at the firm level. The prescription for large firms to behave more entrepreneurially (like small firms), should be treated with caution. At least one small firm strategy has lower returns to scale than its large firm counterpart.

The paper proceeds as follows. We first outline our empirical approach, providing greater details on the measurement tack (including the RQ measure itself), the size contingent theory tack, and the data. We next present results, then provide a summary and discuss implications.

II. Empirical Approach

Our empirical approach to resolving the firm size puzzle follows two tacks: 1) utilizing RQ in lieu of patent intensity to see if the puzzle is merely an artifact of mismeasurement, and 2) testing the size contingent theories of firm size and R&D. We first attempt to replicate the stylized fact that R&D productivity decreases with scale when using patent intensity. We then repeat the test using RQ, to see if the puzzle disappears—does R&D productivity increase with scale). Under the second tack of testing the size contingent theories of firm R&D behavior, we first test the impact of scale on the likelihood of employing each strategy. We then examine
the extent to which this endogenous choice of strategy affects R&D productivity, to see if accounting for endogeneity resolves the puzzle—do the residual effects of scale on R&D productivity become insignificant.

2.1 Replicating Stylized Facts

Our first set of empirics attempt to replicate the stylized facts that R&D increases with scale, while R&D productivity (measured as patents per unit of R&D) decreases with scale. Equation 1 examines the main effects of firm scale on behavior (R&D spending), while equation 2 models the main effects of scale on patent intensity. Both models include firm fixed effects and year effects. Our primary dataset for testing equation 1 comes from the COMPUSTAT North American Annual database. However, to test equation 2, we need to merge that with data from the NBER patent database maintained by Hall, Jaffe and Trajtenberg (2001). The database provides detailed information about patent application and grant date, patent assignee, citation information for each patent and a link between patent assignee and COMPUSTAT GVKEY. This database starts in 1976 and ends at 2006.

\[
\ln R_{it} = \beta_0 + \beta_1 \ln Y_{it} + \gamma_i + \delta_t + \epsilon_{it}
\]

\[
Patent\ Intensity_{it} = \beta_0 + \beta_1 \ln Y_{it} + \gamma_i + \delta_t + \epsilon_{it}
\]

Because we later utilize BRDIS (Business R&D and Innovation Survey) data to examine firm behavior, we also test equations 1 and 2 using that data. BRDIS (which we discuss more fully in the data section) is an annual survey of firms’ R&D behavior conducted by the National Science Foundation (NSF) in conjunction with the U.S Census Bureau. A nice feature of BRDIS data for our purposes is that it includes both public and private firms. Thus it allows us to examine firms too small to be included in COMPUSTAT (because they haven’t gone public).

2.2 The Measurement Tack

Once we replicate the stylized fact with COMPUSTAT data and BRDIS data, we then retest equation 2, replacing patent intensity with RQ, a measure that more closely matches the R&D productivity construct in Schumpeter and later theories of large firm R&D advantage:
2.2.1 The RQ measure

The measure we use for this tack is RQ (short for research quotient). RQ is the firm-specific output elasticity of R&D -- the exponent $\gamma_i$ in firm i’s production function (Equation 4) (Knott, 2008). The way to interpret RQ is that it is the percentage increase in revenues from a 1% increase in R&D, when other inputs and their elasticities are held constant. Accordingly, RQ is the firm-level equivalent of the most common means used by economists to measure industry-wide returns to R&D (Hall, Mairesse, & Mohnen, 2010). Since Schumpeter and later theories of large firm advantage consider the financial returns to R&D, RQ more closely matches the R&D productivity construct in those theories.

\[
\begin{align*}
RQ_{it} &= \beta_0 + \beta_1 \ln Y_{it} + \gamma_i + \delta_t + \epsilon_{it} \\
Y_{it} &= A_i K_{it}^{\alpha_i} L_{it}^{\beta_i} R_{it-1}^{\gamma_i} S_{it-1}^{\delta_i} D_{it}^{\phi_i} e_{it}
\end{align*}
\]

RQ was originally developed to control for heterogeneity in firm R&D capability in a test of absorptive capacity (Knott 2008). It is estimated with a random coefficients model of equation 4 (in log form) using successive 7-year windows of firm financial data. This estimation process and its robustness checks are described in the user manual for the Wharton Research Data Services (WRDS) RQ database\(^2\), where we obtained the RQ data for our first set of empirics. The manual describes the theory underpinning RQ, the functional form for all variables, as well as the logic behind those functional forms. It then compares random coefficients (RC) estimates of the R&D production function to four alternative approaches, including efforts to mimic Levinsohn and Petrin (1993) and Blundell and Bond (1998) in attempting to control for the simultaneity concern that R&D and revenues respond in the same way to shocks—thus biasing the R&D coefficient upward. While there is no best way to resolve simultaneity concerns, the RC model seems to fare better than the alternatives.

In addition to better matching the R&D productivity construct in Schumpeter and other theories of large firm R&D advantage, RQ has other nice features. First, it is universal—it can be

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\(^2\) [https://wrds-web.wharton.upenn.edu/wrds/query_forms/navigation.cfm?navId=379](https://wrds-web.wharton.upenn.edu/wrds/query_forms/navigation.cfm?navId=379)
estimated for all firms who conduct R&D. In contrast, fewer than 50% of firms who conduct R&D patent their innovations (Cooper, Knott and Yang 2018). Moreover, RQ captures innovations that firms strategically choose not to patent, such as process innovations. Thus RQ avoids the problem noted by Acs and Audretsch, that not all innovations are patented. Second, RQ is uniform--it essentially compares dollars of output to dollars of input, thus it is unitless. In contrast, patents have highly variable value—10% of patents account for 85% of the economic value of all patents (Scherer & Harhoff, 2000). Thus RQ avoids the problem that patent intensity doesn’t map cleanly onto returns. Finally, RQ is reliable in that empirical tests over 47 years of data indicate its behavior matches propositions from firm-level models of endogenous growth, e.g., Thompson (1996), Lentz and Mortensen (2008): R&D spending, growth and market value all increase significantly with RQ (Knott and Vieregger 2018). In contrast, two of the three propositions fail to hold when using patent intensity as the proxy R&D productivity.

Of course, RQ has limitations. In particular, it can only capture innovation derived from R&D. Thus, it excludes innovation by the approximately 7% of non-R&D firms who report introducing product or service innovations in the prior three years (Boroush 2010). Further RQ can only measure innovation at the business unit level and above (the level at which you can form a production function). Thus, it can’t be used to measure productivity of particular projects. Finally, the fact that it is unitless means it can’t be used to examine the knowledge content or flows of innovation (things patents are particularly well-suited to).

2.3 The Size Contingent Theory Tack

To implement the size contingent theory tack, we first examine whether firm scale drives strategy in the manners predicted by theory. We then examine how the strategies affect R&D productivity. We utilize BRDIS data (which we discuss under Data and Variables) for both sets of examinations. These data have variables that map onto each of the size contingent theories, and also have financial variables that allow us to estimate RQ. The BRDIS variables mapping onto firm strategies are: portfolio horizon (basic, applied, development), which maps onto Nelson 1959, riskiness (new to market, new to firm, incremental), which maps onto Rosen 1991, and form (product, service, process), which maps onto Cohen and Klepper 1996. For each strategy, we examine both the impact of scale on choice of that strategy (nine separate iterations of
equation 5) and the impact of that strategy on R&D productivity (RQ) (nine separate iterations of equation 6).

\begin{align*}
P_{\text{strategy}}(i) &= \beta_0 + \beta_1 \ln Y_{it} + \varepsilon_i \\
RQ_{ij} &= \beta_0 + \beta_1 \text{strategy}_j + \beta_2 \ln Y_{it} + \beta_3 \text{strategy}_j \times \ln Y_{i} + \varepsilon_i
\end{align*}

2.4 Data and Variables

The data to support these tests come from four sources. The first tack utilizes data on publicly traded firms taken from the COMPUSTAT North American Annual database (1976 to 2012), the Wharton Research Data Services (WRDS) RQ database, and data on patent grants taken from the NBER patent database (1976 to 2006) maintained by Hall, Jaffe and Trajtenberg (2001). Data to support the second tack comes from the NSF’s confidential BRDIS survey (2008-2011).

2.4.1 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. 3 Accordingly, BRDIS data support comparisons of innovative behavior and outcomes between the US and other countries.

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3 The Community Innovation Survey (CIS) is a survey of innovation activity in enterprises in EU member states and ESS member countries. It is designed to provide information on the innovativeness of sectors by type of enterprises, on the different types of innovation, and on various aspects of the development of an innovation.  
http://ec.europa.eu/eurostat/web/microdata/community-innovation-survey
To our knowledge, BRDIS (and its predecessor, SIRD) provide the only large scale longitudinal data of US firms’ R&D practices. While there are three other large scale surveys of US R&D: the Yale survey (Levin, Klevorick, Nelson, and Winter 1987), the Carnegie-Mellon survey (Cohen, Nelson, and Walsh 2000), and the Duke/Georgia Tech American Competitiveness Survey (Arora, Cohen and Walsh 2014), each of these is cross sectional. Accordingly, they can’t be matched to RQ estimates (which require multiple years of financial data). Moreover, because BRDIS data is collected by the Census, firms are compelled to respond, and thus the survey enjoys a higher response rate than the other surveys.

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. We restrict attention to those firms.

BRDIS gathers data on a number of R&D variables. The full surveys for each year are available at http://www.nsf.gov/statistics/srvyindustry/#qs, however we focus attention on the variables related to firm size (ln(worldwide sales)), the additional variables required to estimate RQ (ln(worldwide R&D), ln(employees)) and firm R&D practices corresponding to the size contingent theories.

2.4.1.1 BRDIS R&D practices data

BRDIS contains a number of questions related to firms’ R&D practices. Of those, we utilize the three questions that best match the size contingent theories of firm size and R&D.

Theory 1: Large firms are more likely to conduct basic research (Nelson 1959)

The BRDIS question that best addresses this theory, asks: “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”.

If Nelson is correct, we expect the answer to (a) to increase with firm size.

**Theory 2: Radical innovation decreases with scale (Rosen 1991)**

The BRDIS question that best addresses this theory, asks: “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”

The most radical innovations are goods/services that are new to the market (a). These have inherently higher uncertainty of commercial success than ones which are only new to the company (b). These in turn have higher uncertainty than incremental innovation (goods or services which are unchanged or only marginally modified). If Rosen is correct, we expect the answer to (a) to decrease with scale, while we expect the answer to (c) to increase with scale.

**Theory 3: Process innovation increases with scale; while product innovation decreases with scale (Cohen and Klepper 1996)**

The BRDIS question that best addresses this theory, asks: “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)”

If we interpret both new goods and new services as product innovation, and if Cohen and Klepper are correct, then the answers to (a) and (b) should decrease with scale, while the answer to (c) should increase with scale. Note however that this is a coarser measure of product and process innovation than the percentage of each in Cohen and Klepper.

**2.4.1.2 RQ estimation with BRDIS data**
The RQ data to support test of equation 4 come from the WRDS RQ database. These RQ estimates are derived from the North American COMPUSTAT database. Thus, we can match them to firm scale data from COMPUSTAT. In order to test equation 4 for firms in the BRDIS sample, we need to derive RQ from firms’ financial data in BRDIS. We do so using random coefficients estimation of the firm’s production function in accordance with the general methodology described in the WRDS User’s Manual. One complication with estimation using the BRDIS data is that its input variables differ from those collected from firms’10-K filings (the source for COMPUSTAT data on which the RQs in the WRDS RQ database were derived). While revenues, employees and R&D expenditures are the same in both datasets, BRDIS does not collect either capital or advertising. Accordingly, we employ a model of the following form:

\[
\ln Y_{it} = (\beta_1 + \beta_{1i}) + (\beta_2 + \beta_{2i}) \ln L_{it} + (\beta_3 + \beta_{3i}) \ln R_{it-1} + (\beta_4 + \beta_{4i}) \ln S_{it-1} + \varepsilon_{it}
\]

Firm level data items include (in SMM unless otherwise stated): worldwide sales \((Y_{it})\), labor as full-time equivalent employees \((1000) (L_{it})\), and worldwide R&D \((R_{it})\). From these primary data, we derive a secondary measure: firm-specific spillovers \((S_{it})\) which follows the “density above” functional form in the WRDS User’s Manual.

To test the impact of omitted variable bias on RQ estimates when we lack data on capital and advertising, we estimated equation 7 with COMPUSTAT data and compared the RQ estimates to those in the WRDS RQ database that were generated for the same firms using the full set of inputs. That comparison indicates the RQs are 91.7% correlated across the two approaches.

A second restriction of the BRDIS data is that it 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, Cooper, Knott and Yang 2018) used seven and ten-year windows, respectively. Accordingly, we tested the impact of window size using COMPUSTAT data. 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 a 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 longer window.

Because RQ estimation consumes 4 years of data, we have only one observation for RQ (the 4 year mean). Accordingly, we form four-year averages of our scale variable (*worldwide sales*) and our R&D productivity variables (*RQ* and *patent intensity*) as well as the strategy variables. This yields one observation per firm. Accordingly, our analyses with BRDIS data form a cross-section rather than a panel.

Variables

As mentioned previously, our empirics comprise two datasets: 1) a dataset of public firms that combines variables from COMPUSTAT, the WRDS RQ database, and the NBER patent database, and 2) the confidential BRDIS dataset that is only accessible within US Census Research Data Centers (RDCs).

Our public dataset used to test equations 1-3 comprises three variables: firm scale, measured as \( \ln(\text{Revenues}) \) from COMPUSTAT\(^4\), *firm RQ* from the WRDS RQ database, and *patent intensity*. *Patent intensity* is a derived variable formed by dividing *patents granted* from the NBER patent database, by R&D from COMPUSTAT. This matches the “patents per unit of R&D” outcome measure in the stylized facts regarding firm size and innovation. A summary of the resulting dataset of public firms is provided in Table 1a.

We extract a number of variables from the BRDIS dataset. These include the variables necessary to compute RQ: *worldwide sales* \((Y_{it})\), *labor* as full-time equivalent employees \((1000)(L_{it})\), and *worldwide R&D* \((R_{it})\), the number of *patents*, from which we derive *patent intensity* \((\text{patents/worldwide R&D})\). In addition, we include answers to the questions pertaining to the three size contingent theories of firm R&D behavior: *Basic R&D* (% of total R&D), *Applied R&D* (%), and *Development* (%), *New to Market innovation* (% of sales from), *New to firm innovation* (% of sales from), and *Incremental innovation* (% of sales from), and dummy variables for the question: Did your firm introduce any of the following in the past three years (1=yes, 0=no): *Process R&D*, *Product R&D*, and *Service R&D*.

\(^4\) While there are alternative measures of firm scale, such as assets and the number of employees, the size contingent theories of firm R&D behavior pertain to the scale of output rather than inputs.
A summary of the resulting BRDIS dataset is provided in Table 1b.

III. Results

3.1 Replicating stylized facts

Our first set of empirics attempts to replicate the stylized facts that R&D increases with scale, while R&D productivity (measured as patents per unit of R&D) decreases with scale. Table 2 presents results for equation 1 which tests the impact of scale on behavior (R&D spending) (Model 1) and equation 2, which tests the impact of scale on patent intensity (Model 2). Both models utilize the dataset for public firms, and employ firm fixed effects, year effects and robust standard errors clustered at the firm.

Regarding the impact of scale on R&D investment, results indicate that scale is positive and significant in explaining R&D investment. This matches stylized facts. Indeed, scale explains approximately 46% of intra-firm variance in R&D. The coefficient estimate of 0.529 implies that a 10% increase in the revenues increases R&D 5.3%. This is net of firm fixed effects and year effect.

Regarding the impact of scale on R&D productivity, results in Model 2 indicate patent intensity is negative and significant. A 10% increase in revenue decreases patent intensity by 1.1 percentage points. This also matches stylized facts.

To check the robustness of our replication results, we subdivided the sample into large firms and small firms, using the SBA threshold of 500 employees. Models 3 and 4 present results for large firms, while models 5 and 6 present results for small firms. Both sets of results match those for the full sample: R&D investment increases with scale, while R&D productivity (measured as patent intensity) decreases with scale.

Because we later utilize BRDIS data to examine firm behavior, we also test equations 1
and 2 using that data. These results (presented in models 7 and 8) match those for the public sample. Thus, across all samples and subsamples, we are able to replicate the puzzle that R&D investment increases with scale, while R&D productivity decreases with scale.

3.2 The Measurement tack

Our first effort to resolve the puzzle of seemingly irrational large firms, employs a measurement tack to see if the puzzle is merely an artifact of mismeasurement—using an innovation intensity (counts/R&D) measure of R&D productivity to test a theoretical construct of R&D productivity regarding financial returns. To examine that, we retest equation 2, replacing patent intensity with RQ (equation 3).

The results for the measurement tack are presented in Table 3. As in Table 2, Model 1 utilizes the full set of public firms, while Models 2-4 utilize the large firm subsample, the small firm subsample, and the BRDIS sample, respectively. All models indicate that R&D productivity (measured as RQ) increases significantly with scale. The coefficient on scale is fairly consistent across the models (0.02), meaning that a 10% increase in revenues increases RQ by 0.02 points (roughly 20% of the mean value for RQ in the public sample).

Thus, our results using the RQ measure yield firm behavior and outcomes that are consistent with one another and consistent with Schumpeter and later theories of large scale advantage in R&D: R&D investment and R&D productivity both increase with scale. This means our measurement tack offers one resolution of the prior puzzle of seemingly irrational large firms. Large firms invest more in R&D because they obtain higher returns from their R&D.

3.3 The Size Contingent Theory Tack

To explore the second tack, we next examine firms’ R&D strategies. As mentioned previously, these strategies map onto the three size contingent theories of how firm scale affects R&D behavior and productivity. These strategy data are only available in BRDIS, so we utilize that dataset for all these tests. We examine both the impact of scale on choice of strategy
(equation 5) and the impact of strategy on R&D productivity (RQ) (equation 6).

3.3.1. Choice of R&D Strategy

Results for tests of the impact of scale on choice of R&D strategy (Table 4) provide support for all three theories of size contingent R&D strategy. The percentage of R&D devoted to basic research is increasing in scale, consistent with Nelson (1959). The likelihood of introducing a process innovation is also increasing in scale, consistent with Cohen and Klepper (1996). Note however that the likelihood of introducing product and service innovations is also increasing in scale (though the likelihood of process innovation is 2.5 times that for product innovation). The result that all forms of innovation (product, service, process) are increasing in scale can be explained by measure coarseness. The measure equals one if any innovation was introduced in the prior three years. Thus it can’t be used to gauge the share of process R&D relative to product R&D.

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Insert Table 4 about here

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Finally, the extent of incremental innovation is increasing in scale, while the extent of radical innovation is decreasing in scale. Both results are consistent with Rosen’s (1991) theory regarding the impact of scale on the riskiness of R&D.

Thus, all three theories correctly anticipate how scale affects choice of R&D strategy. This is not a surprise since all three theories were motivated by empirical observations.

3.3.2 Impact of R&D Strategy on Outcomes.

Having demonstrated that firm R&D behavior is consistent with the size contingent theories of R&D strategy, we now turn to the question of returns to those (RQ) (Table 5). Each model in Table 5 captures the impact of the strategy identified in the column header. For example, model 1 captures the impact of basic research on RQ. We allow each strategy to have both intercept and slope (with scale) effects. Table 5 reveals that across the set of strategies, the main effects of scale continue to be significant and of similar magnitude to those in Table 2 (0.014). While the coefficients on strategy tend to be significant, the signs on the intercept and slope terms consistently have opposite sign. Thus the role of strategy is to slightly rotate the relationship
between scale and RQ as shown in Figure 1 for the three horizon strategies. However for all strategies, the net returns to R&D increase with scale (with slopes ranging from 0.018 for service innovation to 0.022 for development). Accordingly, there is no strategy favoring small firms. Rather there are merely strategies for which the penalty for small scale is less severe.

Insert Table 5 about here

Insert Figure 1 about here

In robustness checks, we examined treatment effects models of R&D strategy. The goal of these models is to isolate the true treatment effect of R&D strategy on R&D productivity. This is not our interest. Our interest was determining whether the effects of firm size on R&D productivity were completely absorbed by the strategy. Nevertheless, we ran two-stage treatment effects regressions as well as propensity score matching models for each strategy. Those results indicate there were minimal treatment effects. Thus they are consistent with results in Table 5 showing that scale remains the primary determinant of R&D productivity.

Thus, while scale is significant in explaining firms’ R&D strategies, those strategies appear to have little power in explaining the differential R&D productivity of large and small firms. The primary driver of R&D productivity continues to be scale after we take these strategies into account.

IV. Conclusion

There is a prevailing view in both the academic literature and the popular press that firms need to behave more entrepreneurially. This view is reinforced by stylized facts in the innovation literature that R&D spending increases with size, while R&D productivity decreases with size. This creates a puzzle of seemingly irrational behavior by large firms—they are increasing investment despite decreasing returns. This paper was an effort to resolve that puzzle.
One potential resolution (proffered by three prior theories) is that size affects the type of R&D firms conduct, and that the R&D productivity of those types varies with size. Until recently, we have been unable to test these theories, because we lacked a firm-level measure of R&D productivity matched to the construct (financial returns) in theories of large firm R&D advantage. Accordingly, a second potential resolution is that the puzzle is an artifact of prior mismeasurement, that should disappear when using a measure better matched to the theory.

We exploited two recent developments to explore both potential resolutions. In particular, we utilized a recently created dataset (BRDIS) to pursue the size contingent theory tack; and utilized a recent firm-level measure of R&D productivity (RQ) to pursue the measurement tack. Before pursuing either tack however, we first replicated the stylized facts that R&D spending increases with scale, while R&D productivity (measured as patent intensity) decreases with scale, using both a public dataset and the BRDIS dataset.

We then tested whether results changed when utilizing RQ as the measure of R&D productivity, and found indeed that R&D productivity increased with scale. These results held not only with the full sample of public firms, but with large and small firm subsamples of the public dataset, as well as with the BRDIS dataset. Thus the measurement tack offers one resolution of the large firm irrationality puzzle—R&D investment and R&D productivity both increase with scale when using a measure of R&D productivity better matched to theory.

We next examined whether the size contingent theories of how scale affects R&D strategy offered an additional resolution of the puzzle. We found first that firm size does indeed affect choice of R&D strategy in the directions proposed in each of the size contingent theories. In particular, scale increased the likelihood of incremental R&D (consistent with Rosen, 1991), process R&D (consistent with Cohen and Klepper, 1996) and basic research (consistent with Nelson 1959). However, when we looked at the impact of those strategies on R&D productivity, we found that no theory could resolve the puzzle. Each strategy had minimal effect on RQ. Scale remained the dominant factor affecting RQ after controlling for its impact on choice of strategy.

This raises the question of why is scale still significant after accounting for the large firm strategies. It appears that the ability to amortize fixed costs over larger scale output benefits all R&D strategies, including those favored by small firms. As an example, Procter and Gamble (P&G)’s Crest 3D White Strips was a radical product innovation. Thus, it was a “small firm
strategy” along two dimensions. However, the product was able to exploit all P&G’s complementary assets. It sold through the same channels as their Crest toothpaste, so it could exploit the Crest brand, P&G’s sales organization as well as their distribution channels.

There are limitations to these results. In particular, while the results for the measurement tack are robust, in that they span all the samples and subsamples, and include fixed effects and year effects, the results for the size contingent theory tack all rely on cross-sectional data. This is not because BRDIS is inherently cross-sectional, it is because RQ estimation requires multiple years of observations, and this estimation consumed all years of BRDIS data that we had access to. It is remotely possible that the results regarding the impact of practices on R&D productivity may change with panel data. An additional limitation pertains to the product/process strategy results. The BRDIS measures (yes/no) don’t map cleanly onto theory (share of R&D). Accordingly, there may be stronger results for process versus product innovation if we had a better measure.

Beyond reconciling the puzzle of irrational large firms, which is important for theory, our results offer a broader implication for practice. Our results are consistent with Schumpeter’s (1942) view that large firms are the chief engine of innovation (and accordingly economic growth). 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. Thus they comprise 87% of the economic contribution of industrial R&D. However this merely captures the private returns to their R&D. A further benefit of large firm R&D is that it generates the spillovers upon which small firm innovation free-rides (Acs, Audretsch and Feldman 1994). Thus anti-trust policy may want to consider tradeoffs between the anti-competitive effects of large scale against the innovative benefits of large scale. This implication is reminiscent of Williamson’s (1968) argument that the efficiency benefits of scale may outweigh their anti-competitive effects. We add innovation benefits to his efficiency benefits.

Similarly, for firms, the prescription for them to behave more entrepreneurially (like small firms), should be treated with caution. At least one small firm strategy (radical innovation) has lower returns to scale than the large firm counterpart (incremental innovation).
REFERENCES


Knott, A.M. 2008 “R&D Returns Causality: Absorptive Capacity or Organizational IQ” *Management Science* 54 (12) 2054-2067


TABLE 1. Data Summary

Table 1a. Data on Public Firms
Observations = 32608

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Revenue)</td>
<td>5.59</td>
<td>2.55</td>
</tr>
<tr>
<td>ln(R&amp;D)</td>
<td>2.32</td>
<td>2.41</td>
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<tr>
<td>RQ (7-year)</td>
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<td>0.12</td>
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<tr>
<td>Patent intensity</td>
<td>0.02</td>
<td>0.05</td>
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Table 1b. BRDIS Data Summary
Observations = 2030 (rounded)

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<td>Employees (log)</td>
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<tr>
<td>R&amp;D (log)</td>
<td>8.60</td>
<td>1.95</td>
</tr>
<tr>
<td>Spillover (log)</td>
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<td>R&amp;D Intensity</td>
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</tr>
<tr>
<td>RQ</td>
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<td>0.05</td>
</tr>
<tr>
<td>Basic R&amp;D (percent)</td>
<td>4.20</td>
<td>9.07</td>
</tr>
<tr>
<td>Applied R&amp;D (percent)</td>
<td>14.71</td>
<td>17.81</td>
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<tr>
<td>Development R&amp;D (percent)</td>
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<td>20.83</td>
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<td>Process R&amp;D (percent)</td>
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<td>Product R&amp;D (percent)</td>
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<tr>
<td>Service R&amp;D (percent)</td>
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<td>0.37</td>
</tr>
<tr>
<td>R&amp;D Incremental (percent)</td>
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<td>25.61</td>
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<tr>
<td>R&amp;D New-to-Market (percent)</td>
<td>12.02</td>
<td>19.08</td>
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<tr>
<td>R&amp;D New-to-Firm (percent)</td>
<td>11.10</td>
<td>17.38</td>
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<tr>
<td>Patents granted 2008</td>
<td>15.56</td>
<td>116.75</td>
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</table>

* All variables calculated as 4-year average of BRDIS data
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<thead>
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<th>BRDIS data</th>
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<tr>
<td></td>
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<tr>
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<td>In(R&amp;D)</td>
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<tr>
<td></td>
<td>0.529***</td>
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<td></td>
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<td>-1.528***</td>
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### TABLE 3. Test of Measurement Tack

**Dependent Variable:** RQ

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<td><strong>ln(Sales)</strong></td>
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<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
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<td><strong>Constant</strong></td>
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<tr>
<td></td>
<td>(0.024)</td>
<td>(0.026)</td>
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<tr>
<td><strong>Fixed effects</strong></td>
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<td>Yes</td>
</tr>
<tr>
<td><strong>Year effects</strong></td>
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<td>Yes</td>
</tr>
<tr>
<td><strong>R-squared</strong></td>
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<td>0.192</td>
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<td><strong>N</strong></td>
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<td>22051</td>
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### TABLE 4. Impact of Scale on Choice of R&D Strategy

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<th></th>
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<tbody>
<tr>
<td>ln(Sales)</td>
<td>0.760***</td>
<td>0.221</td>
<td>-0.338</td>
<td>0.086*</td>
<td>0.177***</td>
<td>0.219***</td>
<td>-1.047***</td>
<td>-0.329</td>
<td>1.624***</td>
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<td>SE</td>
<td>0.177</td>
<td>0.242</td>
<td>0.275</td>
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<td>0.032</td>
<td>0.264</td>
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<td>88.680***</td>
<td>1.614***</td>
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TABLE 5. Impact of R&D Strategy On RQ

<table>
<thead>
<tr>
<th>Dependent Variable: RQ</th>
<th>Each Model Represents a Different Strategy (N = 2030)</th>
<th>% Basic</th>
<th>% Applied</th>
<th>% Development</th>
<th>Prob: Product</th>
<th>Prob: Service</th>
<th>Prob: Process</th>
<th>% Sales New-to-Market</th>
<th>% Sales New-to-Firm</th>
<th>% Sales Incremental</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
<td>Model 4</td>
<td>Model 5</td>
<td>Model 6</td>
<td>Model 7</td>
<td>Model 8</td>
<td>Model 9</td>
<td></td>
</tr>
<tr>
<td>Strategy</td>
<td>-0.0006</td>
<td>-0.0013***</td>
<td>0.0010***</td>
<td>0.0850***</td>
<td>0.0610***</td>
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<td>-0.0010***</td>
<td>0.0006*</td>
<td>0.0006***</td>
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</tr>
<tr>
<td></td>
<td>(0.0064)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0140)</td>
<td>(0.0120)</td>
<td>(0.0130)</td>
<td>(0.0001)</td>
<td>(0.0003)</td>
<td>(0.0001)</td>
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<tr>
<td>Strategy*ln(Sales)</td>
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<td>0.0070***</td>
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<tr>
<td></td>
<td>(0.0061)</td>
<td>(0.0001)</td>
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<td>(0.0001)</td>
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<td>(0.0001)</td>
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<tr>
<td>ln(Sales)</td>
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<td>0.0126***</td>
<td>0.0220***</td>
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<td>0.0130***</td>
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<td>0.0164***</td>
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<tr>
<td></td>
<td>(0.0064)</td>
<td>(0.0005)</td>
<td>(0.0010)</td>
<td>(0.0001)</td>
<td>(0.0005)</td>
<td>(0.0009)</td>
<td>(0.0004)</td>
<td>(0.0004)</td>
<td>(0.0004)</td>
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<td>0.0880***</td>
<td>0.0550***</td>
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<td>(0.0050)</td>
<td>(0.0060)</td>
<td>(0.0160)</td>
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<td>(0.0060)</td>
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<td>0.420</td>
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<td>0.434</td>
<td>0.417</td>
<td>0.430</td>
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FIGURE 1. Net Effect of Scale on RQ for Horizon Strategies